WORKING PAPER 271/2024

IS HEALTH INSURANCE ACTUARIALLY FAIR? QUANTIFYING DISCREPANCIES IN THE INDIAN HEALTH INSURANCE SECTOR

Nikhil Rathee
Rupel Nargunam

Mentoring Excellence

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

December 2024

Is Health Insurance Actuarially Fair? Quantifying Discrepancies in the Indian Health Insurance Sector

Nikhil Rathee
MA Actuarial Economics, Madras School of Economics

and

Rupel Nargunam
corresponding author, Assistant Professor, Madras School of Economics
rupel@mse.ac.in

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

December 2024

WORKING PAPER 271/2024

December 2024

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

Phone: 2230 0304/2230 0307/2235 2157
Fax: 2235 4847/2235 2155
Email : info@mse.ac.in
Website: www.mse.ac.in

Is Health Insurance Actuarially Fair? Quantifying Discrepancies in the Indian Health Insurance Sector

Nikhil Rathee and Rupel Nargunam

Abstract

This study investigates the actuarial fairness of health insurance policies by examining discrepancies within the Indian health insurance and their impact on medical costs. By virtue of its creation, the scope of health insurance contracts is to cover medical expenses and the cost of the same is expected to reflect the expected cost of medical services. In practice it is observed that there are discrepancies such as misinformation, accessibility to health care services, hospital quality and inconsistencies in claims processing, increase costs associated with health care of individuals participating in the health insurance, which affect the fairness in pricing of these policies. This study uses Structural Equation Modelling (SEM) to develop latent variables representing these discrepancies and Hierarchical Linear Modelling (HLM) to assess their effect on the cost of medical care. The findings of this study support the presence of region-wise discrepancies in the Indian health insurance sector and the results support the significant impact on the increase in medical expenses. The study concludes with policy recommendations aimed at enhancing the efficiency, effectiveness and fairness of the health insurance policies in India.

Keywords: *Pricing Health Insurance, Actuarial Fairness, Discrepancies, Misinformation, Claim process inconsistencies, Access to Medical Services.*

JEL Codes: *I11, I13, G22, G52*

Acknowledgement

The authors would like to thank the anonymous referees for their valuable, insightful suggestions to improve the paper. The revised version of this paper is submitted to an international journal.

Nikhil Rathee
Rupel Nargunam

INTRODUCTION

Health insurance is a form of collectivism, by construct it is designed to enable individuals to pool their risk of incurring medical expenses. Since the health insurance acts as a binding agreement between the insurer and insured, its realised value is influenced by the multiple factors such as unequal distribution of medical resources, lack of human resources, poor infrastructure, and low-quality medical services. These factors contribute to the disparities in delivery of health care under health insurance and overthrow the underlying principle of designing health insurance contracts. Data from the Indian Human Development Survey-II (IHDS-II) reveals that approximately 40.8 percent of households with health insurance have incurred additional medical expenses that exceed the risk cover. In 2011, India had a doctor-to-population ratio of 1:1457 which is lower than the WHO's recommended ratio of 1:1000 (Deo, 2013). This is emphasizing the critical shortage of human resources in the health sector. Furthermore, India faces numerous obstacles in its health insurance sector, such as resource distribution, infrastructure problems and administrative inefficiencies (Mavalankar et al., 2000) which disrupt the delivery of quality care under health insurance schemes. These unaddressed challenges and associated costs distort the principle of indemnification by which insurance contracts are designed, resulting in health insurance contracts where the expected cost of premiums does not match the true expected cost of medical care.

The objective of this article is to investigate the aforementioned discrepancies present in the Indian health insurance network by examining the nature of these factors individually and highlighting their impact on the cost of medical care for insured households. A comprehensive analysis of these discrepancies is expected to help the pricing actuary to determine the expected costs more efficiently and determine premium rates which are in line with the fundamental principles of insurance contracts. This study focuses on examining the individual impact of each of these factors on expected cost of health care, to account for the variations in costs incurred by individuals from different socio-economic backgrounds. It is crucial as the presence discrepancies cause fluctuations in medical costs, which would in turn indicate that health insurance contracts are not priced accurately and may tend to deviate from the principle of actuarial fairness.

Health Insurance and Actuarial Fairness

To comprehend actuarial fairness in health insurance, it is essential to understand the significance of the definition of health insurance Pitacco, E. (2014). Health insurance is described as a tool for transferring the risk of healthcare costs to another party in exchange for single or series of payments, called insurance premium. The determinisation of premium is of critical importance and should be determined with fairness. Donahue and Barocas (2021, p. 186) define the cost of insurance as "pricing in which each participant in the insurance pool pays their expected costs." In other words, for health insurance to be actuarially fair, the premium paid in advance should be equal to the expected cost of healthcare.

Discrepancies

Discrepancies are unexpected differences that suggest something is wrong between two sets of conditions and needs to be explained. A study at the time when foreign direct investment in the Indian health insurance industry was severely restricted, highlights challenges such as the distribution of resources, improper infrastructure, poor healthcare quality, administrative inefficiencies, lack of awareness, and adverse selection (Mavalankar and Bhat 2000). In this study, we focus on factors that deviate the cost of health insurance from being actuarially fair. More specifically, we identify qualitative variables that are expected to have an impact on the pricing of health care costs. In that regard, this study highlights four discrepancies in the delivery of health care under health insurance schemes in the Indian context, namely: Inconsistencies in claims processing, misinformation, quality of medical care, and access to medical services.

The following subsections give detailed descriptions of the discrepancies addressed by this study:

Misinformation

Inconsistencies in claims processing and misinformation are not uncommon in the health insurance environment. They are observed in the issuance of insurance and during claim submissions. Misinformation arises from differences in knowledge between individuals and insurers, leading to misunderstandings about coverage and benefits. During claim submission, insured individuals experience inconvenience and dissatisfaction, which result in the ongoing insurance policy being overpriced or risk cover going underutilized regarding their actual risk experience. Leinsdorf et al. (1980) suggest that misinformation affects the equilibrium in insurance markets due to lack of access to accurate information that explains the full disclosures of insurance contracts, leading to market inefficiencies such as mispriced policies, adverse selection, and moral hazard. Further, the delay in timely updation of health insurance provider directories can cause insured individuals to inadvertently select out-of-network providers (Kleban, 2019).

