The Demand for Community-Based Micro Health Insurance in Three Regions Across Rural India

By Katrina Milner

An essay submitted to the Department of Economics

in partial fulfillment of the requirements for

the degree of Master of Arts

Queen's University

Kingston, Ontario, Canada

September 2014

Abstract

This study examines the determinants of demand for community-based micro health insurance schemes in rural India and willingness to pay for such plans. The motivation behind this research is to find a model that can price insurance premiums at the lowest possible cost in order to encourage adoption of health insurance plans, while maintaining sustainable community-based operations. The socioeconomic, risk-pooling, health and supply-side determinants of enrolment are examined using a probit model; and the precision of setting premiums and forecasting enrolment using this complex method is compared to the method using only income. It is found that despite their high cost, there is still an important role for more complex models. Based on the results of this study, two recommendations are made to increase the success of community-based schemes: the financial combination of multiple projects to form a diversified portfolio of plans and the offering of multiple coverage options through a single operation to limit the need for more complex pricing models.

Acknowledgments

I am very grateful to my supervisor, Dr. Edwin Neave, for his useful guidance and advice. I would also like to thank Dr. David Dror and the entire Micro Insurance Academy for providing the data and for helpful input and discussion of the results. The opinions expressed in this essay do not necessarily reflect those of the Micro Insurance Academy or Dr. Dror. Finally, I would like to thank my dad, Brian Milner, for his help with editing.

Table of Contents

1. Introduction:

Over the past few decades, the less developed economies have found it increasingly difficult to finance health expenditures. Recent estimates from the World Health Organization show that average annual health spending by the group of least developed countries is around eleven dollars per person, while studies suggest that eighty dollars a head per year would be required to provide basic care (WHO, 2011). A growing number of microfinance institutions, community cooperatives and commercial insurance companies have started to offer health insurance to low-income populations that have never previously been adequately insured against health-related hazards. Community-based microinsurance projects provide viable options in low-income economies to narrow the difference between actual expenditures and needs. Microinsurance can serve as a mechanism to protect low-income communities against uncertainty by pooling, spreading and transferring risk between more and less risk-averse entities.

Traditionally, the decision to provide social protection to vulnerable populations has resided with governments. When they choose not to pool risk and subsidize health care for populations, alternative mechanisms to meet supply-side needs are required. Government failures tend to occur in settings with large informal economies that operate through non-monetary transactions, making it difficult to collect taxes and allocate revenues accordingly (Dror and Preker, 2002). In developed economies without social health insurance schemes, the markets have successfully taken over and adapted to health-care demand with profit-driven private health insurance companies. The allocations provided by these markets can be far from socially optimal; and the model is not applicable in all cases, notably in developing economies with large informal sectors

(Dror & Jacquier, 1999). In such economies, weak demand, combined with little ability to pay for insurance, has resulted in the insufficient supply of health services. Where the market has failed to supply excluded populations – and governments are unable or unwilling to step in – is where community-based micro health insurance (CBHI) schemes come in.

Microinsurance is commonly defined as a "financial arrangement designed to protect low-income populations against perils in exchange for regular premium payments that are proportionate to the likelihood and cost of the risks involved" (Biener & Eling, 2012, p.6). It serves as an instrument to mitigate the consequences from insurable risks by reducing fluctuations in consumption arising from shocks to income (Giesbert, 2010). In this regard, microinsurance is no different than conventional insurance. The difference is that community-based projects involve individuals and households that have little or no other risk-financing mechanism available to them. Community-based insurance initiatives' ability to collect and mobilize funds is derived from strong social capital networks, community institutions and connections with external institutions, such as NGOs (Dror & Preker, 2002).

Microinsurance markets have been exhibiting large growth rates in recent years (Churchill & McCord, 2012)[1]; however, success is limited by subsidy funding limitations and difficulties in pricing premiums (Biener, 2013). When pricing premiums, insurers must take into account that schemes will only cover small population groups, which reduces their ability to pool, transfer and spread risk among persons. As a result, premiums must be high and insurance plans may be unaffordable to target populations.

