Evaluation of the degree of policyholder’s risk for the individual’s health insurance coverage

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Abstract: A policyholder’s degree of health risk could be classified as normal or better than normal or high or bad. We examine the relationship between the policyholder’s degree of health risk and the effect of his demographic factors. A quantitative model is proposed to support decision-underwriting of the insurer by segmenting the health insurance underwriting portfolio to four risk groups, which are different and mutually exclusive (low risk, normal risk, high risk, bad risk) based on some demographic factors affecting the degree of risk. The likelihood of the insured to risk groups has been estimated using polynomial logistic regression analysis, and the degree of risk most likely has been determined to take appropriate underwriting decision. This study is based on experience of one of the insurance companies in Saudi Arabia, and the subjects were selected using a random sample for detailed data on individual health insurance during the period 2013–2015, based on the random numbers generated. We found a relationship between the degree of health risk and the policyholder’s demographic factors. Using this result, we were able to calculate the probabilities of affiliation of the insured for various degrees of risk. This paper presents a model for the rationalization of underwriting decisions in health insurance.

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PUBLIC INTEREST STATEMENT
It is one of the most important activities carried out by insurance companies underwriting activity in risks, where underwriting activity means evaluating the degree of risk of the policyholders. This activity involves preparation to calculating the appropriate insurance premium. This paper is concerned with evaluating policyholder’s degree of risk for the individual health insurance coverage, which could be categorized as follows: (1) low risk, (2) normal risk, (3) high risk, (4) bad risk; according to certain demographic factors (age, residency, nationality, marital status, gender, occupation, and family history) affecting the degree of risk. The results of this paper help to rationalize underwriting decisions in the insurance companies, because the proposed model helps in calculating the probabilities of various policyholders’ degrees of risk for the individual health insurance coverage. Furthermore, categorization of the degree of risk enables the insurer to achieve right underwriting decisions.
the individual health insurance, by classifying the policyholder within the appropriate insurance risk group. In addition, this paper enables to determine the appropriate insurance premium for every policyholder according to his degree of risk and this leads to reduction of the possibility of adverse selection of insurer.

Subjects: Social Sciences; Insurance; Risk Management

Keywords: Health insurance; degree of risk; underwriting; demographic factors

1. Introduction

By the end of 2014, the number of insurance and reinsurance companies licensed in the Saudi market totaled 35 companies, 28 of them are qualified by the Cooperative Health Insurance Council to provide medical insurance services. General insurance includes seven sub-activities namely vehicles, marine, aviation, energy, engineering, insurance, accident, and liability insurance, as well as insurance on property and against fire. The risks to insurance companies vary according to the risk of major insurance activities, as well as competition and growth rates for each insurance activity (Saudi Arabian Monetary Agency (SAMA), 2014).

Medical insurance represented 52% of the insurance market at the end of 2014, and vehicle insurance accounted for 26.5%. Consequently, the medical insurance and vehicle insurance represented 78.5% of the size of the insurance market, while protection and savings insurance represented only 2.6% (Saudi Insurance Sector, 2014).

On the other hand, the total paid claims paid rose by 26% to SAR 20.5 billion in 2014 compared to SAR 16.7 billion in 2013. Net claims incurred for insurance companies amounted to SAR 17.6 billion in 2014 growing 11.2% over the previous year where the figure reached SAR 15.8 billion. The claims of medical insurance accounted for 60% of the total claims incurred during the year (Saudi Insurance Sector, 2014).

Table 1 shows the results of net incurred claims for health insurers that displayed a 6% increase to SAR 10.4 billion, thus the loss ratio decreased to 79% compared to 94% in 2013 (Saudi Insurance Sector, 2014). Table 2, which indicates the loss ratio by line of business, reveals that the loss ratio in the health insurance is the second largest in the various lines of business. Table 3 shows the fluctuations in the loss ratio in the health insurance during the period 2009-2015. These statistics indicate that the underwriting process in the health insurance is not a rational or do not contribute to the improvement of health insurance results over time.

The health insurance underwriting cycle reflects the tendency for health insurance premiums and insurer profitability to systematically fluctuate over time (Patricia Born, 2008). Underwriting in risks is the process by which the insurer decides whether or not to accept a proposal of insurance,
on what conditions, in what proportion, and at what price (Diacon & Carter, 1998). This process is the most important for the technical operations in the insurance company. It also has an effect on the outcomes of the insurer’s business and may, also, lead to losses that the insurance company may not be able to survive. Underwriting of individual health risks are those processes relating to the evaluation of an individual’s exposures to dangers and the possibility of coverage, to help make appropriate underwriting decision. These decisions may be to accept or deny the coverage or acceptance with conditions. Then, it is classified risk unit within the appropriate risk group within its risk underwriting insurer portfolio.

