The effect of access to internet on Health Insurance demand in India's rural versus urban areas in a modern context

Kasi Donepalli

FLAME University

Econometrics-II

Prof.Reshmi Sengupta

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Abstract

Access to quality healthcare is crucial for any individual but however, poor Indian households struggle to pay for their unpredictable health expenses in an increasingly costly healthcare climate in India. Hence, individuals are encouraged to subscribe for health insurances to cover for unexpected exorbitant medical expenses without much burden on their out-of-pocket. However, it is of paramount importance to understand the determinants of health insurance acquisition to better build health insurance products specific to individuals across rural/urban areas,age sex,caste and income sub-groups. The effect of socioeconomic and demographic variables on health insurance demand is well-studied but however, there is lack of literature which empirically ascertains the effect of access to internet devices on health insurance demand. Therefore, this study attempted to employ probit analysis to study the effect of access to internet on health insurance demand by controlling for pre-disposing, enabling, psychosocial and need-based factors using extended Ardensen framework. The results of this study found that access to Internet is positively associated with Health Insurance uptake and the Probit marginal effects at mean estimates suggest that access to Internet increases the likelihood of Insurance uptake by about 1.4% both in rural and urban areas and Interestingly, confidence factor in governments is positively associated with Health Insurance uptake

Introduction

In developing countries like India, access to quality health care is a significant issue which partially stems from inadequate health care budgets. A study found that 45% of the doctors in primary healthcare services were unavailable during their service hours, and moreover, 75.6% of qualified doctors in Madhya Pradesh were working for the private sector in the year 2007(Singh&Badaya,2014).Therefore, by the dynamics of low supply and high demand for quality healthcare leads to increasing costs of healthcare which poses a significant affordability challenge to India's lower and lower-middle income groups.

Out of pocket health spending is a significant factor driving around 6.2% of the Indian population below the poverty line(BPL) every year(Nandi et al.,2013). It is believed that risk sharing mechanisms such as health insurances help families cover unexpected medical expenses without much burden on their out-of-pocket expenses. Lack of access to healthcare and unexpected health expenditures are argued to be one of the major causes of poverty in developing countries, and also, lack of health insurance is believed to have a negative impact on the health of the household in general(Asgary et al.,2004). As a consequence of ill health in developing countries, the skillset of human capital which is essential for a country's economic growth is argued to be mediocre(Asgary et al.,2004).Hence, Health insurance plays a crucial role in lowering the effect of expensive health care on the economic wellbeing of poor households because health insurance provides a family with the financial security to cover for unpredictable medical expenses by paying predictable amounts of insurance premiums spread out over a period of time. However, in order to encourage subscriptions to health insurance programs, it is of paramount importance to understand the factors driving a population's willingness to subscribe for health insurances.

There exists well-established literature on the effect of socio-economic and demographic variables on health insurance demand (Wan et al.,2020). However, the effect of access to internet devices on health insurance demand is still not well-established and it is crucial to study this association due to increasingly rapid mobile phones penetration and digitization of Insurance products delivery mechanisms in India. In addition, the relevance of this study is further amplified with the digital mandate push from the government of India.

Therefore, this study attempts to explore the effect of access to digital devices on health insurance demand across rural and urban areas in India, using the Indian Human Development Survey-II, 2011-2012. This study aims to contribute towards insurance policy making in a digitalized world by empirically determining the impact of consumer access to internet devices on health insurance demand amongst several other demographic, socio-economic and psychosocial variables, and ultimately, contribute towards achieving Universal health coverage.

Literature review

Wan et al.(2020) studied the determinants of private health insurance(PHI) acquisition in China,by using the data from the 4th wave of China Household Finance survey conducted in 2017. This study employed logistic regression analysis and chi-square tests to understand the determinants of a person's decision to buy health insurance. Essentially, this study employed Andersen health services utilization model which assess a person's decision to buy health insurance based on three factors: predisposing factors like age, level of education,marital status, size of household), enabling factors such as income of household, household medical expenses and debt), and need-based factors.The results of this study found that all the factors mentioned above are statistically significant to explain the likelihood of a person subscribing to health insurance.

Yadav et al.(2021) explored the topic of health insurance penetration in India using the latest two rounds of nationally representative datasets of the National Family Health Survey 2005-06 and 2015-16. This study identified the covariates of household's participation and their preferences for different types of health insurance schemes, by employing an average marginal effect of binary, and multinomial logit regression models with conditional categories after checking their Kernel density function. The results of this study indicate that health insurance subscriptions in India is more skewed towards the high-income households and developed states of the country. Also, age, occupation and education level were found to be positively associated with health insurance subscription.

Asgary et al.(2004) conducted a study to estimate rural households' demand for health insuranceand their consensus to pay for health insurance in Iran, using contingent valuation method(CVM). The sample data for this study has been obtained from 2139 households across Iran and employed ordinary least squares linear regression model to study the willingness to pay for health insurance. The results of the survey show that most rural households are willing to pay for health insurance and the amount they are willing to pay is associated with the socio-economic characteristics of the household and the perceived benefits from insurance. The regression results show that age,education level, healthcare facilities of rural areas, access to medical care services and the household's medical needs have a statistically significant impact on the household's willingness to pay for health insurance.

Nandi et al.(2013) studied the determinants of participants in Rashtriya Swasthya Bima Yojana(RSBY) at a district level, by analysing the official data on RSBY enrolment, socio-economic data from the district level household survey 2007-2008, and an additional state-level information on fiscal health, political affiliations, and quality of governance. The Rashtriya Swasthya Bima Yojana (RSBY) was introduced as social health insurance scheme which aims to enhance healthcare access and provide financial risk protection to the poor. Results of this study using multivariate probit and OLS analyses show that political and institutional factors are among the top determinants at explaining the variation in participation and enrolment in RSBY. The districts with lower quality of governance, a pre-existing state-level health insurance scheme, or with a lower level of fiscal deficit to GDP were significantly less likely to participate. In concern to the socioeconomic factors, districts with a higher share of socioeconomically backward castes are less likely to participate.Finally, districts with more non-poor households are more likely to be enrolled in RSBY scheme.

Alesane and Anang.(2018) studied the factor influencing insurance uptake and its implications in policy making for Ghana, using a case of Awutu Senya West District of Ghana. This study used logit model to analyze data collected from 178 randomly selected people working in the microfinance business at the area of the study. The results of the study show that the likelihood of having health insurance is higher amongst younger people whilst lower amongst women. Older women groups were more probable to take up health insurance than older men. This study also found that likelihood of having insurance increases with level of education but decreases with household size.This study culminates its paper by suggesting that socio-demographic variables like age, sex, education level and size of household influences the decision to purchase HI. In addition, advises policy makers to improve efforts towards insurance awareness campaigns and lowering the statutory age for exemption from premium payments in rural areas.