[1] Churchill and McCord estimated that the outreach of microinsurance in Asia, Africa and Latin America in 2011 was approximately 500 million risks covered (2012).

To avoid this accessibility problem, premiums are set to meet the population's willingness and ability to pay, with subsidies filling funding gaps (Biener, 2013). This strategy can lead to unsustainable business practices and makes insurers vulnerable to insolvency risks (Biener, 2013).

This study will examine the determinants of demand for health insurance in rural India and willingness to pay (WTP) for such plans. The purpose of this study is to provide information about the relationship between premiums that cover the cost of health-care schemes and enrolment in such schemes. An important addition and contribution of this paper to the literature is that the role of WTP in predicting actual community-based health insurance (CBHI) enrolment is measured. The link between WTP and enrolment rates is examined to discover any differences in estimated versus actual WTP. More precise predictions of WTP will in turn lead to more precise premium pricing. It is found that there is a difference between the determinants of enrolment and the determinants of WTP with respect to supply-side and socioeconomic factors; but there is little difference in terms of health and risk-pooling factors. Results indicate that previous studies and declarations of WTP cannot solely be used to price premiums. Rather, these should be used in combination with community microfinance focus groups and household surveys.

The remainder of this paper is organized as follows. First, the theoretical determinants of health insurance will be outlined and applied to the context of microinsurance markets. In section two, the existing literature is critically reviewed with the aim of determining the factors that govern willingness to pay. This study will use previously found WTP results as a point of comparison to actual enrolment rates in the empirical analysis. In section three, an empirical analysis will be conducted on enrolment rates in CBHI schemes in three regions across rural India. Analysis will focus on determinants of enrolment and any differences with the determinants of WTP. Next, a cost value analysis of two methods will be conducted to determine the most cost-efficient and precise method to price premiums. The first method employs a novel approach of setting premiums according to a set portion of a household's food expenditure. The second method uses detailed socioeconomic, supply-side and health information from household surveys in combination with enrolment rates. The food expenditure method is lower cost than the household survey method; however, this comes at the sacrifice of less accurate enrolment predictions. Finally, two recommendations are made based on the results of the empirical analysis. These are to offer a variety of coverage plans through a single CBHI scheme in order to reduce the need for household surveys and to financially merge separate schemes to diversify risk, thereby reducing risks associated with asymmetric information problems.

2. Theoretical Orientation

Stemming from the seminal work of John von Neumann and Oskar Morgenstern (1944), the concepts of risk aversion and expected utility theory hold as the basic framework for insurance markets today. Risk-averse persons purchase insurance to avoid loss in the face of shocks by paying small premiums that must be sufficiently large to cover future losses. In this benchmark model, based on the assumption of perfect markets, the decision to purchase is a factor of risk aversion, cost, probability of risk and supply (Giesbert, 2010). In the context of micro health insurance markets, the benchmark model is only a small part of the picture, as full market information is unlikely.

Deviations from the standard model can be explained by informational asymmetries arising in imperfect markets with incomplete information. Numerous studies[2] have analyzed the role of asymmetric information in insurance markets. These models predict that riskier individuals are more likely to purchase insurance (adverse selection); and once this purchase has been made, they will behave in ways that increase risk (moral hazard). Both of these behaviours drive up the price of insurance, creating a market with two classes of people divided by risk type. The insurance market will have a separating competitive equilibrium where individuals self-select, based on preferences, into which category they fall (Rothschild & Stiglitz, 1976). High-risk types will fully insure, while low-risk types will only partially insure, both at the actuarially fair price, with low-risk types paying a lower premium per dollar of coverage (Rothschild & Stiglitz, 1976). In a case where the insurer cannot differentiate high types from low types, the market will form a pooling equilibrium, where all insured pay the same premiums, causing the low-risk types to gradually drop out of the market (Akerlof, 1970).