In some very exceptional circumstances, an underwriter may have little previous experience to assess potential claims, and he then must base his assessment largely on gut reaction. However, far more commonly, an underwriter has the benefit of experience of many similar previous claims, and this can be analyzed and used. He can then determine the major underwriting factors (that is, the characteristics that are most likely to influence annual claims costs under the contract) and then classify contracts according to those factors. Identifying and measuring these factors or characteristics require detailed statistical analysis (Diacon & Carter, 1998).

There are several procedures performed by the underwriter in underwriting health risks, as follows:

(i) Determine major underwriting factors affecting the degree of health risk, which depends on the underwriter’s experience. According to these factors, they are insured and divided into different risk groups from each other, and each risk group of the insured is similar in the degree of health risk.

(ii) Measure the average annual claims for each risk group, using the frequency distribution data for each of the number of claims and the size of claims.

(iii) Evaluation of the proposed health risk, through the study of factors affecting the degree of risk, and classification of the proposed health risk within the appropriate risk group.

Underwriting health risks process aims to minimize the adverse effects that the insurance company may be exposed to, as a result of selection against the company through the new insurance applicants. As well as minimizing the degree of danger in inherent risks within heterogeneous

| Table 2. Loss ratio by line of business in Saudi Insurance Market (2015) |
|-----------------------------|-----------------------------|
| Line of Business            | Loss Ratio |
| Health Insurance            | 77 %         |
| Motor Insurance             | 88.3%        |
| Motor Property/Fire Insurance | 53%           |
| Engineering Insurance       | 49%          |
| Accident and Liability Insurance | 26.8%       |
| Marine Insurance            | 46.9%        |
| Energy Insurance            | 7.1%         |
| Aviation Insurance          | 26.8%        |

| Table 3. Loss ratio of health insurance (2009–2015) |
|-----------------------------------------------|
| Years  | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
| Loss Ratio | 74.8% | 71.5% | 73% | 81.4% | 94% | 79.2% | 77% |
groups. Adverse selection plays a prominent role in the insurance literature owing to its negative implications for the insurer’s financial performance and stability. Adverse selection could be a manageable problem for the insurer (Lee Colquitt, Fier, Hoyt, & Liebenberg, 2012; Viswanathan et al., 2007). Therefore, it is the insurance companies that must follow strict underwriting, and that each branch of the insurance branches practiced.

This paper concerning the study of underwriting health risks, as the subscription of this type of insurance is especially important, because the factors affecting the degree of health risks are many, such as age, gender, nationality, marital status, occupation, and place of residence. Underwriting decision on the health risks in this paper is as follows:

- Acceptance of insurance coverage with a discount price.
- Acceptance of insurance coverage at the normal price.
- Acceptance of insurance coverage with the increase in the price.
- Denial of insurance coverage.

2. Literature review

Arrow, Mossin, and Smith have demonstrated that when insurance is priced at actuarially fair rates, the insured prefers policies that offer full coverage. As insurance is not a costless business, insurers sell policies above the actuarially fair premium to cover their expenses. Smith has shown that when health insurance is available at a cost that exceeds the actuarially fair value and the probability of loss is greater than zero, the optimal level of insurance coverage will depend on an individual’s degree of risk aversion and the cost of insurance. For a given risk-averse individual, the optimal level of insurance will decrease as the cost of insurance increases. Depending on the shape of the utility function, the optimal level of health insurance may be zero, or it may exceed the value of the asset, human capital, subject to risk (Browne, 1992). At the equilibrium underwriting, low risks obtain greater coverage than they would without underwriting (Brown & Kamiya, 2012). Based on the underwriting behavior of insurance companies in 1988, medical conditions were classified into three categories: conditions that led to denial of coverage, conditions that led to exclusion restrictions, and conditions that led to higher premiums (Kapur, 2004).

There is a paucity of empirical evidence that is consistent with the existence of adverse selection in the U.S. insurance market. Some potential reasons for the lack of evidence include the fact: (i) that insurers effectively use underwriting and pricing to counteract adverse selection; or (ii) that consumers either do not have, or fail to take advantage of, private information. (Lee Colquitt et al., 2012) Discussion about several strategies to prevent or to counteract the observed negative spillover effects of supplementary insurance. Health insurers may have become more inclined to calculate risk-rated premiums and to use medical underwriting to prevent high-risk applicants from enrolling (Roos & Schut, 2012). The U.S. health care reform debate and legislation discussed the potential effects of the mandate that individuals have health insurance in conjunction with proposed premium subsidies and health insurance underwriting and rating restrictions (Harrington, 2010). An indicator of underwriting profitability in property-liability insurance have changed over time. The findings asserted that underwriting profit has worsened in recent years, and combined ratios are non-stationary. The study affirmed that lifestyles and one’s health have an important impact on the underwriting process in health care field (Leng, 2006). A number of alternative explanations have been offered for insurance underwriting cycles. However, no study till date has empirically evaluated this tendency in the health insurance industry. The study used national data over the period from 1960 to 2004 to test if various theories pertaining to price movements in the property and casualty insurance industry can also explain premium behavior in the health insurance industry. The empirical results provide strong support for the capacity constraint, fluctuation in interest rate, and rational expectations with institutional intervention hypotheses (Patricia Born, 2008). Underwriters considered the certain background medical information about four pairs of hypothetical applicants. One member of each pair was described as having positive genetic test
information. In seven instances, an adverse underwriting action was taken on applicants based on their genetic test result; in two others, participants indicated uncertainty as to how to underwrite an applicant with genetic test information. In seven of these 92 applications, underwriters said that they would deny coverage, place a surcharge on premiums, or limit covered benefits based on an applicant’s genetic information (Pollitz, Peshkin, Bangit, & Lucia, 2007).