Bradley et al.(2002) assessed the 1995 Andersen health services use model to suggest changes to improve the explanatory power of the model when used in studies of healthcare and services. This study primarily used twelve focus groups of African-American and white individuals of ages 65 or greater, living in Connecticut in the year 2000. This study found that psychosocial factors such as attitudes and knowledge, social norms and perceived control are identified as factors determining the use of health services, and therefore, expanding the Andersen model to include psychosocial factors. My study will try to incorporate psychosocial factors such as confidence to determine the insurance uptake.

Supakankunti.(2001) studied the determinants of health card uptake in Thailand,health insurance card scheme was initiated as a Health Card Project (HCP) in 1983 which is primarily based on risk sharing mechanism of health expenditures. Uninsured Thai citizens can subscribe to this card and avail insurance for a fee of ($0.67), irrespective of the kind of illness treated.This study employed logistic regression analysis to find significant predictors/variables of health card uptake and non-uptake. The results of the study found that employment, education, and existing illnesses are essential determinants influencing card purchase. Secondly, households having symptoms of illness were more probable to subscribe for health card, and also, suggested that health card scheme improved accessibility to health care and shown to have increased levels of satisfaction amongst health card holders.

Chakrabarti and Shankar.(2018) studied the effect of a household assets, exposure to media demographic and caste of households on health insurance use in India, by analysing the National Family Health Survey-III data. The results of this study have shown that richer households are more likely to subscribe for health insurance and access to media has a positive correlation with HI subscription. Lower subscription rates are seen in the scheduled tribe groups in rural and urban areas as well, and the Muslim groups living in urban regions. There was a significant regional disparity observed in health insurance subscription, and the likelihood of health insurance subscription is higher in urban areas.

Literature gap

After an extensive review of literature, it is found that there are limited comprehensive studies which empirically assess the effect of access to digital devices on a person's willingness to purchase health insurance in India. It is important to study this association because of rapid digitalization in the Insurance industry offering innovative insurance products online, and further intensified with the digital mandate push from the Indian government.

Access to digital devices would enable consumers to gain awareness and understand the significance of various health insurance schemes offered by both the government and private players, through either insurance companies marketing campaigns or social media. Subsequently, the search costs of acquiring a health insurance will be substantially lower, as consumers can now compare health insurance products across various platforms online and then, make a well-informed and well-suited insurance purchase. Also, due to digitalization of Insurance product delivery systems, the transaction costs are significantly lower as an insurance purchase and payment of insurance premiums can be both done online without any physical body movement.

Research question: To study the effect of access to internet on health insurance demand in India's rural verus urban areas.

This study hypothesizes that a greater percentage of the Indian urban population have health insurance than the rural counterparts, and access to digital devices increases the likelihood of a person having health insurance.

Methodology

Sample: This study obtains household data from the Indian Human Development Survey-II conducted in 2011-2012. IHDS-I is a nationally representative survey of 41,554 households conducted in 2004-2005, while IHDS –II has re-interviewed 83% of the original households as well as split households residing within the village and an additional sample of 2134 households. The final sample size for IHDS-II is 42,152 households with 27,579 rural and 14,573 urban. These households are from 33 states and union territories, 384 districts, 1420 villages and 1042 urban blocks located in 276 towns and cities. Data has been collected in the form of two one-hour interviews in each household covering topics concerning health, education, employment, economic status, marriage, fertility, gender relations, social capital, village infrastructure, wage levels, and panchayat composition. The sample for this study includes all the household members who have been living in the same house and sharing the same kitchen for more than 6 months with total income greater than or equal to zero and of the age groups zero to ninety-nine. This paper will also attempt to perform a sub-sample regression analysis between rural and urban areas to compare the determinants of health Insurance uptake in both the areas.

Table 1: Description of Variables in the study

Variable	Code	Type	Description
Health Insurance status of a Household	HHealth_Ins	Binary	= 1 if a household has a government or private Health Insurance, else, 0, if neither.
Has access to Internet	Int_access	Binary	=1 if a household owns a computer or laptop or a mobile phone, else, 0, if neither.
Caste	caste	Categorical	=1 if General(Brahmin/ OBC/forward) =2 if Scheduled Caste(SC) =3 if Scheduled Tribe =4 if other castes
Religion	religion	Categorical	=1 if Hindu =2 if Muslim =3 if Christian =4 If others(Sikhs, Buddhism, Jainism,Tribal, others or none)
Urban Residence status	urban	Binary	=1 if household living in urban areas = 0 if living in rural
Faced major illness/accidents with large amounts of expenditure	major_illness	Binary	=1 if had a major illness/accident with large amounts of expenditure =0 if no
Household has some kind of financial security	fin_secure	Binary	=1 if a household has bought securities/fixed deposits/Bank savings/part of a credit society/post office account/gets pensions or has LIC = 0 if none above
Confidence in government hospitals and doctors to provide good care	conf_ghosp	Binary	=1 if confident = 0 if little to no confidence
Confidence in courts to deliver justice	conf_courts	Binary	=1 if confident = 0 if little to no confidence
Confidence in banks to keep money safe	conf_banks	Binary	=1 if confident = 0 if little to no confidence
Confidence in government to take care of its people	conf_gov	Binary	=1 if confident = 0 if little to no confidence
Age of male head in the household	head_age	Continuous	Age in numbers
Household had debt in the last five years	debt	Binary	=1 if had loans in the past 5 years, else, 0.