Although some of the basic predictions of traditional insurance theory hold true, microinsurance markets break several of the premises associated with conventional wisdom. In application, there is often a difference between normative theory and descriptive theory, with normative theory not serving as a good guide for practical implementation. In microinsurance markets, several assumptions from normative theory not adhered to. Low levels of technical knowledge and awareness of products in informal economies make it difficult for individuals to understand the intrinsic value of insurance and assess the need for different levels of coverage based on health risks. This

[2] Studies include those by Akerlof (1970) and Rothschild and Stiglitz (1976).

causes the predictions of Rothschild and Stiglitz not to hold. Predictions are further undermined, because CBHI schemes offer one type of coverage plan that does not allow for self-identification based on desired level of coverage. Furthermore, traditional theory prescribes that populations are either formally insured or have no coverage at all; however, in the empirical analysis it will be seen that informal risk-pooling mechanisms, such as household income-sharing, protect against risks and substitute for formal insurance in informal economies. It should be noted that this assumption is broken even more frequently in traditional insurance markets where populations have access to even more informal opportunities. Finally, in traditional markets willingness to pay has been associated with a monetary declaration of marginal utility (Dror & Firth, 2014). In the review of the WTP literature, it is plain that this is not the case, as WTP is affected by availability of health care, income, location, health and socioeconomic parameters. Evidently, the assumptions of normative theory are replaced with the more practical realities of descriptive theory.

The design of microinsurance products changes the impact of adverse selection and moral hazard. Moral hazard is manifested in three ways in the health insurance market: ex-ante demand-side moral hazard, where the insured person reduces preventative behaviours; ex-post demand-side moral hazard, where the insured over-consumes health services; and supply insurance moral hazard, where the health-care system oversupplies at additional costs (Vaté & Dror, 2002). By nature, CBHI is less prone to moral hazard problems, since its community foundation provides self-checks for fraudulent behaviour. Adverse selection poses another risk to microinsurance markets. Adverse selection destabilizes the market, because risk-pooling requires a low distribution of losses in order to sustain low premiums. When riskier individuals enroll in CBHI schemes, high claim rates force high premiums. CBHI projects face some risk of adverse selection, especially at the start, when insurance-aware persons are most likely to face risk (Dror & Jacquier, 1999). This being said, communities are shielded from most adverse selection problems when policies insure entire households for higher "en bloc" premiums, thus increasing relevant information needed to prevent false disclosure of risks.

3. Review of the Literature

Several empirical studies have estimated willingness to pay (WTP) for community-based insurance products in the context of developing countries, with the purpose of providing valuations for policy-makers and microinsurance companies. Estimating the willingness of people to pay is key to successfully providing effective insurance, as it will only be purchased if "the package suits their needs, the premium is affordable and if they expect the contract to be executed as promised" (Binnendijk et al., 2013, p.68). The purpose of this review is to determine the factors that govern WTP in order to compare these to the determinants of actual enrolment.

Empirical studies show that there is a significant and positive interdependence between nominal levels of WTP for micro health insurance and income measured directly and via proxies. It is common practice for proxies to be used in place of income, because at the household level there are so many sources of revenue – most arising from work in the informal sector – that reliable estimates cannot be obtained with direct methods (Dror & Koren, 2012). Aseno-Okyere et al. (1997) and Dror et al. (2007) used self-reported income from household surveys in Ghana and India to find a positive and significant trend. Onwujekwe et al. (2010) constructed wealth and income variables based on asset information collected from household surveys in Nigeria. It was found that higher socioeconomic groups have higher WTP. Dong et al. (2003) and Gustafsson-Wright et al. (2009) used consumption and expenditure data as a substitute for income in Burkina Faso and Namibia, respectively, also finding an upward trend. Finally, Mathiyazhagan's 1998 study of rural India showed an upward trend between WTP and income in three groupings. The methodology of the elicitation of income was not provided. Despite the different methods of measuring income, all empirical studies point to a positive relationship between income and WTP in nominal terms.