Accessibility and Quality of Health care

Accessibility and quality of health care discrepancies related to the additional expenditure incurred by individuals. These costs are associated with obtaining medical care services in the same vicinity or for access better quality medical services provided by hospitals within the insurance network. When individuals incur significantly higher expenses to access these services, it indicates that the insurance premium does not accurately represent the true medical costs borne by the insured. Consequently, these unaccounted inconsistencies lead to the deviation from actuarially fair health insurances policies, as the premium does not reflect the actual expected cost of medical care. Assessing patient satisfaction from the quality of health care services provided, Raposo et al. (2009) finds factors such as cleanliness, temperature, comfort, effective administration, and good nursing behaviour significantly influence patients' positive perceptions of facilities, thereby enhancing overall satisfaction. Xiong et al. (2018) examines the role of health insurance within the context of the Universal Medical Insurance System (UMIS) in China, in enhancing both the accessibility and affordability of medical services across diverse populations and regions, suggest that a unified system helps to create a more inclusive and sustainable health insurance system.

DATA AND MODELLING METHODOLOGY

Data

The primary focus of this study is to quantify the discrepancies in health care the delivery of health care under insurance schemes. In this regard, a set of variables that constitute the factors mentioned in section 1.2 are chosen. The data sources include the India Human Development Survey II (IHDS-II), which covers over 42,000 households across India and provides data on health insurance coverage, health utilization, and economic status. The Indian Insurance Statistics (IIS) Handbook 2011-12, published by the IRDAI, offers detailed statistics on the insurance market, including policy numbers, consumer complaints, and insurer performance metrics. The National Health Profile (NHP) 2011, compiled by the Central Bureau of Health Intelligence, provides information on health infrastructure, healthcare professionals, disease prevalence, and public health finances. Additionally, data from Tata AIG Ltd. on hospitals registered under ROHINI (Registry of Hospitals in Network of Insurance) offers insights into the accessibility and quality of services from managed hospitals.

Table 1: Describing the Variables Used for Research

Variable	Description	Summary Statistic	Data Source
STATEID	Identifier for the state of each surveyed household.	Numeric value from 1 to 34	IHDS-II
CO34	Medical cost incurred by a household (in-patient)	Mean - 6414.4 Standard deviation - 34604.72 Max – 4000000 Min - 0	IHDS-II
QC8	Medical Treatment wait time	Mean - 28.10795 minutes. Standard deviation – 33.78 Max – 760 minutes. Min – 0 minutes.	IHDS-II
OG5	Respondent knowledgeable about health and education expense	Very little knowledge (1) Somewhat (2) Very knowledgeable (3)	IHDS-II
QC3	Medical treatment location	Same Village/Town (1) Another Village (2) Other Town (3) District Town (4)	IHDS-II
HHEDUC	Highest adult education	none (0) 1st class (1) – 12th class (12) 1-year post-secondary 2-years post-secondary Undergraduate level of educations (15) Above Undergraduate level of educations (16)	IHDS-II
NOC	Number of complaints filed against insurance providers.	Mean – 627 Standard deviation – 839.67 Max – 3516 Min – 5	Indian Insurance Statistics Handbook
Nogovdr	Number Allopathic doctors in a state	Mean – 3494 Standard deviation – 3836.59 Max – 14509 Min – 19	NHP
AcceNABH	status of hospitals, which reflects their compliance with the specific healthcare quality and the safety standards set by accreditation bodies such as NABH.	NABH - Pre-entry Level NABH - Higher level Pre-accredited	Tata AIG general insurance

Source: Author's contribution using IHDS, IIS, NHP, TATA AIG

Tables 1, 2, and 3 provide an overview of the variables used in this study. Table 1 presents the variables collected for the research, while Tables 2 and 3 display the transformed quantitative and qualitative variables, respectively. In Table 1, STATEID, CO34, OG5, QC8, QC3, and HHEDUC are variables sourced from IHDS-II. Among these, STATEID, OG5, QC3, and HHEDUC are qualitative variables, while CO34 and QC8 are quantitative. The NOC variable, collected from the IIS Handbook 2011-12, is quantitative. The qualitative variables used in this study are Nogovdr, sourced from NHP 2011, and AcceNABH, obtained from Tata AIG Ltd.

As these variables are collated from different sources and represent varying levels of aggregation. IHDS-II provides household-level data, IIS Handbook 2011-12 offers data from complaint addressal centres, NHP supplies state-level aggregate data, and Tata AIG's data lists individual hospitals with NABH accreditation in each Indian state. Suitable transformation was applied to normalise the varying levels. The NOC variable from the IIS Handbook was proportionally distributed across states based on population coverage by complaint addressal centres. The "AcceNABH" variable from Tata AIG was aggregated at the state level to represent the number of hospitals with specific accreditation making them quantitative variable from qualitative. Following these transformations, the variables were combined with IHDS-II data, resulting in a dataset with both household-level and state-level aggregates.

From Table 1, it is evident that the standard deviation of some quantitative variables is 100 times greater than that of other variables, implying that the variance of these variables would be 10,000 times higher, which could impact the modelling process. To achieve a better fit, natural logarithmic transformations of the variables were applied to all the quantitative variables. The transformed variables are given in Table 2.