Highest adult education in the household	educ_level	Categorical	=0 if studied less than 10th standard =1 if studied 10th or 11th class =2 if studied 12th class or one year postsecondary =3 if studied more than or equal to 2 year post secondary or bachelors or advanced bachelors
Household Total Income	income	Continuous	Total Income of household
Number of people in a household	N_persons	Continuous	Number of individuals in a household
Interaction term(conf_gov*income)	conf_gov * income	conf_gov – Binary income- Continuous	Captures the additional effect of income on Health Insurance given that households are confident in the government to take care of them as opposed to non-confident groups

Source: Author's work

Table 2: Summary statistics of variables in the model

Variable	Type	Mean	N	Std Dev	min	max
HHealth_Ins	Binary	0.10	41700	0.31	0	1
Int_access	Binary	0.80	41669	0.4	0	1
caste	Categorical	1.43	41614	0.7	0	3
religion	Categorical	1.29	41699	0.70	0	3
urban	Binary	0.35	41700	0.48	0	1
major_illness	Binary	0.26	41621	0.44	0	1
fin_secure	Binary	0.99	27241	0.09	0	1
conf_ghosp	Binary	0.54	41619	0.5	0	1
conf_courts	Binary	0.67	41490	0.47	0	1
conf_banks	Binary	0.90	41566	0.3	0	1
conf_gov	Binary	0.3	41497	0.46	0	1
head_age	Continuous	49.1	35865	13.5	15	99
debt	Binary	0.53	41672	0.5	0	1
educ_level	Categorical	0.96	41689	1.2	0	3
income	Continuous	129469.6	41700	217085.5	0	1.14 x 10^7
N_persons	Continuous	4.85	41700	2.32	1	33

Source: Author's Calculation

65.13% of the households in this sample are from rural areas, while, 34.87% are from urban areas. Irrespective of the regions, 80.24% of households have Internet access and whereas 19.76% do not. Amongst the urban households 91.11% have Internet access and 8.89% do not, whereas, in rural households 25.58% do not have access to Internet. In concern to the proportion of Health Insurance holders, only 10.85% have health Insurance and 89.15% of households do not have. In the urban households, 87.55% do not have health Insurance and only 12.45% have acquired Health Insurance, while, in rural households 90% of the families do not have a health insurance. Similarly, the mean values in table 2 shows the proportion of sample opting =1 for each binary variable, the mean income in this study sample is 129469.6 rupees and the mean head adult age in the household is 49.1 years.

Justification for the choice of variables

This paper adopts an extended form of Andersen model of health services framework from Bradley et al.(2002), by including the role of psychosocial factors such as confidence in government hospitals to provide good care, banks to keep money safe, government to take care of its people and courts to provide justice as more control variables for the study in addition to pre-disposing, enabling and need-based factor under the simple Andersen model(Wan et al.,2020).I believe confidence factor is important to consider because a household's perceptions on future certainty and faith in institutions drives them to think about their own future financial security. Several of the studies covered in literature review such as Wan et al.(2020) and Alesane and Anang.(2018) highlight the significance of education levels, age, income and debt as major determinants of Health Insurance uptake and hence, my model accounted for these variables as controls.

Three sets of control vectors determining the decision to buy health insurance:

Predisposing factors: This vector consists of factors that increase the likelihood of an individual to seek health services. It includes demographic variables like head adult age, and social variables like level of education and size of household which pre-disposes households to acquire health insurance

Enabling factors: This vector consists of factors that support health-seeking behavior and, in specific to our study, provide support for individuals to purchase Health Insurance(HI). It includes household income and debt to acquire HI. In addition, variables of caste, urban residence status and religion are also incorporated as controls in this study as works from Chakrabarti and Shankar in (2018) suggests Inter-regional disparities in Health Insurance uptake and at same time Inter-caste and religion as well. Household debt and medical expenses will also be taken into account, as these expenses give a glimpse into the estimated insurance covered based on their historical spending.

Need-based factors: This vector represents factors associated with the health status of the household which lead to a derived demand in health insurance. This vector consists of variables capturing the evaluated health status of a household such as the households if a household had faced large amounts of expenditure on any major illness/accidents

Empirical model

Linear Probability Model will be used as a benchmark model for this study and then, Probit sub-sample analysis will be employed to study the likelihood of a household having health insurance (a binary dependent variable) given a household's access to Internet (main independent variable) and controlled for other variables from the predisposing, psychosocial,enabling and need-based factors in India's rural vs urban areas.

LPM model

$$\begin{aligned} HHealth\_Ins = {} & \beta_0 + \beta_1 Int\_access + \beta_2 caste + \beta_3 religion + \beta_4 major\_illness \\ & + \beta_5 fin\_secure + \beta_6 conf\_ghosp + \beta_7 conf\_gov + \beta_8 conf\_banks \\ & + \beta_9 income + \beta_{10} conf\_courts + \beta_{11} N\_persons + \beta_{12} debt + \beta_{13} head\_age \\ & + \beta_{14} edu\_level + \beta_{15} urban + \beta_{16} confgov * income + \varepsilon \end{aligned}$$

Probit model for urban sample:

$$\begin{aligned} & P(HHealth_{Ins} = 1 | X\ if\ urban == 1) \\ & = \phi(\beta_0 + \beta_1 Int\_access + \beta_2 caste + \beta_3 religion + \beta_4 major\_illness \\ & + \beta_5 fin\_secure + \beta_6 conf\_ghosp + \beta_7 conf\_gov + \beta_8 conf\_banks \\ & + \beta_9 income + \beta_{10} conf\_courts + \beta_{11} N\_persons + \beta_{12} debt + \beta_{13} head\_age \\ & + \beta_{14} edu\_level + \beta_{15} urban + \beta_{16} (confgov * income)) + \varepsilon \end{aligned}$$

Probit model for rural sample:

$$\begin{aligned} & P(HHealth_{Ins} = 1 | X\ if\ urban == 0) \\ & = \phi(\beta_0 + \beta_1 Int\_access + \beta_2 caste + \beta_3 religion + \beta_4 major\_illness \\ & + \beta_5 fin\_secure + \beta_6 conf\_ghosp + \beta_7 conf\_gov + \beta_8 conf\_banks \\ & + \beta_9 income + \beta_{10} conf\_courts + \beta_{11} N\_persons + \beta_{12} debt + \beta_{13} head\_age \\ & + \beta_{14} edu\_level + \beta_{15} urban + \beta_{16} (confgov * income)) + \varepsilon \end{aligned}$$