Studies also examined the associations between willingness to pay and socio-economic variables. Common factors of analysis were sex, education, age and household size. Results were mixed, and no consistent trend can be observed. Gender was found to be insignificant in several studies (Dong et al., 2003; Mathiyazhagan, 1998), while other studies (Onwujekwe et al., 2010; Aseno-Okyere et al., 1997; Gustafsson-Wright et al., 2010; Dror et al., 2007) found males to have higher WTP than females. Education was consistently found to have a positive impact on WTP, i.e. those with higher levels of education should be willing to pay more for insurance. Mathiyazhagan found household size to increase WTP for the household as a whole; but Dror et al. and Onwujekwe et al. found household size to decrease WTP per person. Finally, age was found to have non-significant results (Aseno-Okyere et al., 1997; Dong et al., 2003; Mathiyazhagan, 1998; Onwujekwe et al., 2010) or a negative correlation (Gustafsson-Wright et al., 2010; Dror et al., 2007) with WTP. The large variation in the effect of socioeconomic variables is likely to be a result of the diverse locations of study.

Intuitively, exposure to recent health expenditures arising from insurable risk should increase WTP, because it increases knowledge of the inherent merits of health insurance. The cited studies measured this relationship using a variety of proxies to capture the cost of illnesses and injury. Aseno-Okyere et al. (1997) and Dong et al. (2003) measured expenditure on health care in the previous thirty days, while Onwujekwe et al. (2010) measured out-of-pocket expenditures for health care. Dror et al. (2007) measured household hospitalizations in the past year. Finally, Mathiyazhagan (1998) used a combination of hospital visits, ill respondents and lost income due to illness. Aseno-Okyere et al., Dong et al., Mathiyazhagan and Dror et al. all found a positive correlation between expenditure and WTP; however, Onwujekwe et al. found a negative association. This discrepancy likely stems from the proxy used. Out-of-pocket expenditures are not the best tool to demonstrate the value of insurance when data from experiences with insurance providers are available. Overall, a positive relationship between health expenditures and willingness to pay for insurance is present.

Another important category of interest is the accessibility of health-care services. The accessibility of such services varies across locations, and health insurance can only be offered where people have reasonable access to health infrastructure. It is anticipated that villages that are located farther from hospitals, pharmacies and clinics will be less likely to enroll in CBHI programs regardless of income and will have a low WTP. This assumption is confirmed in the literature. Dong et al. obtained a negative relationship between individual WTP and distance from health-care facilities (2003) and Dror et al. found a negative association between WTP and distance to the nearest preferred hospital.

Other studies were not conducted across different locations; therefore, it was not possible to test the effect of location and distance.

The main insight to be gained from the reviewed literature is that the large diversity of WTP elicitation methods makes a simple, standardized model of prediction unlikely. The basic factors that govern WTP are socioeconomic parameters that differ by location of study, experience with insurable risk that increases WTP, proximity to health services that increases WTP and nominal income that also increases WTP. These results will be used as a comparison tool against actual enrolment rates in the empirical analysis.

4. Empirical Analysis

India is one of the fastest-growing emerging economies in the world, but its health status remains a major concern despite its relatively high portion of GDP dedicated to health spending[3] (Bhat & Jain, 2006). As in most developing countries, the vast majority of India's low-income rural population works in the informal sector (Binnendijk et al., 2013). These populations are largely ignored by the public sector and are too high-cost and high-risk for the private sector to insure. It follows that India houses the largest growing microinsurance initiatives across the globe.