Jason Brown and Mark Warshawsky use numerous demographic and health characteristics, this allows for analysis of disability and mortality risk across a number of dimensions, and they find that different risk groups at age 65 have similar projected long-term care expenses, but that the level—periodic—premium structure of most long-term care insurance policies creates incentives for individuals to separate into different risk pools according to observable characteristics, justifying the underwriting observed on the market (Brown & Warshawsky, 2013).

2.1. Objective of the study
The objective of this paper is to evaluate the degree of risk of the policyholder for the individual’s health insurance coverage, by examining the relationship between the degree of the individual’s health risk and demographic factors affecting the insured and then, propose a quantitative model to support decision-underwriting of the insurer. Achieving this aim helps reduces the possibility of adverse selection of insurer, because every policyholder will pay the insurance premium that commensurate with his degree of risk as well as denying coverage to policyholder with bad risk.

3. Methodology
This paper is for measuring the risks associated with the process of individual health insurance underwriting. A random sample of 1658 insured individuals was obtained from one of the Saudi insurance companies during the period 2013–2015, based on the random numbers generated, for detailed data on individual health insurance. The data were analyzed using Cluster Analysis, One-Way ANOVA, and Multinomial Logistic Regression.

3.1. Assumptions of the model
We assume the following:

(i) The degree of individual health risk varies from one person to another depending on the policyholder’s demographic factors.

(ii) The degree of health risk of policyholder is one out of four mutual alternatives, which are as follows: low, normal, high, and bad risk.

(iii) Insurer’s underwriting decision making for individual health risk of policyholder depends on the category of the degree of risk.

3.2. Mathematical framework
Cluster Analysis is for dividing the data obtained to the risk groups or clusters that are different and mutually exclusive, and each has its own characteristics, which considers all risk groups internally homogeneous and different from the other risk groups. We can perform analysis of variance test in one direction (One-Way ANOVA), to make sure the differences means of various groups of risks, and test the following null hypothesis:

\[ H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 \]

3.3. Multinomial or polytomous logistic regression
When the dependent variable is qualitative, discrete, and has several limits or responses, and independent variables are a mixture of quantitative types of variables (discrete and continuous) it would be appropriate to use a Multinomial Logistic Regression. This model has many uses in the process of life, especially in the medical field, when a dependent random variable has several responses, such as assessing the prospects for the symptoms of a disease that (no—there is simple
there is an average—there are chronically), or when it comes to choose the way of one of the ways of the diet, and in all the previous cases are estimated probability of each response from the variable responses, and determine the most probable value, so as to support making the right decision (Cohen, Patricia Cohen, & West, 2003).

The probability of responses is calculated as follows:

- Model for Probability of Low risk group
  \[
  \hat{P}(Y = 0/X) = \frac{e^{h_0(x)}}{1 + e^{h_0(x)} + e^{h_1(x)} + e^{h_2(x)}}
  \]

- Model for Probability of Normal risk group
  \[
  \hat{P}(Y = 1/X) = \frac{e^{h_1(x)}}{1 + e^{h_0(x)} + e^{h_1(x)} + e^{h_2(x)}}
  \]

- Model for Probability of High risk group
  \[
  \hat{P}(Y = 2/X) = \frac{e^{h_2(x)}}{1 + e^{h_0(x)} + e^{h_1(x)} + e^{h_2(x)}}
  \]

- Model for Probability of Bad risk group
  \[
  \hat{P}(Y = 3/X) = \frac{1}{1 + e^{h_0(x)} + e^{h_1(x)} + e^{h_2(x)}}
  \]

where

\[
\begin{align*}
  h_0(x) &= \hat{\alpha}_0 + \sum_{i=1}^{n} \hat{\beta}_{0i}X_i \\
  h_1(x) &= \hat{\alpha}_1 + \sum_{i=1}^{n} \hat{\beta}_{1i}X_i \\
  h_2(x) &= \hat{\alpha}_2 + \sum_{i=1}^{n} \hat{\beta}_{2i}X_i
\end{align*}
\]