Results

Table 3: OLS specification regression (LPM model)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins
Int_access	0.035***	0.033***	0.031***	0.031***	0.022***	0.022***	0.022***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
1.caste(SC)		-0.005	-0.010***	-0.011***	-0.005	-0.005	-0.005
		(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
2.caste(ST)		-0.016***	-0.028***	-0.027***	-0.016**	-0.016**	-0.016**
		(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
3.caste(Other)		0.020	0.023	0.023	0.056***	0.056***	0.056***
		(0.015)	(0.014)	(0.015)	(0.022)	(0.022)	(0.022)
1.religion(Muslim)			-0.041***	-0.041***	-0.045***	-0.045***	-0.045***
			(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
2.religion(Christian)			0.072***	0.073***	0.086***	0.087***	0.086***
			(0.011)	(0.011)	(0.015)	(0.015)	(0.015)
3.religion(Other)			-0.043***	-0.042***	-0.059***	-0.059***	-0.059***
			(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
major_illness				0.013***	0.012***	0.012***	0.012***
				(0.004)	(0.005)	(0.005)	(0.005)
fin_secure					0.017	0.017	0.017
					(0.021)	(0.021)	(0.021)
conf_ghosp						0.001	0.002
						(0.004)	(0.004)
conf_banks							-0.003
							(0.008)
_cons	0.080***	0.084***	0.092***	0.088***	0.096***	0.095***	0.098***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.021)	(0.022)	(0.022)
N	41669	41584	41584	41515	27143	27122	27099
R-sq	0.002	0.002	0.006	0.007	0.006	0.006	0.006
adj. R-sq	0.002	0.002	0.006	0.006	0.006	0.006	0.005
rmse	0.311	0.311	0.310	0.310	0.334	0.334	0.334
Standard errors in parantheses							
*p<0.1 **p<0.05 ***p<0.01							

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins
Int_access	0.023***	0.011**	0.011*	0.014**	0.013**	0.020***	0.012*	0.010	0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
1.caste(SC)	-0.005	0.000	-0.000	0.000	-0.001	0.005	0.008	0.008	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
2.caste(ST)	-0.017**	-0.012	-0.011	-0.010	-0.009	-0.001	0.003	0.005	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
3.caste(Other)	0.056***	0.057***	0.056***	0.055**	0.050**	0.061**	0.062**	0.061**	0.061**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.024)	(0.024)	(0.024)	(0.024)
1.religion(Muslim)	-0.045***	-0.042***	-0.043***	-0.041***	-0.040***	-0.040***	-0.037***	-0.039***	-0.039***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
2.religion(Christian)	0.088***	0.080***	0.079***	0.077***	0.081***	0.082***	0.077***	0.077***	0.077***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.017)	(0.017)	(0.017)	(0.017)
3.religion(Other)	-0.059***	-0.067***	-0.067***	-0.068***	-0.063***	-0.071***	-0.070***	-0.069***	-0.069***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
major_illness	0.012***	0.014***	0.014***	0.014***	0.010**	0.010*	0.010**	0.011**	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
fin_secure	0.019	0.016	0.016	0.016	0.013	0.026	0.025	0.024	0.024
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
conf_ghosp	0.001	0.001	0.004	0.004	0.005	0.003	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
conf_banks	-0.005	-0.005	0.005	0.005	0.002	0.002	0.002	0.003	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
conf_gov	0.014***	0.015***	0.017***	0.017***	0.017***	0.016***	0.016***	0.017***	0.022***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
income		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
conf_courts			-0.019***	-0.019***	-0.019***	-0.020***	-0.020***	-0.020***	-0.020***
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N_persons				-0.002**	-0.003***	-0.004***	-0.004***	-0.003***	-0.003***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
debt					0.037***	0.037***	0.040***	0.041***	0.041***
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
head_age						0.001***	0.001***	0.001***	0.001***
						(0.000)	(0.000)	(0.000)	(0.000)
1.educ_level(10th)							0.006	0.005	0.005
							(0.006)	(0.006)	(0.006)
2.educ_level(12th)							0.013*	0.011	0.011
							(0.007)	(0.007)	(0.007)
3.educ_level(>12th)							0.033***	0.029***	0.029***
							(0.007)	(0.007)	(0.007)
urban								0.013**	0.012**
								(0.005)	(0.005)
1.conf_gov*income									-0.000
									(0.000)
_cons	0.094***	0.087***	0.090***	0.099***	0.086***	0.033	0.035	0.031	0.029
	(0.022)	(0.022)	(0.023)	(0.023)	(0.023)	(0.025)	(0.025)	(0.025)	(0.025)
N	27034	27034	27006	27006	27005	23462	23461	23461	23461
R-sq	0.006	0.013	0.013	0.013	0.016	0.019	0.020	0.020	0.020
adj. R-sq	0.006	0.012	0.013	0.013	0.016	0.018	0.019	0.019	0.019
rmse	0.335	0.334	0.334	0.334	0.333	0.334	0.334	0.334	0.334
Standard errors in parantheses									
*p<0.1 **p<0.05 ***p<0.01									

Firstly, the simple OLS regression illustrated by specification (1) between HHealth_Ins and Int_access yields a statistically significant(p<0.01) positive association, with the beta coefficient being 0.035. Households with access to Internet are predicted to have 3.5% higher chances of having health Insurance as opposed to households without Internet access.

Specification (2) has an additional variable of caste other than Int_access, the results illustrate that only ST caste is statistically significant at 1% levels and it suggests that ST households are 1.6% less likely to have health Insurance than General Caste households. While, SC households are 0.5% less likely to have Health Insurance compared to General caste. However, Other caste group households are predicted to have 2% higher probability of having health Insurance than General caste Households.

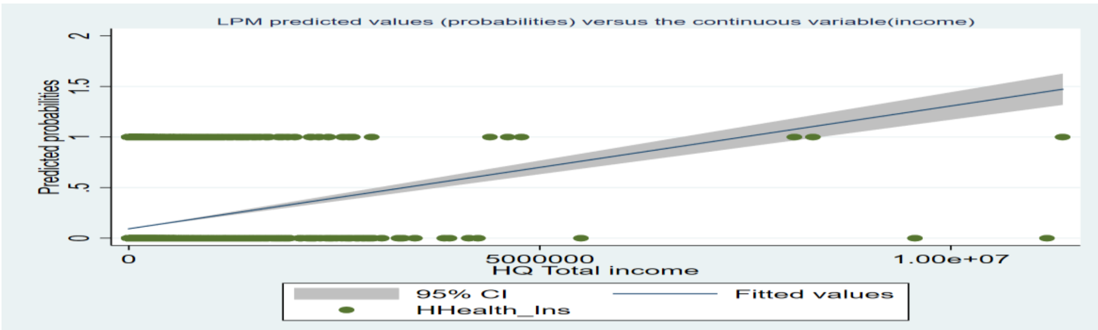
Further specifications were tabulated by adding one variable each to the regressions ranging from religion, major illness, fin_secure, conf_ghosp, conf_banks, conf_gov, income, conf_courts, N_persons, debt , head_age, educ_level, urban to an interaction term of conf_gov * income. Specification (16) is the final specification including all the control variables with the main independent variable(Int_access) of our study. As per Specification (16) Int_access becomes statistically insignificant to explain changes in Health Insurance status of households when the model is fully adjusted with control variables. However, it still holds a positive relationship suggesting that households with Internet access have a 1% higher chance of holding Health Insurance. Secondly, Only Other castes category is statistically significant at 5% levels to explain changes in Health Insurance status of households as opposed to General caste category. There is 6.1% higher chances for other caste groups than General category households to have health Insurance. Religion groups are all statistically significant at 1% levels, and Muslim households are 3.9% less likely to have Health Insurance than Hindu families. Whereas Christian households are 7.7% more probable of having health Insurance than Hindu households and other religion households are 6.9% less likely to have Health Insurance than Hindu households.