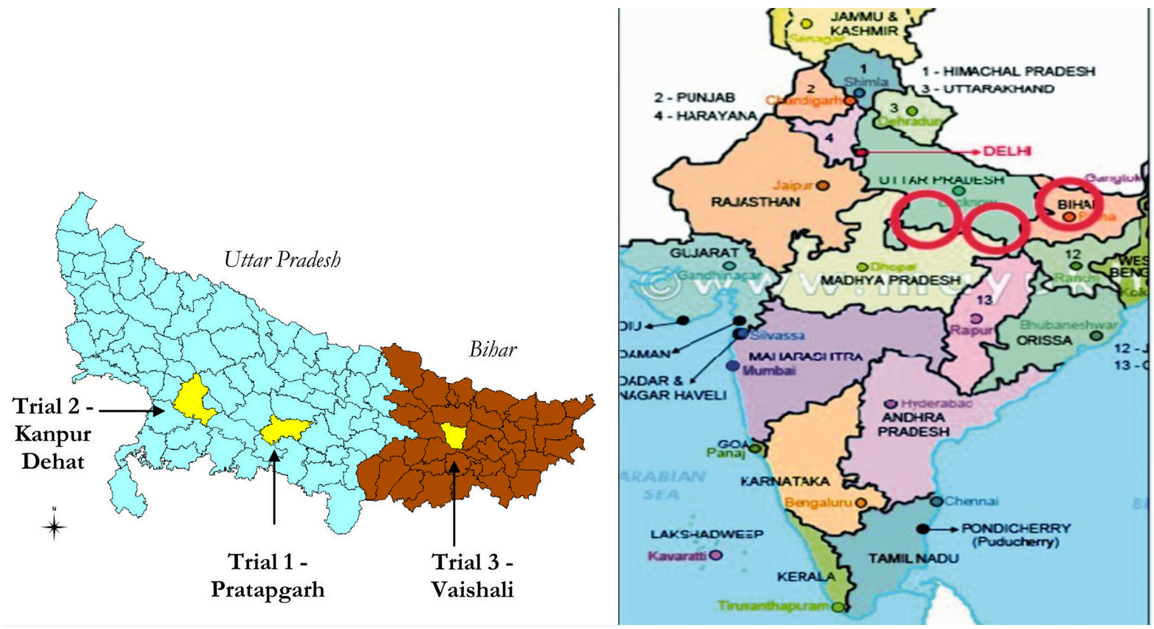
Analysis will examine CBHI enrolment rates in rural India to determine both supply and demand factors that predict enrolment. CBHI enrolment rates will be taken as a measure of the difference in declaration of WTP versus actual WTP. Bonan's et al. (2013) study of micro health insurance in Senegal found WTP to be the single most important variable in predicting effective purchase of the product, when conducting WTP

[3] India spends approximately six percent of its GDP on health expenditure; however, public expenditure is only 0.9 percent, far below that of comparable economies (Bhat & Jain, 2006).

elicitations with a follow-up enrolment triangulation. Based on this result, empirical analysis will use enrolment to measure any differences in actual versus estimated declarations of WTP. Analysis will also measure the predictability and accuracy of two WTP methodologies in forecasting enrolment.

4.1 Data Description:

Figure 1[4]: Location of Study



The data used in this paper were provided by the Micro Insurance Academy in New Delhi, India. The Micro Insurance Academy is a non-profit leader in the microinsurance domain. The data were collected using household surveys in three areas of rural India in 2010. The three locations of study are Pratapgarh in Uttar Pradesh, Kanpur Dehat in Uttar Pradesh and Vaishali in Bihar. Both states are highly populated, low-income and among the least urbanized in the country. A total of 3,686 households and 23,876 individuals were included in the survey. The survey queried respondents

[4] Figure 1 is taken from Panda et al., 2013.

about expenditures on consumption and health-related expenses, savings, household dynamics, social characteristics and detailed health conditions and care.

There are three key points concerning the dataset at hand. First, households surveyed are only able to enroll in CBHI through female self-help group (SHG)[5] members. Second, prior to the collection of the data, eligible households participated in insurance education and preparatory activities. Third, the benefit packages and premiums differed by location. Analysis will be based on the combination of the household survey described above, premium and enrolment features[6] and cost estimates of the household surveys.