Table 2: Describing Transformation of the Quantitative Variables

Variable Name	Description	Summary Statistics
log_CO34	log_CO34 = log (CO34 +1)	Mean – 3.57 Std dev – 4.41 Max – 14.22 Min – 0
log_QC8	Log_QC8 = log (QC8 + 1)	Mean –2.85 Std dev – 1.09 Max – 6.58 Min – 0
log_NABH_P	log_NABH_P = log (NABH_pre_entry + 1), where NABH_pre_entry is the total number of hospitals with NABH accreditation entry level.	Mean – 2.14 Std dev – 1.67 Max – 5.15 Min – 0
log_NABH_H	log_NABH_H = log (NABH_Higher + 1), where NABH_Higher is the total number of hospitals with NABH accreditation level above entry and below full accreditation.	Mean – 2.51 Std dev – 1.70 Max – 4.80 Min – 0
log_NABH_A	log_NABH_A = log (NABH_accrediated + 1), where NABH_accrediated is the total number of hospitals with NABH full accreditation.	Mean – 2.31 Std dev – 1.63 Max – 4.90 Min – 0
log_NOC	log_NOC = log (noc +1)	Mean –6.40 Std dev – 1.20 Max – 8.16 Min – 2.30
log_num_doc	log_num_doc = log (Nogovdr +1)	Mean –8.33 Std dev – 0.832 Max – 9.58 Min – 4.04

Source: Author's Contribution using IHDS, IIS, NHP, TATA AIG

From Table 1, the qualitative variable has been also transformed into dummy variables such as: OG5 has been divided into OG5_1, OG5_2 and OG5_ 3; QC3 has been divided into QC3_1, QC3_2, QC3_3 and QC3_4; HHEDUC variable has been grouped into 2 categories, above undergraduate level of education and below undergraduate level of education, captured with Education_Group. The transformed dummy variables are given in Table 3.

Table 3: Describing Transformation of the Qualitative Variables.

Variables	Description	Counts
OG5_1	OG5_1 = 1, if household claim to have very little knowledge of medical expenses. OG5_1 = 0, ow	Count of 1s – 403 Count of 0s – 4171
OG5_2	OG5_2 = 1, if household claim to have some knowledge of medical expenses. OG5_2 = 0, ow	Count of 1s – 1144 Count of 0s – 3430
OG5_3	OG5_3 = 1, if household claim to have very knowledge of medical expenses. OG5_2 = 0, ow	Count of 1s – 3027 Count of 0s – 1547
Education _Group	Education_Group = 1, if the highest adult education is undergraduate level of education and above or else = 0	Count of 1s – 1094 Count of 0s – 3480
QC3_1	$QC3$_1 = 1, if the medical treatment location is Same Village/Town or QC3_1 = 0	Count of 1s – 2863 Count of 0s – 1171
QC3_2	$QC3$_2 = 1, if the medical treatment location is Another Village. QC3_2 = 0, ow	Count of 1s – 731 Count of 0s – 3843
QC3_3	$QC3$_3 = 1, if the medical treatment location is Other Town QC3_3= 0, ow	Count of 1s – 723 Count of 0s – 3851
QC3_4	$QC3$_4 = 1, if the medical treatment location is District Town. QC3_4= 0, ow	Count of 1s – 257 Count of 0s – 4317

Source: Author's Contribution using IHDS, IIS, NHP, TATA AIG.

Empirical Analysis

As the discrepancies are qualitative in nature and cannot be measured directly from the data, they are modelled as latent variables using modelling techniques. Structural Equation Modelling (SEM) is used to define the latent variables and Hierarchical Linear Modelling (HLM) is to control for state-specific constant. As the latent variables are constructed from data sources of which some data represent state-level aggregates, the latent variable developed would also comprise of similar attribute. In such circumstances there arises the need to use models which control for state-specific constant, this motivates the use of HLM in this study.

Structural Equation Modelling (SEM)

SEM, also known as path analysis, is a statistical technique used to understand complex relationships between observed and latent variables (Muthén, 1983). This method is useful in testing theoretical models to examine the direct and indirect interaction of variables. Latent variables, representing abstract concepts, are inferred from measurable indicators. SEM uses factor analysis to validate these relationships. The general form of the measurement model which relates the observed variables (X) to latent variables (ξ) is given as follows: Latent variables, representing abstract concepts, are inferred from measurable indicators. SEM uses factor analysis to validate these relationships. The measurement model links observed variables (X) to latent variables (ξ) with the equation

$$X = Λ\_X\ ξ + \delta \tag{1}$$

where, Λ_X represents factor loadings and δ represents measurement errors.

The fitted model used for construction of the latent variables is given as follows:

$$MI = \alpha_1\ OG5\_2 + \alpha_2\ OG5\_3 + \alpha_3\ Education\_Group + \varepsilon_{MI} \tag{2}$$

$$\mathrm{NetMedQ} = \beta_1 log\_NABH\_H + \beta_2\ log\_NABH\_P + \beta_3 log\_NABH\_A + \varepsilon_{NetMedQ} \tag{3}$$

$$\mathrm{MSA} = \gamma_1 QC3\_2 + \gamma_2 QC3\_3 + \gamma_3 log\_QC8 + \gamma_4 lognumdoc + \varepsilon_{MSA} \tag{4}$$

where, MI, NetMedQ, and MSA are the latent variables constructed from the observed variables in Table 2 and 3; OG5_2, OG5_3, and Education_Group for MI, log_NABH_H, log_NABH_P, log_NABH_A for NetMedQ and QC3_2, QC3_3, log_QC8 and log_num_doc for MSA. The coefficients α, β, and γ represent the values associated with each variable, and ε represents the error terms. The values for all the coefficients α_i, β_i, and γ_i, $i = 1,2,3$, of the latent variables MI, NetMedQ, and MSA used in this study are estimated.

Hierarchical Linear Modelling (HLM)

HLM also referred to as multilevel modelling is ideal for analysing clustered data. Unlike ordinary least squares (OLS) regression, HLM accounts for the correlation of data within clusters, which violates the independence of errors assumption (Santos, 2023). HLM effectively handles data structured at multiple levels, allowing for regression equations at each level and accommodating both fixed and random effects. Given that this research involves both aggregate data and household-level data, it suggests that HLM is the most suited and effective model for the analysis.