Subsequently, major illness holds a positive relationship with HHealth_Ins with a coefficient of 0.011 and is statistically significant at 5% levels. Households who had suffered with major illness are 1.1% more likely to have Health Insurance than households who did not have a major illness. fin_secure, conf_ghosp, conf_banks are all satistically insignificant at 10% levels to explain variation in Health Insurance status of households but confidence in government(conf_gov) is statistically significant at 1% levels and households with confidence in their governments are 2.2% more likely to have Health Insurance than non-confident households. Income is also statistically significant at 1% levels but has a negligible effect on health Insurance status of a household with almost 0% more likelihood of acquiring Health Insurance for a unit increase in income. Households with highest adult education greater than 12^{th} standard are 2.9% more likely to have Health Insurance than the reference category of education levels less than 10^{th} standard and similarly, urban households are 1.2% more probable to acquire health insurance than rural counterpart.

Finally, from specification (1) to (16) as more control variables are accounted for in the model, the R-squared value increased from 0.002 to 0.02. Hence, the explanatory power of the model has been improved to better explain variation in Household Health Insurance status.

The major problem with LPM model in Binary dependent variable analysis is that the predicted probabilities can sometimes be beyond the range 0 and 1, which defies the laws of probability as can be seen in the below scatter plot between LPM predicted probabilities and continuous variable of income. Hence, this study will further employ Probit model to study the effect of a households Internet access on Health Insurance status of a household.

Figure 1: LPM predicted values(probabilities) versus the continuous variable(income)



Diagnostic tests

OVTEST: The full OLS model has omitted variable bias as the p-value reported is 0.000, and hence, reject the null that model has no omitted variables and the model is mispecified.

VIF Test for multicollinearity: The mean VIF test for multicollinearity suggests there is low level of multicollinearity between independent variables as the mean VIF test results are below 5(at 1.18).

Heteroskedasticity test: Rvfplot in OLS ideally looks like a random scatter of points. The plot below is not randomly scattered. Hence, heteroskedasticity exists. Homoskedasticity assumption is violated when dichotomous dependent variable is used.

Figure 2 : LPM model RVFPLOT

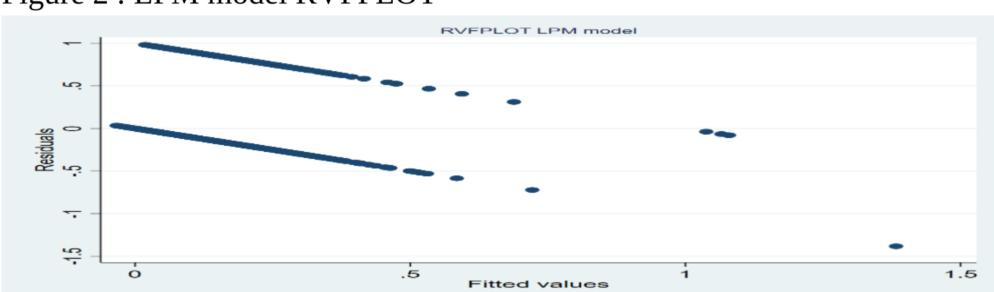


Table 4 : Probit sub-sample specification regression (if urban=0)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins
Int_access	0.169***	0.163***	0.159***	0.159***	0.085***	0.086***	0.088***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.033)	(0.033)	(0.033)
1.caste(SC)		0.039	0.029	0.026	0.074**	0.074**	0.074**
		(0.025)	(0.026)	(0.026)	(0.031)	(0.031)	(0.031)
2.caste(ST)		-0.075**	-0.131***	-0.121***	-0.048	-0.048	-0.047
		(0.036)	(0.038)	(0.038)	(0.045)	(0.045)	(0.045)
3.caste(Other)		0.131	0.141	0.141	0.304***	0.304***	0.305***
		(0.090)	(0.091)	(0.091)	(0.116)	(0.116)	(0.116)
1.religion(Muslim)			-0.221***	-0.224***	-0.162***	-0.162***	-0.162***
			(0.040)	(0.040)	(0.051)	(0.051)	(0.051)
2.religion(Christian)			0.387***	0.390***	0.448***	0.446***	0.449***
			(0.058)	(0.058)	(0.069)	(0.069)	(0.069)
3.religion(Other)			-0.388***	-0.388***	-0.466***	-0.467***	-0.470***
			(0.064)	(0.064)	(0.074)	(0.074)	(0.074)
major_illness				0.113***	0.093***	0.094***	0.094***
				(0.023)	(0.028)	(0.028)	(0.028)
fin_secure					0.057	0.059	0.059
					(0.131)	(0.131)	(0.130)
conf_ghosp						0.020	0.017
						(0.025)	(0.025)
conf_banks							0.055
							(0.051)
_cons	-1.411***	-1.410***	-1.379***	-1.412***	-1.320***	-1.332***	-1.384***
	(0.022)	(0.024)	(0.025)	(0.026)	(0.134)	(0.135)	(0.141)
N	27139	27111	27111	27081	16974	16964	16949
pseudo R-sq	0.003	0.003	0.010	0.011	0.010	0.010	0.010