3.3.1. Estimating model parameters

The likelihood can be generalized to include G outcome categories by taking the product of each individual's contribution across the G outcome categories (Hosmer & Lemeshow, 1989; Saudi Insurance Sector, 2014):

\[
L(Y) = \prod_{j=1}^{n} \prod_{g=0}^{g-1} P(Y = g/X)^{y_{gj}}
\]

where \( y_{gj} = \begin{cases} 
1 & \text{if the jth subject has } D = g \\
0 & \text{if otherwise}
\end{cases} \)

3.3.2. Wald test

We test the significance of interaction term at each level, for example:

\( H_0 : \beta_{g1} = 0; g = 1, 2, \ldots g - 1 \)

\( H_0 : \beta_{g2} = 0; g = 1, 2, \ldots g - 1 \)

Wald test Statistic:
\[ Z = \frac{\hat{\beta}_y}{\hat{\sigma}_y} \sim N(0, 1) \]

### 3.4. Data description

#### 3.4.1. Dependent variable
Dependent variable is the degree of risk, assuming that the Y has several response variables (A, B, C, D), where

- C: Low risk group (cluster 0)
- A: Normal risk group (cluster 1)
- B: High risk group (cluster 2)
- D: Bad risk group (cluster 3)

\[ y = \begin{cases} 
0 & \text{if } y = C \\
1 & \text{if } y = A \\
2 & \text{if } y = B \\
3 & \text{if otherwise} 
\end{cases} \]

#### 3.4.2. Independent variables
Independent variables are health insurance underwriting factors (policyholder’s demographic factors) as follows:

X1: Age

Age affects annual claim costs differently, depending on the type of benefit involved, although both frequency and severity generally increase with the advancement in age for all types of benefits. Most individual medical expense policies are limited as to the amount and type of coverage after a certain age, such as 65 or 70, although some companies have made lifetime coverage available (Black & Skipper, 2000).

X2: Residence

This variable is qualitative, and was regarded as a binary classification (inside the city/other), where

\[ X_2 = \begin{cases} 
1 & \text{if inside the city} \\
0 & \text{if otherwise} 
\end{cases} \]

X3: Nationality

This variable is qualitative, and was regarded as a binary classification (Saudi/other), where

\[ X_3 = \begin{cases} 
1 & \text{if Saudi} \\
0 & \text{if otherwise} 
\end{cases} \]

X4: Marital status:

This is a qualitative variable, and was considered a three-category variable (Married/Single/others), where:

\[ X_{41} = \begin{cases} 
1 & \text{if Married} \\
0 & \text{if otherwise} 
\end{cases} \]
As with life insurance, a person's gender is of considerable significance in health insurance underwriting. Females show higher disability rates than males at all but the upper ages in most studies. This is true even for policies that exclude or limit coverage of pregnancy, miscarriage, abortion, and similar occurrence (Black & Skipper, 2000). This variable is qualitative, and was regarded as a binary classification (Male/other), where

\[ X_5 = \begin{cases} 1 & \text{if Male} \\ 0 & \text{if otherwise} \end{cases} \]

Occupational risk has two offsetting effects on the purchase of personal accident, sickness, and health insurance (Diacon & Carter, 1998). This variable is qualitative, and was regarded as a binary classification (Employee/other), where

\[ X_6 = \begin{cases} 1 & \text{if Employee} \\ 0 & \text{if otherwise} \end{cases} \]

There's not much you can do about your gene pool. However, a family history of stroke, cancer, or other serious medical conditions may predispose you to these ailments and lead to higher rates. Carriers are usually interested in any conditions your parents or siblings have experienced, particularly if they contributed to a premature death. Some carriers put more emphasis on your family's health than others. However, it is likely to have some impact on your premium. This is a qualitative variable, and was considered a four-category variable (Fit/Middle/Not fit/etc.), where

\[ X_{71} = \begin{cases} 1 & \text{if fit} \\ 0 & \text{if otherwise} \end{cases} \]
\[ X_{72} = \begin{cases} 1 & \text{if middle} \\ 0 & \text{if otherwise} \end{cases} \]
\[ X_{73} = \begin{cases} 1 & \text{if not fit} \\ 0 & \text{if otherwise} \end{cases} \]

Appendix A shows descriptive statistics of various demographic factors. It can be observed that age is only the variable in ratio scale, and the rest of the variables are in nominal scale.

4. Data analysis and findings of the study
The data of individual health insurance claims and policyholder’s demographic factors collected were analyzed using IBM SPSS statistics 22.