Level 1 Model (Within-Group Relationships)

The general form of the model which describes the relationship between a dependent variable and one or more independent variables within a group is given below:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij} \tag{5}$$

where, Y_{ij} is the outcome variable for individual i in group j, X_{ij} is the predictor variable for individual i in group j, β_{ij} and β_{ij} are the coefficients for group j, which can vary from group to group, r_{ij} represents the residuals at the individual level, assumed to be normally distributed.

Level 2 Model (Between-Group Relationships)

The general form of the model which explains how the coefficients β_{0j} and β_{1j} from the Level 1 model vary across groups is given below:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \tag{6}$$
$$\beta_{01} = \gamma_{10} + \gamma_{11}W_j + u_{1j} \tag{7}$$

where, γ_{00} and γ_{10} are the intercepts for β_{0j} and β_{ij}, respectively, γ_{01} and γ_{11} describe how β_{0j} and β_{1j} change with a group-level predictor W_j, u_{0j}

and u_{1j} are the random effects for group j, indicating variation across groups not explained by W_j.

The fitted model used for regressing the natural logarithm of medical cost of the insured on the above specified latent variables is given below:

$$log_e(CO34)_{ij} = \lambda_0 + \lambda_1\ MI\_scores_{ij} + \lambda_2\ NetMedQ\_scores_{ij} + \lambda_3\ MSA\_scores_{ij} + \lambda_4\ log\_NOC_{ij} + u_{0j} + \epsilon_{ij} \quad (8)$$

where, λ_0 is the intercept term and $\lambda_{i's}$ are the predictor variables' coefficients, namely MI_scores, NetMedQ_scores, MSA_scores and log_NOC , $log_e(CO34)$ is the predicted variable; u is random effect error term; ε is residual error term.

RESULTS

The empirical results of the study are presented in this section.

Descriptive Analysis

Plots of the latent variables, namely average medical cost insured by households, average waiting period for medical treatment, distribution of ROHINI with NABH accreditations, and Number of complaints respectively in India are given in Figures 1, 2, 3 and 4. respectively

Figure 1 Average medical cost in Rs

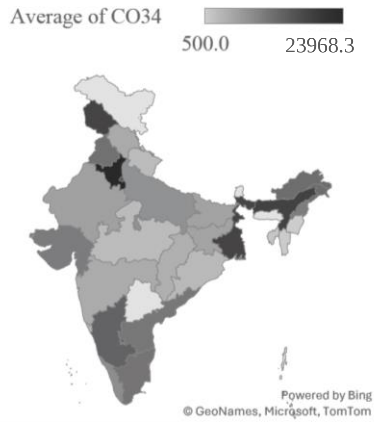


Figure 2 Average waiting time for medical treatment in minutes

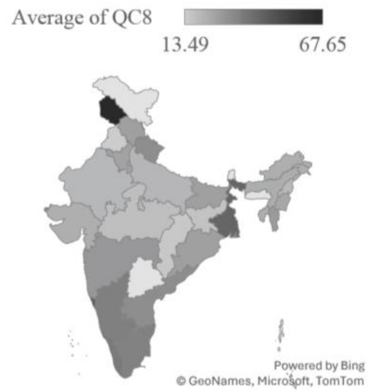


Figure 3 Distribution of hospital in insurance network

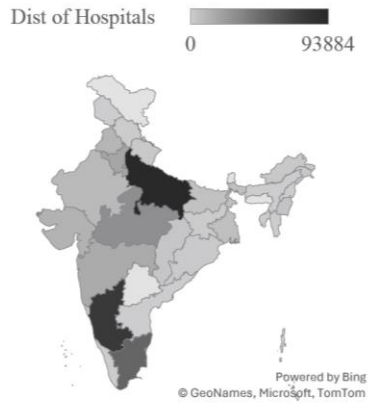
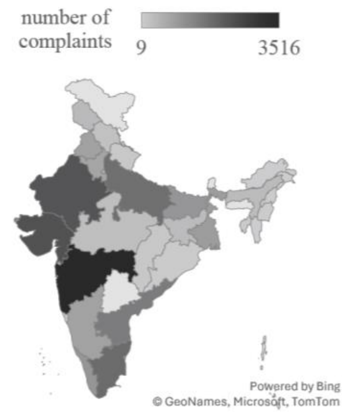


Figure 4 Number of complaints statewise



In Figure 1, the average medical cost incurred by the household participating varies from INR500 to INR24000, with maximum in Delhi INR23,968.30 and lowest by Chandigarh and Manipur. In Figure 2 the average waiting period before receiving medical treatment varies from 13 to 68 minutes, with Jammu and Kashmir (including the territory of Ladakh) showing the maximum average waiting time of 67 minutes and lowest in Punjab 13 minutes. In Figure 3, the state-wise distribution of hospitals with NABH accreditation is displayed. Tripura has no hospitals with NABH accreditation while Uttar Pradesh shows the maximum number of hospitals with NABH accreditation totalling to 93,884. In Figure 4, the number of complaints filed state-wise against non-life insurance ranging from 5 to 3,600 is displayed. The union territory Daman and Diu show has the least number of complaints equal to 9, while Maharashtra has the maximum number of complaints filed totalling to 3,516.

Comparing Figures 1 and 2, we see that Jammu and Kashmir, Kerala, Tamil Nadu, West Bengal and Karnataka show darker colouring which indicates that the average waiting time is more than the average medical cost, whereas the colouring is lighter in Madhya Pradesh. This suggests that medical care cost and average waiting time are positively related that may be attributed to high demand of the services which impacts the duration of waiting time to receive medical attention. Similarly, Figures 3 and 4, suggest that Rajasthan, Gujarat, Maharashtra, Karnataka, Bihar showing contrast in the colouring shades which suggest that the number of hospitals with NABH accreditation and number of complaints filed against non-life insurance schemes have a negative relationship. Figures 2 and 3 suggest that the average waiting period for medical treatment and the distribution of hospital in the insurance network are negatively correlated for the states Uttar Pradesh, Bihar, Madhya Pradesh, Jammu and Kashmir. Kerala, West Bengal Andhra Pradesh, Assam, Bihar, Karnataka show contrast in the colouring shades which can be inferred as the number of hospitals in an insurance network is high than the average waiting time to receive medical care is less.