Standard error in Parantheses
*p<0.1 **p<0.05 ***p<0.01

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins
Int_access	0.092***	0.078**	0.076**	0.074**	0.065*	0.095**	0.072*	0.073*
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.037)	(0.038)	(0.038)
1.caste(SC)	0.072**	0.079**	0.076**	0.076**	0.076**	0.104***	0.114***	0.113***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.034)	(0.034)	(0.034)
2.caste(ST)	-0.052	-0.045	-0.040	-0.041	-0.028	0.028	0.040	0.038
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.048)	(0.048)	(0.048)
3.caste(Other)	0.310***	0.313***	0.313***	0.314***	0.290**	0.331***	0.328***	0.330***
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.126)	(0.126)	(0.126)
1.religion(Muslim)	-0.167***	-0.163***	-0.166***	-0.167***	-0.158***	-0.137**	-0.126**	-0.127***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.056)	(0.056)	(0.056)
2.religion(Christian)	0.450***	0.438***	0.431***	0.432***	0.480***	0.467***	0.443***	0.444***
	(0.069)	(0.070)	(0.070)	(0.070)	(0.070)	(0.077)	(0.078)	(0.078)
3.religion(Other)	-0.470***	-0.485***	-0.484***	-0.484***	-0.454***	-0.539***	-0.540***	-0.539
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.084)	(0.084)	(0.084)
major_illness	0.093***	0.095***	0.093***	0.092***	0.068**	0.063**	0.064**	0.065**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)	(0.030)	(0.030)
fin_secure	0.067	0.065	0.068	0.068	0.046	0.123	0.125	0.126
	(0.131)	(0.131)	(0.131)	(0.130)	(0.132)	(0.146)	(0.146)	(0.146)
conf_ghosp	0.013	0.012	0.028	0.028	0.035	0.032	0.034	0.034
	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)
conf_banks	0.043	0.044	0.086	0.086	0.072	0.084	0.086	0.086
	(0.051)	(0.051)	(0.053)	(0.053)	(0.053)	(0.057)	(0.057)	(0.057)
conf_gov	0.067**	0.068**	0.079***	0.079***	0.074***	0.077***	0.079***	0.094***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.029)	(0.029)	(0.033)
income		0.000***	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
conf_courts			-0.088***	-0.088***	-0.095***	-0.101***	-0.102***	-0.102***
			(0.029)	(0.029)	(0.029)	(0.031)	(0.031)	(0.031)
N_persons				0.001	-0.001	-0.006	-0.007	-0.007
				(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
debt					0.232***	0.241***	0.245***	0.244***
					(0.027)	(0.030)	(0.030)	(0.030)
head_age						0.006***	0.005***	0.005***
						(0.001)	(0.001)	(0.001)
1.educ_level(10th)							0.048	0.049
							(0.039)	(0.039)
2.educ_level(12th)							0.057	0.058
							(0.044)	(0.044)
3.educ_level(>12th)							0.094**	0.097**
							(0.041)	(0.041)
1.conf_gov*income								-0.000
								(0.000)
_cons	-1.401***	-1.412***	-1.403***	-1.408***	-1.504***	-1.890***	-1.890***	-1.895***
	(0.142)	(0.142)	(0.142)	(0.143)	(0.145)	(0.169)	(0.169)	(0.169)
N	16915	16915	16899	16899	16899	14690	14689	14689
pseudo R-sq	0.011	0.012	0.013	0.013	0.018	0.022	0.023	0.023

Standard error in Parantheses
*p<0.1 **p<0.05 ***p<0.01

The above table shows the Probit specification regression for the sub-sample of rural households in this study. As per specification (1), the coefficients of Internet_access is positive and statistically significant at 1% levels and as more control variables are added till specification (15), the sign still remains positive but becomes a statistically significant variable at only 10% levels. Positive sign on coefficients indicates a higher likelihood of HHealth_Ins being 1. From the final specification (15) it can be interpreted that all caste groups are highly statistically significant at 1% levels except ST caste group, and the coefficients are positive which indicates a higher likelihood of Health Insurance acquisition. In concern to the effect of religion, Muslim and other religion groups have a negative coefficient which implies that the likelihood of Hhealth_Ins being equal to one reduces. However, Christian has a positive coefficient and is statistically significant at 1% levels. Similarly, Muslim group is highly statistically significant at 1% levels. Major illness, fin_secure, conf_ghosp, conf_banks, conf_gov, income, debt , head_age, educ_levels have positive coefficients. While, conf_courts, N_persons have negative coefficients implying a lower likelihood of health insurance acquisition of households.

Transition from specification (1) to specification (15) improves the pseudo R-squared from 0.003 to 0.023, implying that the model is able to better predict the outcome. Since the magnitude of Probit coefficients cannot be directly interpreted, this study will further interpret marginal effects at means for this sub-sample analysis of rural households.

Table 5 - Probit sub-sample specification regression (if urban=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins
Int_access	0.221***	0.212***	0.187***	0.187***	0.122*	0.122*	0.122*
	(0.051)	(0.052)	(0.052)	(0.052)	(0.072)	(0.072)	(0.072)
1.caste(SC)		-0.144***	-0.187***	-0.187***	-0.174***	-0.174***	-0.175***
		(0.037)	(0.037)	(0.037)	(0.044)	(0.044)	(0.044)
2.caste(ST)		-0.034	-0.118	-0.117	-0.030	-0.031	-0.031
		(0.073)	(0.075)	(0.076)	(0.087)	(0.088)	(0.088)
3.caste(Other)		0.048	0.086	0.085	0.172	0.171	0.175
		(0.104)	(0.105)	(0.105)	(0.118)	(0.118)	(0.118)
1.religion(Muslim)			-0.282***	-0.282***	-0.328***	-0.327***	-0.327***
			(0.042)	(0.042)	(0.051)	(0.051)	(0.051)
2.religion(Christian)			0.199***	0.201***	0.169**	0.173**	0.161*
			(0.069)	(0.070)	(0.082)	(0.082)	(0.082)
3.religion(Other)			-0.098	-0.097	-0.146*	-0.146*	-0.143*
			(0.079)	(0.079)	(0.086)	(0.086)	(0.086)
major_illness				0.011	0.013	0.013	0.015
				(0.031)	(0.036)	(0.036)	(0.036)
fin_secure					0.135	0.136	0.137
					(0.211)	(0.211)	(0.211)
conf_ghosp						-0.006	-0.001
						(0.031)	(0.031)
conf_banks							-0.083
							(0.055)
_cons	-1.357***	-1.323***	-1.257***	-1.259***	-1.266***	-1.264***	-1.191***
	(0.049)	(0.051)	(0.052)	(0.052)	(0.223)	(0.223)	(0.227)
N	14530	14473	14473	14434	10169	10158	10150
pseudo R-sq	0.002	0.003	0.009	0.009	0.008	0.008	0.009
Standard error in Parantheses							
*p<0.1 **p<0.05 ***p<0.01							