4.1. Groups of individual health insurance risks
The individual health insurance to four groups or clusters of claims data are divided according to the demographic factors influencing (age, residence, nationality, marital status, gender, occupation, and family history). These groups are internally homogeneous and mutually exclusive, using cluster analysis technique. Table 4 provides the number of claims in each risk group. We assume that clusters are levels outcome of dependent variable. Table 5 shows Descriptive Statistics of group risks mean of claims, standard deviation, standard error of the estimate, and confidence interval of 95% for each risk group or cluster. In addition, we observed from the table that cluster 3...
is the most dangerous risk groups and cluster 0 is the lowest dangerous risk groups. Thus, the total numbers of claims have been divided into four graded risk groups. One way ANOVA tests the differences between the average amount of claims for the risk groups.

\[ H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 \]

Table 6 provides F value and its level significance \( p \)-value is zero, so we reject the null hypothesis and accept the alternative that there are differences between the means of amount of claims for the four risk groups.

### 4.2. Underwriting model in the individual health risks

Multinomial Logistic Regression is used to calculate the probabilities of the policyholder’s affiliation for different groups of risk, to determine the most likely value. Using the following equations (Appendix B):

\[
h_0(x) = 61.907 + 0.413X_1 - 12.053X_2 - 14.212X_3 - 27.868X_{41} - 14.833X_{42} - 11.640X_5 + 17.55X_6 - 0.971X_{71} - 9.615X_{72} - 12.724X_{73}
\]

\[
h_1(x) = 52.358 + 0.173X_1 - 9.58X_2 - 12.065X_3 - 12.037X_{41} + 1.552X_{42} - 11.277X_5 + 17.284X_6 - 2.182X_{71} - 12.002X_{72} - 12.154X_{73}
\]

\[
h_2(x) = 42.589 + 0.028X_1 + 1.947X_2 - 10.111X_3 - 9.746X_{41} + 1.201X_{42} - 8.003X_5 + 18.486X_6 - 9.629X_{71} - 18.031X_{72} - 17.607X_{73}
\]

#### 4.2.1. Goodness of fit

4.2.1.1. Likelihood ratio test. As with a standard logistic regression, we can use a likelihood ratio test to assess the significance of the independent variable in our model (Kleinbaum & Klein, 2003).

In this paper, we have a four-level outcome variable and \( p \) independent variables for each of the outcome comparison. We are being by fitting a full model (with the exposure variable in it) and then comparing that to a reduced model containing only the intercept. The null hypothesis is that the beta coefficients corresponding to the exposure variable are both equal to zero. The likelihood ratio test is calculated as negative two times the log likelihood (log L) from the reduced model minus negative two times the log likelihood from the full model. The resulting statistic is distributed approximately chi-square, with degree of freedom (df) equal to the number of parameters set equal to zero under the null hypothesis, as follows:

\[ H_0 : \beta_{gi} = 0; \ g = 1, 2, \ldots, g - 1; \ i = 1, 2, \ldots, p \]

Likelihood ratio test statistic:

\[ -2 \log L_{\text{reduced}} - (-2 \log L_{\text{full}}) \sim \chi^2 \]

Table 7 shows that negative two times the log likelihood for the reduced model is 1,087.161, and the full model is 259.957. The difference is 827.204. The chi-square \( p \)-value for this test statistic,
## Table 5. Descriptive statistics of group risks

| Cluster | N   | Mean  | Std. Deviation | Std. Error | 95% Confidence Interval for Mean | Minimum | Maximum |
|---------|-----|-------|----------------|------------|----------------------------------|---------|---------|
|         |     |       |                |            | Lower Bound          | Upper Bound |         |         |
| 0       | 1,523 | 510.25 | 1,429.613 | 36.633 | 438.39 | 582.10 | 0 | 7,509 |
| 1       | 108  | 14,196.69 | 6,454.852 | 621.118 | 12,965.40 | 15,427.99 | 7,588 | 32,581 |
| 2       | 22   | 54258.59 | 13,488.263 | 2875.707 | 48,278.23 | 60,238.95 | 35,239 | 81,000 |
| 3       | 5    | 1,22310.80 | 15,747.082 | 7042.309 | 1,02,758.22 | 1,41,863.38 | 1,05,200 | 1,48,000 |
with 30 degrees of freedom, is 0. We conclude that the independent variables (policyholder's demographic factors) are statistically significant at the 0.01 level.

4.2.1.2. McFadden $R^2$. McFadden in multinomial logistic regression model is similar to the coefficient of determination in linear regression, and has the same concept and characteristics. It has been calculated by McFadden in 1974, where (Cohen et al., 2003; Lattin, Douglas Carroll, & Green, 2003)

\[
\text{McFadden } R^2 = 1 - \frac{\log L_{\text{full}}}{\log L_{\text{reduced}}}
\]

It also has other measures similar to the measure, such as the following: $R^2_{Cox}$, $R^2_{Cox\text{ Snell}}$

\[
R^2 = \frac{\log L_{\text{full}} - \log L_{\text{reduced}}}{\log L_{\text{full}} - 1}
\]

\[
R^2_{Cox\text{ Snell}} = 1 - \left(\frac{\log L_{\text{reduced}}}{\log L_{\text{full}}}\right)^{2/n}
\]

It also has another measure called Nagelkerke, which depends on $R^2_{Cox\text{ Snell}}$ by dividing the largest estimated value. Table 8 according to McFadden shows that 75.4% of the variation in the degree of risk is to interpret variations in policyholder's demographic factors. 39.3%, 81.2% according Cox Snell and Nagelkerke, respectively.