4.2 Descriptive Statistics:

Table 1: Household Summary Statistics by Location

Variable	Pratapgrah	Kanpur Dehat	Vaishali
	Mean	Mean	Mean
Household Head is Female =1	0.256351	0.1084656	0.2480916
Age of Household Head	46.20554	44.88889	41.99237
Caste:			
SC	0.3893333	0.226257	0.3859649
ST	0.5093333	0.5810056	0.5243665
Household Size	7.232845	6.818905	6.267458
Education of most educated female (years)	6.21709	6.78836	4.568702
RSBY =1	0.1801386	0.1534392	0.4847328
Other Insurance =1	0.039261	0.0185185	0.0438931
Income Pooling	0.88	0.85	0.68
No Income Pooling	0.1180556	0.1534392	0.3187023
Partial Income Pooling	0.0069444	0.0555556	0.1068702
Pharmacy Distance (km)	1.751732	4.393617	1.57271
Doctor Distance (km)	1.752887	5.253968	1.528626

[5] SHGs consist of small groups of low-income women who pool savings and provide loans to households on an as needed basis. Funds are stored in banks or cooperative organizations, and it is estimated that there were 40 million members in India as of 2012 (Panda et al., 2013).

[6] A full description of premium and enrolment features can be found in Panda et al., 2013 and will only be described on an as needed basis in this study.

Hospital Distance (km)	9.004695	44.41509	3.770992
Monthly per capita Expenditure (INR)			
Quintile 1	522.0191	524.6131	535.8733
Quintile 2	762.1606	786.6168	765.2031
Quintile 3	1002.969	1021.894	1002.332
Quintile 4	1340.598	1348.333	1341.003
Quintile 5	2132.417	2627.404	2273.045
Household expenditure on health (INR)(past 30 days)	1189.46	2508.016	1791.45
Number of hospital visits (past 30 days)	0.1385681	0.1878307	0.1812977
Number of pregnancies (past 30 days)	0.1732102	0.1746032	0.1698473
Number of short-term illnesses (past 30 days)	0.1524249	0.2328042	0.1717557
Long-term illness =1	0.4572748	0.2275132	0.2461832
Number of observations:	433	378	524

Table 1 reports summary statistics for household by location. Socioeconomic variables of interest are: age of the household head, gender of the head, caste, household size and education of the most educated female in the household. It can be seen that most of the household heads are male. Over half of the sample are members of a Scheduled Tribe (ST), the average household has seven members and the most educated female in the household has an average of six years of formal education. Risk-pooling variables of interest are insurance products (national insurance and private insurance) and income pooling. Vaishali's higher use of national insurance (RSBY), as compared to the other two locations, should be noted. Due to the sensitivity of collecting data related to income and the reticence to provide exact amounts, two times monthly per capita household food expenditure is used as a proxy for income. This proxy is then categorized into quintiles.

The supply of health services measured through distances to the local doctor, hospital and pharmacy differ by location. It can be seen that Kanpur Dehat is relatively less supplied by health services. Regardless of location, pharmacies and doctors are available at closer proximities than hospitals. Finally, experience with insurable risk is measured with health expenditures and total illnesses of all members in the household. Total health expenditure of the household for a month is calculated to include total hospital bills, cost of medicines, cost of labs and tests, ambulance fees, transportation costs and lost income.

4.3 Estimating Enrolment:

The probability of enrolment is estimated at both the household and individual level. Individual regressions are estimated using a probit model and the marginal effects are presented in Table 2. A probit model is chosen to represent the dichotomous dependent variable that is estimated to follow the cumulative distribution function most closely. The probit regression coefficients give the change in the z-score for a one-unit change in the predictor. Marginal effects are calculated and displayed in order to interpret the results in a more meaningful manner. All marginal effects displayed are deviations of the explanatory factors from the base level. The household enrolment ratio regression is estimated using ordinary least squares because the dependent variable takes on a range of values between zero and one, and the results are presented in Table 3.