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins	HHealth_Ins
Int_access	0.123*	0.028	0.028	0.059	0.049	0.107	0.064	0.065
	(0.072)	(0.073)	(0.073)	(0.073)	(0.073)	(0.087)	(0.087)	(0.087)
1.caste(SC)	-0.177***	-0.140***	-0.141***	-0.133***	-0.143***	-0.112**	-0.093*	-0.093*
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.047)	(0.048)	(0.048)
2.caste(ST)	-0.036	-0.046	-0.051	-0.041	-0.035	-0.049	-0.041	-0.041
	(0.088)	(0.089)	(0.089)	(0.089)	(0.089)	(0.096)	(0.096)	(0.096)
3.caste(Other)	0.176	0.189	0.180	0.168	0.141	0.181	0.196	0.196
	(0.118)	(0.119)	(0.119)	(0.119)	(0.120)	(0.128)	(0.129)	(0.129)
1.religion(Muslim)	-0.328***	-0.286***	-0.292***	-0.261***	-0.268***	-0.302***	-0.274***	-0.274***
	(0.051)	(0.052)	(0.053)	(0.053)	(0.053)	(0.058)	(0.059)	(0.059)
2.religion(Christian)	0.177**	0.157*	0.153*	0.143*	0.140*	0.168*	0.163*	0.163*
	(0.083)	(0.084)	(0.085)	(0.085)	(0.084)	(0.090)	(0.090)	(0.090)
3.religion(Other)	-0.146*	-0.216**	-0.219**	-0.230***	-0.210**	-0.225**	-0.226**	-0.224**
	(0.087)	(0.088)	(0.089)	(0.088)	(0.089)	(0.096)	(0.096)	(0.096)
major_illness	0.016	0.030	0.028	0.033	0.016	0.026	0.030	0.031
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.039)	(0.039)	(0.039)
fin_secure	0.147	0.124	0.116	0.114	0.092	0.144	0.140	0.139
	(0.211)	(0.210)	(0.211)	(0.211)	(0.211)	(0.227)	(0.227)	(0.227)
conf_ghosp	-0.005	0.006	0.022	0.019	0.019	0.016	0.020	0.021
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.035)	(0.035)	(0.035)
conf_banks	-0.093*	-0.106*	-0.056	-0.053	-0.055	-0.072	-0.076	-0.076
	(0.055)	(0.056)	(0.059)	(0.059)	(0.059)	(0.063)	(0.063)	(0.063)
conf_gov	0.069**	0.084**	0.096***	0.102***	0.100***	0.086**	0.091**	0.105**
	(0.035)	(0.035)	(0.036)	(0.036)	(0.036)	(0.038)	(0.038)	(0.053)
income		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	(0.000)***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
conf_courts			-0.102***	-0.101***	-0.103***	-0.096**	-0.098**	-0.099**
			(0.036)	(0.037)	(0.037)	(0.039)	(0.039)	(0.039)
N_persons				-0.024***	-0.027***	-0.025***	-0.024***	-0.024***
				(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
debt					0.156***	0.153***	0.167***	0.167***
					(0.032)	(0.034)	(0.034)	(0.034)
head_age						0.001	0.000	0.000
						(0.001)	(0.001)	(0.001)
1.educ_level(10th)							0.022	0.023
							(0.056)	(0.056)
2.educ_level(12th)							0.094*	0.094*
							(0.056)	(0.056)
3.educ_level(>12th)							0.153***	0.154***
							(0.048)	(0.048)
1.conf_gov*income								-0.000
								(0.000)
_cons	-1.209***	-1.264***	-1.244***	-1.169***	-1.197***	-1.341***	-1.340***	-1.344***
	(0.228)	(0.226)	(0.227)	(0.229)	(0.229)	(0.260)	(0.260)	(0.260)
N	10119	10119	10107	10107	10106	8772	8772	8772
pseudo R-sq	0.009	0.029	0.030	0.031	0.034	0.036	0.038	0.038
Standard error in Parantheses								
*p<0.1 **p<0.05 ***p<0.01								

The above table shows the Probit specification regression for the sub-sample of urban households in this study. As per specification (1), the coefficients of Internet_access is positive and statistically significant at 1% levels and as more control variables are added till specification (15), the sign still remains positive but becomes a statistically insignificant variable at only 10% levels. Positive sign on coefficients indicates a higher likelihood of Hhealth_Ins being 1. From the final specification (15) it can be interpreted that all caste groups are statistically insignificant at 10% levels except SC caste group which is only statistically significant at 10% levels. The coefficients on SC and ST groups are negative while positive on other caste groups, and this implies a lower likelihood of Health Insurance acquisition being in SC and ST groups. In concern to the effect of religion, Muslim and other religion groups have a negative coefficient however, Christian group has a positive coefficient and is statistically significant at 10% levels. Similarly, Muslim group is highly statistically significant at 1% levels while other religions at 5% levels. Major illness, fin_secure, conf_ghosp, conf_gov, income, debt, head_age, educ_levels have positive coefficients. While, conf_banks, conf_courts, N_persons have negative coefficients implying a lower likelihood of health insurance acquisition of households.

Transition from specification (1) to specification (15) improves the pseudo R-squared from 0.002 to 0.038, implying that the model is able to better predict the outcome. Since the magnitude of Probit coefficients cannot be directly interpreted, this study will further interpret marginal effects at means for this sub-sample analysis of rural households.

Table 6 - Comparison of Probit marginal effects at means between rural and urban households

Probit(urban=0)	dy/dx	Std. Err.	P>z
Int_access	0.014	0.008	0.056
caste			
SC	0.023	0.007	0.001
ST	0.007	0.010	0.435
other	0.075	0.034	0.025
religion			
Muslim	-0.024	0.010	0.015
Christian	0.113	0.024	0.000
Other	-0.078	0.008	0.000
major_illness	0.013	0.006	0.033
fin_secure	0.025	0.029	0.391
conf_ghosp	0.007	0.005	0.228
conf_banks	0.017	0.011	0.129
conf_gov	0.016	0.006	0.008
income	0.000	0.000	0.045
conf_courts	-0.020	0.006	0.001
N_persons	-0.001	0.001	0.219
debt	0.048	0.006	0.000
head_age	0.001	0.000	0.000
educ_level			
10th pass	0.010	0.008	0.219
12th pass	0.011	0.009	0.194
>12th	0.020	0.009	0.022