Latent Variable Development – Structural Equation Modelling

The SEM is fitted on the following three latent variables: Misinformation (MI), Network Medical Quality (NetMedQ), and Medical Service Availability (MSA). The estimates of the fitted model are given in Table 4.

Table 4: Estimators of parameters from SEM

Latent Variable	Indicator	Estimate	Std. Err	z-value	P-value
MI	OG5_2	1.000	-	-	-
	OG5_3	-1.325^{***}	0.179	-7.414	0.000
	Education_Group	-0.091^{***}	0.017	-5.238	0.000
NetMedQ	log_NABH_H	1.000	-	-	-
	log_NABH_P	0.981^{***}	0.004	247.339	0.000
	log_NABH_A	0.959^{***}	0.004	244.920	0.000
MSA	QC3_2	1.000	-	-	-
	QC3_3	-0.917^{*}	0.486	-1.884	0.060
	log_QC8	8.170^{***}	2.570	3.179	0.001
	log_num_doc	-21.462^{***}	6.691	-3.208	0.001

Source: Author's Contribution using IHDS, IIS, NHP, TATA AIG

From the estimated values of the fitted model given in Table 4, we see that the coefficient α_2 of OG5_3 and α_3 of Education_Group are negative and significant at the 1% level. OG5_2 at 1.000 serves as a scaling factor for the latent variable MI. The interpretation for α_2 and α_3 is as follows: if the insured individual claims to be very knowledgeable about medical and education expenditure (OG5_3=1), the MI variable decreases by 1.325 units compared to those with no knowledge; however, if the highest adult education in the household is a undergraduate level of education's degree or above (Education_Group=1), the MI variable decreases by 0.091 units compared to households with lower education levels, repectively.

For NetMedQ, the estimated coefficients β_2 of NABH_P and β_3 of NABH_A are positive and significant at the 1% level. Log_NABH_H at

1.000 serves as a scaling factor for the latent variable NetMedQ. The interpretation of β_2 and β_3 as follows: if the number of hospitals with pre-entry level accreditation increases by 1%, the NetMedQ variable increases by 0.981 units. Similarly, a 1% increase in hospitals with pre-accreditation leads to a 0.959 unit increase in Network Hospital Quality, respectively.

For MSA, the estimated coefficient γ_2 of QC3_3 is significant at the 10% level, while the coefficients γ_1, γ_3, and γ_4 are significant at the 1% level, with positive and negative signs respectively. QC3_2 at 1.000 serves as a scaling factor for the latent variable MSA. The interpretation of γ_2, γ_3 and γ_4 as follows: if persons get treatment in other town the MSA will decrease by 0.917 units, a percentage change in the waiting time of medical treatment (log_QC8) leads to an 8.170 unit increase in MSA. However, a 1% increase in the number of doctors (log_num_doc) results in a 21.462 unit decrease in MSA.

After estimating these parameters, the scores for the latent variables MI, MSA, and NetMedQ were computed as MI_scores, MSA_scores, and NetMedQ_scores. These scores are used in the hierarchical linear model (HLM) for further analysis.

Regression – Hierarchical Linear Modelling

Since HLM can accommodate for both fixed and random effects in a model, it is used in the furtherance of this analysis. The level 1 model which accounts for within-group relationship are the part of fixed effects and level 2 model explain how the coefficients (intercept and slopes) from the Level 1 model may vary across groups, which are capture by random effects.

RANDOM EFFECTS

The estimates of the fitted level 2 model from HLM are given result in Table 5.

Table 5: Random Effects Estimates from HLM

Group	Component	Estimate	Std. Dev.
STATEID	(Intercept)	2.187	1.479
Residual		17.098	4.135

Source: Author's Contribution using IHDS, IIS, NHP, TATA AIG

The STATEID group accounts for the variation in the baseline level of log_CO34 across different Indian states. The estimated variance of 2.187 signifies a significant difference in the starting point of log_CO34. The standard deviation of 1.479 indicates that, on average, states deviate from the mean intercept by about 1.479 units of log_CO34. This substantial heterogeneity suggests that there might be state-specific factors influencing the baseline levels of log_CO34. These factors could potentially include variations in policies, economic disparities, or differences in healthcare infrastructure across states. The Residual group captures the remaining unexplained variation in log_CO34 that the model could not account for through the fixed effects or the random intercepts by state-wise categorization.

FIXED EFFECTS

The estimates of the fitted level 1 model from HLM are given in Table 6.

Table 6: Fixed Effects estimates from HLM

Predictor	Estimate	Std. Error	t value
MI_scores	0.5969**	0.2344	2.546
log_NOC	0.8305***	0.2315	3.588
MSA_scores	-30.8388**	12.1783	-2.532
NetMedQ_scores	-0.4908**	0.2440	-2.012

Source: Author's Contribution using IHDS, IIS, NHP, TATA AIG

The estimated coefficient λ_1 of MI_scores is significant at the 5% level, indicating a positive relationship between MI and log_CO34. This implies that a one unit increase in misinformation leads to a 0.59%

increase in the cost of medical care by the insured. The estimated coefficient λ_4 of log_NOC is significant at the 1% level, showing that a 1% increase in the number of complaints results in a 0.83% increase in medical care costs. The estimated coefficient λ_3 of MSA_scores is significant at the 5% level. This shows a negative relationship between medical service availability and medical care costs, where a one unit increase in MSA_scores leads to a 30.83% decrease in medical care costs. Lastly, the estimated λ_2 of NetMedQ_scores is significant at the 5% level. This suggests that a one unit increase in the number of hospitals with good health care quality standards leads to a 0.49% decrease in medical care costs.