MathCAD version 3.1 was applied for obtaining multiple logistic regression model, attachment 6 applications, describes the different degree of risk, depending on the policyholder’s demographic characteristics. Appendix C shows how various demographic factors affect the degree of risk of policyholders. For example, case 1 considers the case of a male policyholder aged 30 years with middle medical history. The resulting degree of risk was high. When some of the above demographic variables are changed, as illustrated in case 2, the degree of risk will also change from high to low risk and hence it can be noted that the demographic factors of the policyholder affect the degree of risk.

Table 6. One way ANOVA test results

| Sum of Squares | Df | Mean Square | F     | Sig. |
|---------------|----|-------------|-------|------|
| Between Groups | 1.515E11 | 3 | 5.051E10 | 6,746.891 | .000 |
| Within Groups | 1.238E10 | 1654 | 7,485,672.514 | |
| Total | 1.639E11 | 1657 | |

Table 7. Model fitting information

| Model     | Model Fitting Criteria | Likelihood Ratio Tests | -2 Log Likelihood | Chi-Square | df | Sig. |
|-----------|------------------------|------------------------|-----------------|------------|----|------|
| Intercept Only | 1,087.161 | | |
| Final | 259.957 | 827.204 | 30 | .000 |

Table 8. Pseudo R-square

| Cox and Snell | .393 |
| Nagelkerke | .812 |
| McFadden | .754 |
5. Discussion of the results

The results show that the policyholder’s demographic characteristics affect the degree of risk. The same has been demonstrated in Appendix C for six different cases. According to Nagelkerke coefficient, 81.2% of the variation in the degree of risk is explained by variations in policyholder’s demographic factors.

6. Conclusion

We examined the relationship between the policyholder’s degree of individual health risk and the effect of demographic factors. Data of 1,658 insured were obtained from one Saudi insurance company, and we got a detailed data about individual health insurance during the period 2013–2015. We estimated the policyholders’ probabilities to risk groups and determined the degree of most likely risks. This helps the insurer in making underwriting decisions in individual health risks. This paper presented a model for the rationalization of underwriting decisions in the individual health insurance, by classifying the policyholder within the appropriate insurance risk group. In addition, this paper contributes to determine the appropriate insurance premium for every policyholder according to his degree of risk as well as denying coverage to policyholder with bad risk. This leads to reduction in the possibility of adverse selection of insurer.

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Appendix A. Descriptive statistics of various demographic factors

|                   | N    | Minimum | Maximum | Mean  | Std. Deviation | Variance |
|-------------------|------|---------|---------|-------|----------------|----------|
| Age X1            | 1,658| 18      | 66      | 51.70 | 8.770          | 76.912   |

| Residence X2      | Frequency | Percent | Cumulative Percent |
|-------------------|-----------|---------|--------------------|
| Inside the city   | 1,149     | 69.3    | 69.3               |
| Outside the city  | 509       | 30.7    | 100.0              |
| Total             | 1,658     | 100.0   |                     |

| Nationality X3    | Frequency | Percent | Cumulative Percent |
|-------------------|-----------|---------|--------------------|
| Saudi             | 1,128     | 68.0    | 68.0               |
| Non Saudi         | 530       | 32.0    | 100.0              |
| Total             | 1,658     | 100.0   |                     |

| Marital status X4 | Frequency | Percent | Cumulative Percent |
|-------------------|-----------|---------|--------------------|
| Married           | 645       | 38.9    | 38.9               |
| Single            | 1,013     | 61.1    | 100.0              |
| Total             | 1,658     | 100.0   |                     |

| Gender X5         | Frequency | Percent | Cumulative Percent |
|-------------------|-----------|---------|--------------------|
| Male              | 1,137     | 68.6    | 68.6               |
| Female            | 521       | 31.4    | 100.0              |
| Total             | 1,658     | 100.0   |                     |

| Occupation X6     | Frequency | Percent | Cumulative Percent |
|-------------------|-----------|---------|--------------------|
| Employee          | 1,335     | 80.5    | 80.5               |
| Unemployed        | 323       | 19.5    | 100.0              |
| Total             | 1,658     | 100.0   |                     |

| Family History X7 | Frequency | Percent | Cumulative Percent |
|-------------------|-----------|---------|--------------------|
| Fit               | 546       | 33      | 33                 |
| Middle            | 702       | 42.3    | 75.3               |
| Not fit           | 410       | 24.7    | 100                |
| Total             | 1,658     | 100.0   |                     |
Appendix B. Parameter estimates of Multinomial Logistic Regression