Probit(urban=1)	dy/dx	Std. Err.	P>z
Int_access	0.014	0.019	0.456
caste			
SC	-0.020	0.010	0.044
ST	-0.009	0.020	0.661
other	0.048	0.035	0.163
religion			
Muslim	-0.054	0.010	0.000
Christian	0.041	0.024	0.092
Other	-0.045	0.017	0.008
major_illness	0.007	0.009	0.436
fin_secure	0.030	0.050	0.540
conf_ghosp	0.005	0.008	0.554
conf_banks	-0.017	0.014	0.227
Conf_gov	0.021	0.009	0.018
income	0.000	0.000	0.000
conf_courts	-0.022	0.009	0.012
N_persons	-0.005	0.002	0.004
debt	0.037	0.007	0.000
head_age	0.000	0.000	0.858
educ_level			
10th pass	0.005	0.011	0.684
12th pass	0.020	0.012	0.096
>12th	0.034	0.010	0.001

The above sub-sample marginal effects can be compared to understand the effect of determinants of Health Insurance acquisition in rural versus urban households. Firstly, having Internet access in rural areas leads to 1.4% higher chances of acquiring Health Insurance and is statistically significant at 10% levels. Similarly, in urban areas, there is 1.4% higher chances for households with Internet access as opposed to no Internet access households to subscribe for HI. In rural areas, SC groups are 2.3% more likely than general caste group to acquire Health Insurance while ST groups are only 0.7% more likely than general caste households. The other caste groups have 7.5% more likelihood of subscribing to health Insurance than general caste group. While in the urban areas, SC groups are 2% less likely to acquire Health Insurance than general caste category, and the ST groups are 0.9% less likely. The other caste groups have a

4.8% higher likelihood of subscribing to Health Insurance than general caste groups in urban areas.

Muslims and other religious groups in rural areas, are 2.4% and 7.8% less likely to subscribe to Health Insurance (HI) but Christians are 11.3% more likely than Hindu groups to buy HI. Whereas, in urban regions, Muslims and other religious groups are 5.4% and 4.5% less likely to subscribe to HI than Hindu households. Christians in urban areas have a 4.1% more likelihood to acquire HI than Hindu groups.

Rural households who have suffered major illness are 1.3% more likely to acquire HI while in urban areas only 0.7% higher chances than households who have not suffered a major illness. Similarly, rural households with debt are 4.8% more likely to acquire HI than no debt households while in the urban areas, only 3.7% higher chances of acquiring Health Insurance if has debt compared to non-debt households.

It is surprising to note that a unit increase in age of household adult(head_age) and income does not improve the chances of subscribing to HI in urban regions. However, though marginal effect of income is zero in rural areas but a unit increase in age is associated with 0.1% higher chances of subscribing to HI. A unit increase in N_persons in the household causes 0.1% lesser chances of acquiring HI in rural areas while in the urban areas, it is 0.5% less likely respectively. Households who are confident in their government are 1.6% more likely to have HI in rural areas as opposed to a 2.1% more likelihood in urban areas, and conf_gov variable in both rural and urban households is statistically significant at $p<0.05$.

Ultimately, in both rural and urban areas, all education levels(educ_level) adults in a household indicate a higher likelihood of acquiring HI than less than 10th studied adults in the household category. Adults in the rural household with highest adult education greater than 12th standard are 2% more likely to subscribe for HI than less than 10th studied adults in the household. Similarly, in urban regions, households with adults greater than 12th standard education are 3.4% more likely to subscribe to HI than less than 10th studied adults in the household. >12th educ_level in rural areas is statistically significant at 5% levels whereas in urban areas at 1% levels. Urban households with highest adult education higher than 12th standard are more probable to subscribe for health Insurance than rural households at the same level of education.

Conclusion,Discussion and Limitations

This study was successful at answering its research question and found that access to Internet is positively associated with increased Health Insurance uptake both in rural and urban areas. Though, in urban areas, Probit marginal effects at means suggests that Int_access is a statistically insignificant variable. The Probit results in comparison to the benchmark OLS regression are almost similar, both models identify positive relationship between Int_access and HI uptake , however, since LPM predicted probabilities range beyond [0,1], the LPM estimates are inaccurate. The results of this study are in line with literature such as Supakankunti.(2001) and Alesane and Anang.(2018) as the results of this study also find that age, education levels and household size as significant variables. Also, with increase in household size our results indicate a lower likelihood of HI uptake which is aligned with the same reported result in Supakankunti.(2001). In concern to the effect of Muslim households, this study found that urban households are 5.4% less likely to take HI as opposed to Hindu households, and this result is in tandem with the same findings in the works of Chakrabarti and Shankar.(2018), and at the same time, caste and religion were found to be significant determinants of Health Insurance uptake in our study as well.

This study has made an inherent assumption that households with computers, mobiles and laptops are connected to Internet as well, because IHDS-II survey data did not have a direct variable for households with Internet access. However, this assumption could have had spill over effects on to the reliability of our results as the Int_access variable in our study is not exactly counting the households with Internet access but just the possession of laptop or mobile or a computer. Capturing the data on access to Internet is essential because Internet is the gateway to get connected with knowledge across the globe which includes resources and awareness campaigns of Health Insurance uptake. Therefore, in the future it is recommended to capture data on household's access to Internet.

Secondly, there was a rapid rise in Internet users in India in the past few years. Statistics suggest that there were only 125.9 million internet users in India during the year 2011 and whereas, in 2020 there were 749.07 million users(Basuroy,2022). Higher number of internet users implies equally higher number of laptops/mobiles/computers. In this context, the IHDS-II survey data is obsolete to conduct an empirical analysis in the year 2022 as the data is collected in the year 2011-2012. Hence, the results of this study may not be a reliable estimate for the effect of internet access on HI uptake in today's world.

Lastly, I was not very well equipped with endogeneity tests for Probit analysis and subsequently, could not identify if IV-Probit and bi-probit model were needed for the purposes of my study. However, in the future the basic Probit model used in this study can be built on further.

In conclusion, this study recommends policy makers to consider the enormous influence of Internet and education (especially, greater than 12th standard) on Health Insurance uptake and therefore, design policies to digitally promote Insurance campaigns and expedite the process of online insurance delivery systems. In addition, this study also highlights the disparities in

Insurance uptake between religions and castes in India, hence, it is imperative for policymakers to make suitable interventions to make Health Insurance Universal regardless of caste and religion. This study also identified that the confidence factor in the government is a highly statistically significant variable through Probit marginal effects analysis and holds a positive relationship with Health Insurance uptake in households, and this finding could further be validated and generalized by conducting the study over a large sample involving several countries data.

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