The model is specified as follows:

$$(1) Individual\ \ Enrolment = \alpha + \beta_1 SES + \beta_2 RP + \beta_3 SS + \beta_4 HE + \varepsilon$$

$$(2) Enrolment\ Ratio = \alpha + \beta_1 SES + \beta_2 RP + \beta_3 SS + \beta_4 HE + \mu$$

The definition of variables is as follows:

Individual enrolment is a binary variable that takes on a value of one when an individual is enrolled and a value of zero otherwise. Enrolment ratio represents the number of household members enrolled in CBHI divided by the total possible enrolment. This dependent variable captures intra-household dynamics that household enrolment ignores. SES is a vector of socioeconomic characteristics; RP is the household's risk-pooling characteristics; SS are the supply-side parameters; and HE is a vector of health events that includes long-term illnesses, short-term illnesses, hospitalizations and pregnancies, as well as their costs.

All regressions are broken down by location, as package composition, socioeconomic characteristics and supply-side factors all differ in each of the locations of study. The regressions are tested for heteroskedasticity, and the null hypothesis of homoskedasticity is rejected; therefore, robust standard errors are used. Regressions are tested for endogeneity and selection bias of the dependent variables by evaluating if weak endogeneity between the error term and enrolment rates is present[7]. The null hypothesis of weak exogeneity is not rejected; therefore, no instrumental variables are used.

Table 2: Probit regression marginal effect estimates at the individual level (Regression 1)

VARIABLES	(1) All	(2) Pratapgrah	(3) Kanpur Dehat	(4) Vaishali
Age	-0.00168***	-0.00117	-0.00154**	-0.00258***
	(0.000544)	(0.00108)	(0.000727)	(0.000988)
Gender	0.0313***	0.0164	0.0126	0.0536***
	(0.0118)	(0.0218)	(0.0180)	(0.0201)
ST Caste	0.0710***	0.0289	0.0105	0.116**
	(0.0269)	(0.0585)	(0.0302)	(0.0486)
SC Caste	0.0331	-0.0166	0.0318	0.0647
	(0.0261)	(0.0580)	(0.0281)	(0.0474)
OC Caste	0.0472	0.0203	0.0377	-0.00898
	(0.0307)	(0.0660)	(0.0336)	(0.0563)
Secondary Education	-0.0253*	-0.0372	-0.0406**	0.000299
	(0.0136)	(0.0245)	(0.0183)	(0.0261)
Middle Education	0.0198	0.0358	-0.0164	0.0187
	(0.0171)	(0.0307)	(0.0251)	(0.0310)
Primary Education	0.0455***	0.0641**	0.0408*	0.0318
	(0.0156)	(0.0305)	(0.0244)	(0.0250)
Household Size	-0.00315	0.00126	-0.0127***	-0.00762
	(0.00209)	(0.00332)	(0.00344)	(0.00465)
Spouse of Head	0.0497**	0.0532	0.0309	0.0566
	(0.0235)	(0.0440)	(0.0423)	(0.0366)
Child of Head	-0.0902***	-0.0928*	-0.137***	-0.0583

[7] The test for endogeneity is conducted using the method outlined in Kihaule, 2013.