DISCUSSION

The results of model fitting given in Tables 4, 5 and 6 indicate the presence of discrepancies health care provided by insurance schemes. This significantly influences the medical costs incurred by households participating in health insurance policies. The following discussion delves into the specific impact of each discrepancy on actuarial fairness within health insurance.

Impact of Discrepancies in Medical Care Services Under Health Insurance Schemes in India

Misinformation (MI)

In this study, the differences in knowledge between insured and insurer is defined as misinformation. This latent variable comprises of the variables which correspond to level of knowledge of medical information and education background. This is quantitatively represented in Table 4 as: OG5_1, OG5_2, OG5_3, and Education_Group.

The estimated results indicate that the presence of misconceptions and lack of knowledge on health conditions and the related medical treatments. Households with very little knowledge represented by OG5_1, spend less on medical care, often choosing cheaper, lower quality services. Those with some knowledge represented by OG5_2, have the capacity to spend more on higher quality, more expensive health care services. Highly knowledgeable households represented by OG5_3 make cost-effective choices for quality care. The categorization across levels of education shows that households with an undergraduate level of education or higher incur lower costs. The results of our analysis confirm the presence of information gap which leads to inaccurate risk assessments, causing health insurance mispricing and making it actuarially unfair (Kleindorfer & Kunreuther, 1980). Hence, awareness programs on diseases, health care and access to basic education can lead to a better management of medical expenses, leading to fairer health insurance costs which aligning premiums with actual healthcare expenses and risks.

Network Medical Care Quality (NETMEDQ)

In this study, the quality of health care provided by the empaneled hospitals within the insurance framework are examined. The latent variable assesses the quality of medical care within an insurance network is constructed taking into account its crucial role in measuring healthcare costs and insurance fairness. It includes three indicators, namely, log_NABH_H, log_NABH_P, and log_NABH_A, which are tabulated in Table 4.

The estimated results show a positive relationship with NetMedQ which suggest that increase in the number of NABH accredited hospitals improve medical care provided by the network of empaneled hospitals. We see that a higher quality network tends to reduce healthcare costs by providing effective and efficient care, reducing the need for repeated treatments. Failure to maintain high-quality care in the network leads to overpriced insurance policies, as households might seek more expensive out-of-network services (Raposo, Alves, & Duarte, 2009), resulting in actuarial unfairness. To ensure fairness, insurers must maintain rigorous quality standards and increase the number of accredited hospitals, aligning premiums with the true value of services provided.

Medical Service Availability (MSA)

The accessibility to quality health care is a crucial determinant in determining the costs associated with medical services. The latent variable used in this study measures the accessibility to medical services in an Indian state. This latent variable comprises of the variables which correspond to the geographical location of the health care provider and number of allopathy doctors available in the respective Indian state. This is quantitatively represented in Table 4 as: QC3_2, QC3_3, log_QC8 and log_num_doc.

The estimated results show that QC3_2 and log_QC8 show a positive relationship with MSA, suggesting that when medical services are more accessible and when more healthcare providers such as hospitals or clinics are available, there is a positive impact on the perception towards medical care. However, we see that the estimates of QC3_3 and log_num_doc show a negative relationship with MSA, this indicates the presence of challenges in accessibility to quality health care. This is most common in rural parts of India where medical services are predominantly available in distant locations and it reduces overall accessibility. Hence, enhancing service availability through expanded infrastructure and clearer communication about coverage limitations could help mitigate these issues (Xiong, et al., 2018).

Inconsistencies in Claims Processing (log_NOC)

In this study, the inconveniences caused by the insurer and the insured at the time of submission of health insurance claims is called as inconsistencies in claims processing. This variable is pivotal in determining the fairness of health insurance pricing as indemnification is the underlying principle of insurance. It is quantitively measured by the logarithmic transformation of the number of complaints from an Indian state and is given in Table 6.

As shown in Table 6, a proportional increase in medical costs is associated with a corresponding rise in the number of complaints. An increase in complaints also indicates which can result in the mispricing of health insurance, either making it overpriced or underpriced. Consequently, as inconsistencies in the claims process increase, so do medical costs, leading to actuarial unfairness in health insurance. Therefore, it is essential to streamline the claims processing by including measures that allow for transparency, active grievance redressal which will minimize inconsistencies and lead to fairness in health insurance.

CONCLUSION

This study begins by highlighting critical findings from the Indian Human Development Survey-II (IHDS-II), which reveal that approximately 40.8 percent of households with health insurance have incurred additional medical expenses exceeding their risk cover. With a doctor-to-population ratio of 1:1457 in 2011, far below the WHO's recommended 1:1000, the shortage of healthcare resources in India is evident (Deo, 2013). Furthermore, systemic issues such as uneven resource distribution, poor infrastructure, and administrative inefficiencies (Mavalankar et al., 2000) continue to disrupt the delivery of quality care under health insurance schemes. These unaddressed challenges lead to a mismatch between the expected cost of premiums and the actual cost of medical care, raising concerns about the fairness of actuarial principles underlying these insurance policies.

Building on these foundational observations, the study employed SEM and HLM to examine how discrepancies like misinformation, accessibility, hospital quality, and claims process inconsistencies impact medical costs and the fairness of health insurance pricing. The results of the study show statistically significant estimates of these discrepancies which lead to the mismatch of experience adjustments used in actuarial valuation in comparison to the realised costs incurred by insured households.

Misinformation, driven by knowledge gaps, leads to differences in medical spending. Households with less skills obtained through education tend to incur lower initial costs, possibly sacrificing quality, while more informed households make cost-effective decisions. Reducing misinformation through education can align consumer perceptions with reality, supporting actuarial fairness. The quality of care within insurance networks, as indicated by NABH accredited hospitals, enhances health outcomes and reduces costs. Improved facilities in hospitals and accountability in the role of medical practitioners could help insurers maintain fair premium structures, ensuring customers receive the true value for their premiums. Medical service availability significantly impacts costs associated with good quality healthcare. Limited access to services often leads to higher expenditures due to travel or higher local prices, resulting in unfair high premiums. Expanding infrastructure and clear communication about coverage could mitigate these issues. Inconsistencies in the claim process, reflected by rising complaints, suggest inefficiencies that increase medical costs. Including customer friendly policies such as transparency, grievance redressal within the scope of processing health insurance claims can reduce these inconsistencies.