| y | Parameter Estimates | 95% Confidence Interval for Exp(B) |
|---|---------------------|----------------------------------|
|   | B       | Std. Error | Wald | df | Sig. | Exp(B) | Lower Bound | Upper Bound |
| .00 | Intercept | 61.907 | 475.690 | .017 | 1 | .896 |          |          |
|    | x1      | .413 | .114 | 13.261 | 1 | .000 | 5.152 | 1.210 | 1.889 |
|    | x2      | -12.053 | 176.060 | .005 | 1 | .945 | 5.830E-6 | 8.003E-156 | 4.247E144 |
|    | x3      | -14.212 | 186.338 | .006 | 1 | .939 | 6.730E-7 | 1.647E-165 | 2.749E152 |
|    | x4      | -27.868 | 349.163 | .006 | 1 | .936 | 7.889E-13 | .000 | .000 |
|    | x5      | -14.833 | 277.387 | .003 | 1 | .957 | 3.617E-7 | 2.792E-243 | 4.685E229 |
|    | x6      | -11.640 | 195.921 | .004 | 1 | .953 | 8.808E-6 | 1.502E-172 | 5.167E161 |
|    | x7      | -14.212 | 186.338 | .006 | 1 | .939 | 6.730E-7 | 1.647E-165 | 2.749E152 |
| 1.00 | Intercept | 52.358 | 386.444 | .018 | 1 | .892 |          |          |
|    | x1      | .173 | .111 | 2.440 | 1 | .118 | 1.189 | .957 | 1.479 |
|    | x2      | -9.580 | 176.059 | .003 | 1 | .957 | 6.911E-5 | 9.503E-155 | 5.026E145 |
|    | x3      | -12.065 | 186.337 | .004 | 1 | .948 | 5.757E-6 | 1.411E-164 | 2.349E153 |
|    | x4      | -12.037 | 212.069 | .003 | 1 | .955 | 5.921E-6 | 1.814E-186 | 1.932E175 |
|    | x5      | -9.716 | 261.975 | .000 | 1 | .997 | 3.847E-13 | 3.847E-224 | 3.731E222 |
|    | x6      | -9.615 | 16.196 | .352 | 1 | .553 | 6.675E-5 | 1.092E-18 | 6.078E9 |
|    | x7      | -12.724 | 16.109 | .624 | 1 | .430 | 2.979E-6 | 5.779E-20 | 1.536E8 |
| 2.00 | Intercept | 42.589 | 397.735 | .011 | 1 | .915 |          |          |
|    | x1      | .028 | .116 | .059 | 1 | .809 | 1.028 | .820 | 1.290 |
|    | x2      | 1.947 | 200.272 | .000 | 1 | .992 | 7.004E-7 | 2.361E-170 | 2.078E171 |
|    | x3      | -10.111 | 186.339 | .003 | 1 | .957 | 4.062E-5 | 9.933E-164 | 1.661E154 |
|    | x4      | -9.746 | 212.072 | .002 | 1 | .963 | 5.851E-5 | 1.785E-185 | 1.918E176 |
|    | x5      | 1.201 | 1.566 | .588 | 1 | .443 | 3.324 | .154 | .715 |
|    | x6      | -8.003 | 195.924 | .002 | 1 | .967 | 5.672E-7 | 1.927E163 |          |
|    | x7      | 18.486 | 290.206 | .000 | 1 | .995 | 1.068E8 | .000 | .000 |

The reference category is 3.00.

Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.
Appendix C. Effect of various demographic factors on the degree of risk of policyholders

Case_1

| Risk factors | Age | Inside | Outside | Nationality | Marital status | Gender | Occupation | Medical History |
|--------------|-----|--------|---------|-------------|----------------|--------|------------|----------------|
|   | 30  | ✓      |         |             |    | ✓         | ✓   | ✓        | ✓              |
| $h_0(x)$     | 16.459 | ✓      |         | Low-risk    | Low-risk      | 0.104 |            |                |
| $h_1(x)$     | 17.871 | ✓      |         | Normal risk | Normal risk   | 0.426 |            |                |
| $h_2(x)$     | 17.971 | ✓      |         | High risk   | High risk     | 0.471 |            |                |
| $h_3(x)$     | 17.971 | ✓      |         | Bad risk    | Bad risk      | 7.377E-9 |            |                |
| $h_4(x)$     | 17.971 | ✓      |         | Sum         | Sum           | 1      |            |                |