In summary, this study highlights the importance of experience studies in actuarial science and the need for updating experience assumptions to maintain actuarial fairness in pricing health insurance. The discrepancies present in health insurance costs, including misinformation, inadequate healthcare resources, and systemic inefficiencies, significantly impact the alignment between insurance premiums and actual medical costs. Addressing these issues by improving public knowledge on healthcare schemes and practices, enhancing the quality of healthcare provided, and expanding accessibility to medical sericves, can lead to more equitable insurance pricing that truly reflects the risks and costs faced by households. By adopting these strategies, policy makers and insurers can foster greater trust and satisfaction among policyholders which coule lead to client retention and at large a healthier society. The scope of this analysis is restricted to the IHDS-II data. Future research should continue to identify and mitigate additional discrepancies within the health insurance sector, while also exploring the ethical and legal implications of these disparities, especially in relation to vulnerable populations, to promote equity and efficiency in the health insurance sector.

REFERENCES

Abel-Smith, Brian. (1992). Health insurance in developing countries: lessons from experience. *Health policy and Planning, 7*, 215 - 226.

Al-Rawashdeh, Firas. (2016). Determinates of demand on purchasing insurance policies: Case of Jordan. *International Review of Management and Marketing, 6*, 1094-1102.

Arnold, Jens Matthias; Javorcik, Beata; Lipscomb, Molly; Mattoo, Aaditya. (2016). Services reform and manufacturing performance: Evidence from India. *The Economic Journal, 126*(590), 1-39.

Deo, Madhav G. (2013). Doctor population ratio for India - the reality. *The Indian journal of medical research, 137*(4), 632-635.

Desai, S., Vanneman, R., National Council of Applied Economic Research. (2015, 7 28). *India Human Development Survey-II (IHDS-II), 2011-12.* Ann Arbor, Michigan: Inter-university Consortium for Political and Social Research (ICPSR). Retrieved from Inter-university Consortium for Political and Social Research: https://doi.org/10.3886/ICPSR36151.v6

Donahue, Kate and Barocas, Solon. (2021). Better together? how externalities of size complicate notions of solidarity and actuarial fairness. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 185--195).

Eckstein, David; Künzel, Vera; Schäfer, Laura. (2021). *The global climate risk index 2021.* Bonn: Germanwatch. Retrieved from https://bvearmb.do/handle/123456789/1306

Gollier, Christian. (2007). *The Determinants of the Insurance Demand by Firms.* Toulouse School of Economics (LERNA and IDEI). Toulouse: Toulouse School of Economics. Retrieved from http://tse-fr.eu/pub/7278

Heras, Antonio J and Pradier, Pierre-Charles and Teira, David. (2020). What was fair in actuarial fairness ? *History of the Human Sciences*, 91-114. Retrieved 1 5, 2024

Hoyt, Robert E; Khang, H0. (2000). On the Demand for Corporate Property Insurance. *The Journal of Risk and Insurance*, 91-107.

Huta, V. (2014). When to Use Hierarchical Linear Modeling. *The Quantitative Methods for Psychology, 10*(1), 13-28.

Kajwang, B. (2020). Contribution of Industrial All Risks Insurance to the Growth of Manufacturing Firms in Kenya. *Journal of Developing Country Studies, 5*(1), 36-48.

Kleban, J. (2019). Countering Misinformation in the Health Care System: The Care for Stricter Regulations within Health Insurance Proovider Directories. *CARDOzO L. REv., 41*, 1185.

Kleindorfer, P. R., & Kunreuther, H. (1980). Misinformation and Equilibrium in Insurance Markets. In *Economic Analysis of Regulated Markets* (pp. 67-90). Springer.

Krummaker, Simone. (2016). *Corporate Demand for Insurance: Empirical Evidence from Germany.* London: University of London. Retrieved from https://openaccess.city.ac.uk/id/eprint/24066/

Levy, H., & Meltzer, D. (2008). The Impact of Health Insurance on Health. *Annu. Rev. Public Health, 29*, 399-409.

Lieberthal, R. D. (2016). Defining Health Insurance. In R. D. Lieberthal, *What Is Health Insurance (Good) for ?* (pp. 3-32). Springer.

Linnerooth-Bayer, J., & Mechler, R. (2009). Insurance against losses from natural disasters in developing countries. *New York, NY*.

Mavalankar, Dileep, Ramesh Bhat. (2000). Health insurance in India: opportunities, challenges and concerns. *Ahmedabad: Indian Institute of Management*, 1-16.

Mayers, D., & Smith Jr, C. W. (1982). On the Corporate Demand for Insurance. In *Foundations of Insurance Economics: Readings in Economics and Finance* (pp. 190-205). Springer.

Motsepe, Molatelo. (2018). *An Industry Level Analysis of Demand for Insurance in South Africa.* University of Cape Town, Faculty of Commerce. Cape Town: Graduate School of Business (GSB). Retrieved from http://hdl.handle.net/11427/28411

Mushonga, F. B., & Mishi, S. (2022). Natural hazard insurance demand: A systematic review. *Jàmbá: Journal of Disaster Risk Studies, 14*(1), 1223.

Muthén, B. (1983). Latent variable structural equation modeling with categorical data. *Journal of Econometrics, 22*(1-2), 43-65.

Nasir, H. U. (2024). Actuarial fairness: what does it mean and when is it desirable? *School of Graduate Studies Electronic Theses and Dissertations*, 154.