Probabilities Degree of Risks

Low-risk 0.104
Normal risk 0.426
High risk 0.471
Bad risk 7.377E-9

Degree of Risk

( ) Low-risk
( ) Normal risk
(II) High risk
( ) Bad risk

Sum 1
### Case 2

| Risk factors | Age | Inside | Outside | Nationality | Marital status | Gender | Occupation | Medical History |
|--------------|-----|--------|---------|-------------|----------------|--------|------------|----------------|
| $h_0(x)$     | 40  | ✓      |         | Saudi       |✓              | ✓      | Employee   | Low-risk       |
| $h_1(x)$     | 40.873 | Probabilities Degree of Risk | Low-risk | 0.543       | Degree of Risk |        |            | ( ) Low-risk    |
| $h_2(x)$     | 40.698 | Normal risk | 0.426   |            |                  |        |            | ( ) Normal risk|
| $h_3(x)$     | 34.656 | High risk | 0.001084|            |                  |        |            | ( ) High risk   |
|              |      | Bad risk | 0       |            |                  |        |            | ( ) Bad risk    |
|              |      | Sum      | 1       |            |                  |        |            | Sum 1          |

Degree of Risk

- Low-risk: 0.543
- Normal risk: 0.426
- High risk: 0.001084
- Bad risk: 0
### Case_3

| Risk factors | Age | Inside | Outside | Saudi | Non | Married | Single | male | female | Employee | non | Fit | Middle | Non |
|--------------|-----|--------|---------|-------|-----|---------|--------|------|--------|----------|-----|-----|--------|-----|
|              | 35  | √      | √       |       |     | √       |        | √    |        |          |     |     |        |     |

- **h_0(x) = 63.896**
  - Probabilities
  - Degree of Risks
  - Low-risk: 0.71
  - Degree of Risk
  - (M) Low-risk

- **h_1(x) = 63.002**
  - Normal risk: 0.29
  - ( ) Normal risk

- **h_2(x) = 43.516**
  - High risk: 1E-9
  - ( ) High risk

- **Bad risk: 0**
  - ( ) Bad risk

- **Sum: 1**
| Risk factors | Age | Inside | Outside | Nationality | Marital status | Gender | Occupation | Medical History |
|--------------|-----|--------|---------|-------------|----------------|--------|------------|----------------|
| h0(x)        | -7.504 | √      |         | Low-risk    | 2.602E-4       | Degree of Risk |
| h1(x)        | -0.949 |        |         | Normal risk | 0.183          | Normal risk |
| h2(x)        | 0.315 |        |         | High risk   | 0.345          | High risk |
| Bad risk     | 0.472 |        |         |             |                | Bad risk |
| Sum          | 1    |        |         |             |                |             |

Case 4
| Risk factors | Age | Inside | Outside | Saudi | Non | Married | Single | male | female | Employee | non | Fit | Middle | Non |
|--------------|-----|--------|---------|-------|-----|---------|--------|------|--------|----------|-----|-----|---------|-----|
| $h_0(x)$     | 33  | √      |         |       |     |         | √      | √    |        |          |     |     |         |     |
| $h_1(x)$     | 18.238 | |
| $h_2(x)$     | 18.479 | |
| Degree of Risks |     |         |         |       |     |         |        |      |        |          |     |     |         |     |
| Low-risk     |     |         |         |       |     |         |        |      |        |          |     |     |         |     |
| Normal risk  |     |         |         |       |     |         |        |      |        |          |     |     |         |     |
| High risk    |     |         |         |       |     |         |        |      |        |          |     |     |         |     |
| Bad risk     |     |         |         |       |     |         |        |      |        |          |     |     |         |     |
| Sum          |     |         |         |       |     |         |        |      |        |          |     |     |         | 1   |

Case 5

Awwad & Ismail, Cogent Business & Management (2018), 5: 1477499
https://doi.org/10.1080/23311975.2018.1477499
| Risk factors | Age | Inside | Outside | Saudi | Non | Married | Single | male | female | Employee | non | Fit | Middle | Non |
|--------------|-----|--------|---------|-------|-----|---------|--------|------|--------|-----------|-----|-----|--------|-----|
| $h_0(x)$     | 33  | ✓      | ✓       | ✓     | ✓   | ✓       | ✓      | ✓    | ✓      | ✓         | ✓   |     |        | ✓   |
| $h_1(x)$     | 17.698 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |     |        | ✓ |
| $h_2(x)$     | 18.39 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |     |        | ✓ |
| $h_3(x)$     | 18.055 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |     |        | ✓ |
| Probabilities | Degree of Risks | Low-risk | 0.226 | Degree of Risk | ( ) Low-risk |
| $h_1(x)$     | 18.39 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Normal risk | 0.451 |
| $h_2(x)$     | 18.055 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | High risk | 0.323 |
| $h_3(x)$     | 17.698 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Bad risk | 4.653E-9 |
| Sum          | 1    | ✓      | ✓       | ✓     | ✓   | ✓       | ✓      | ✓    | ✓      | ✓         | ✓   |     |        | ✓   |