Prokopjeva, Evgenija; Chernova, Galina; Kuznetsova, Nataliya P; Kalayda, Svetlana; Ivanov, Leonid. (2020). Insurance instruments in risk management of the manufacturing sector of a region: the case of the Republic of Khakassia (Russia). *Investment Management & Financial Innovations, 17*(4), 299.

Rao, M. S., & Srinivasulu, R. (2013). Contribution of insurance sector to growth and development of the Indian economy. *IOSR journal of Business and Management, 7*(4), 45-52.

Raposo, M. L., Alves, H. M., & Duarte, P. A. (2009). Dimensions of service quality and satisfaction in healthcare: a patient's satisfaction index. *Service Business, 3*, 85-100.

Regan, L., & Hur, Y. (2007). On the corporate demand for insurance: The case of Korean nonfinancial firms. *Journal of Risk and Insurance, 74*(4), 829-850.

Rothchild, C. (2011). The efficiency of Category discrimination in insurance markets. *Jounral of Risk and Insurance, 78*(2), 267-385.

Santos, Gustavo. (2023, March 15). *Multilevel Regression with R*. Retrieved from Towards Data Science: https://towardsdatascience.com/multilevel-regression-with-r-eb3eb7d8de88

Southwell, Brian G; Otero Machuca, Jessica; Cherry, Sabrina T; Burnside, Melissa; Barrett, Nadine J. (2023). Health misinformation exposure and health disparities: observations and opportunities. *Annual review of public health, 44*, 113-130.

Wood, Glenn L.; Morris, Richard L. (2010). Consumer Complaints Against Insurance Companies. *Journal of Personal Finance,, 9*.

Wright, S. (1918). On the nature of size factors. *Genetics, 3*(4), 367.

Xiong X, Zhang Z, Ren J, Zhang J, Pan X, Zhang L, et a. (2018, 3 7). Impact of universal medical insurance system on the accessibility of medical service supply and affordability of patients in China. (D.-H. Kimon Bekelis, Ed.) *PLoS ONE, 13*(3), e0193273. doi:https://doi.org/10.1371/journal.pone.0193273

Yoshida, K., & Deyle, R. E. (2005). Determinants of Small Business Hazard Mitigation. *Natural Hazards Review, 6*(1), 1-12.

Zhou, F., & Botzen, W. (2021). Firm level evidence of disaster impacts on growth in Vietnam. *Environmental and Resource Economics, 79*(2), 277-322.

Zhu, M., Kui, C., & Fang, Y. (2011). Demand for corporate insurance in China: empirical analysis with province-level panel data. *Chinese Economy, 44*(6), 15-29.

Zou, H., & Adams, M. B. (2006). The corporate purchase of property insurance: Chinese evidence. *Journal of Financial Intermediation, 15*(2), 165-196.

MSE Monographs

- * Monograph 34/2015
  Farm Production Diversity, Household Dietary Diversity and Women's BMI: A Study of Rural Indian Farm Households
  Brinda Viswanathan

- * Monograph 35/2016
  Valuation of Coastal and Marine Ecosystem Services in India: Macro Assessment
  K. S. Kavi Kumar, Lavanya Ravikanth Anneboina, Ramachandra Bhatta, P. Naren, Megha Nath, Abhijit Sharan, Pranab Mukhopadhyay, Santadas Ghosh, Vanessa da Costa and Sulochana Pednekar

- * Monograph 36/2017
  Underlying Drivers of India's Potential Growth
  C.Rangarajan and D.K. Srivastava

- * Monograph 37/2018
  India: The Need for Good Macro Policies *(4th Dr. Raja J. Chelliah Memorial Lecture)*
  Ashok K. Lahiri

- * Monograph 38/2018
  Finances of Tamil Nadu Government
  K R Shanmugam

- * Monograph 39/2018
  Growth Dynamics of Tamil Nadu Economy
  K R Shanmugam

- * Monograph 40/2018
  Goods and Services Tax: Revenue Implications and RNR for Tamil Nadu
  D.K. Srivastava, K.R. Shanmugam

- * Monograph 41/2018
  Medium Term Macro Econometric Model of the Indian Economy
  D.K. Srivastava, K.R. Shanmugam

- * Monograph 42/2018
  A Macro-Econometric Model of the Indian Economy Based on Quarterly Data
  D.K. Srivastava

- * Monograph 43/2019
  The Evolving GST
  Indira Rajaraman

MSE Working Papers
Recent Issues

* Working Paper 262/2024
  Empowerment of Scheduled Tribes and other Traditional Forest Dwellers for Sustainable Development of India
  Ulaganathan Sankar

* Working Paper 263/2024
  How Green (performance) are the Indian Green Stocks – Myth Vs Reality
  Saumitra Bhaduri & Ekta Selarka

* Working Paper 264/2024
  Elementary Education Outcome Efficiency of Indian States: A Ray Frontier Approach
  Jyotsna Rosario & K.R Shanmugam

* Working Paper 265/2024
  Are the Responses of Oil Products Prices Asymmetrical to Global Crude Oil Price Shocks? Evidence from India
  Abdhut Deheri & Stefy Carmel

* Working Paper 266/2024
  Drivers and Barriers to the Adoption of Renewable Energy: Investigating with the Ecological Lens
  Salva K K & Zareena Begum Irfan

* Working Paper 267/2024
  A Multi-Criteria Decision-Making Model to Determine the Share of Variable Renewable Energy Sources
  Salva K K & Zareena Begum Irfan

* Working Paper 268/2024
  Determinants of Renewable Energy in Asia: Socio-Economic and Environmental Perspective
  Salva K K & Zareena Begum Irfan

* Working Paper 269/2024
  Adaptive Analysis of 3E Factors (Economy, Energy, and Environment) for Renewable Energy Generation in the South and South-East Asian Region
  Salva K K & Zareena Begum Irfan

* Working Paper 270/2024
  Detecting and Forecasting Financial Bubbles in The Indian Stock Market Using Machine Learning Models
  Mahalakshmi Manian and Parthajit Kayal

---

* Working papers are downloadable from MSE website http://www.mse.ac.in