	(0.0243)	(0.0479)	(0.0383)	(0.0406)
Spouse of Child of Head	-0.140***	-0.0812	-0.137***	-0.209***
	(0.0297)	(0.0555)	(0.0510)	(0.0472)
Grandchild of Head	-0.199***	-0.189***	-0.184***	-0.230***
	(0.0266)	(0.0527)	(0.0410)	(0.0465)
Parent of Head	-0.178***	-0.187***	-0.140***	-0.191***
	(0.0296)	(0.0515)	(0.0476)	(0.0541)
Sibling of Head	-0.263***	-0.284***		-0.237***
	(0.0292)	(0.0555)		(0.0743)
In-Law of Head	-0.212***		-0.193***	-0.0458
	(0.0409)		(0.0480)	(0.111)
2nd Income Quintile	0.0270*	0.103***	0.0464***	-0.0165
	(0.0153)	(0.0253)	(0.0179)	(0.0274)
3rd	0.0742***	0.0896***	0.171***	0.0103
	(0.0166)	(0.0300)	(0.0289)	(0.0276)
4th	0.0241	0.0741**	0.0687***	-0.0322
	(0.0161)	(0.0313)	(0.0225)	(0.0288)
5th	0.0343**	-0.0155	0.0938***	-0.00372
	(0.0172)	(0.0322)	(0.0224)	(0.0323)
RSBY	-0.0203*	-0.00539	-0.0296	-0.0184
	(0.0120)	(0.0242)	(0.0214)	(0.0188)
Private Health Insurance	-4.17e-05*	-0.000129***	-2.72e-05***	0.000106
	(2.47e-05)	(4.99e-05)	(5.16e-06)	(0.000127)
No income Pooling	0.0623***	0.130***	0.124***	0.0180
	(0.0141)	(0.0355)	(0.0296)	(0.0205)
Partial Income Pooling	-0.0112	0.0908	0.0580	-0.0606**
	(0.0220)	(0.113)	(0.0410)	(0.0290)
Travel Time Doctor	-1.04e-05	0.00185*	0.000191	-0.000521
	(0.000280)	(0.00101)	(0.000244)	(0.000619)
Travel Time Hospital	0.000209*	0.000858***	7.71e-05	5.09e-05
	(0.000109)	(0.000276)	(8.98e-05)	(0.000437)
Travel Time Pharmacy	-0.000258	-0.00300***	0.000547*	-0.00135*
	(0.000357)	(0.000927)	(0.000332)	(0.000774)
Short Term Illnesses	0.0355**	0.0565**	0.0214	0.0181
	(0.0149)	(0.0243)	(0.0224)	(0.0280)
Long Term Illness (Dummy)	0.0211*	0.0527**	0.00684	-0.00393
	(0.0123)	(0.0229)	(0.0167)	(0.0218)
Number of Pregnancies	0.0355	0.00415	0.0543	0.0566
	(0.0313)	(0.0584)	(0.0482)	(0.0531)
Number of Hospital Visits	0.00863	-0.0203	0.0144	0.0192
	(0.0318)	(0.0628)	(0.0448)	(0.0536)
Health Expenditure	1.64e-06	5.51e-06	3.02e-08	2.73e-06
	(1.86e-06)	(4.99e-06)	(2.02e-06)	(3.51e-06)
Kanpur Dehat	-0.123***			
	(0.0148)	-	-	-
Vaishali	0.0267*	-	-	-
	(0.0148)			
Observations	7,063	2,198	2,010	2,777

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Enrolment ratio regression using OLS at the household level (regression 2)

	(1)	(2)	(3)	(4)
VARIABLES	All	Pratapgrah	Kanpur Dehat	Vaishali
Age	-0.00291***	-0.00168	-0.00167	-0.00483***
	(0.000750)	(0.00146)	(0.00117)	(0.00126)
Gender	0.0357	-0.0453	0.0630	0.0756*
	(0.0262)	(0.0446)	(0.0560)	(0.0415)
ST Caste	0.102**	0.0902	-0.0349	0.191**
	(0.0490)	(0.107)	(0.0617)	(0.0962)
SC Caste	0.0537	0.0312	0.00720	0.111
	(0.0475)	(0.109)	(0.0565)	(0.0933)
OC Caste	0.0792	0.0955	-0.00406	0.124
	(0.0566)	(0.129)	(0.0695)	(0.117)
Female Education	-0.00154	-0.000123	-0.00570	-0.00103
	(0.00254)	(0.00455)	(0.00448)	(0.00451)
RSBY	-0.0144	0.00500	-0.0220	-0.00851
	(0.0241)	(0.0484)	(0.0465)	(0.0353)
Private Health Insurance	-0.0428	-0.0497	-0.0279	-0.0808
	(0.0457)	(0.0788)	(0.107)	(0.0715)
No Income Pooling	0.0626**	0.148**	0.132**	0.0164
	(0.0267)	(0.0573)	(0.0511)	(0.0387)
Partial Income Pooling	-0.0317	-0.0808	0.0586	-0.0686
	(0.0405)	(0.151)	(0.0704)	(0.0525)
Travel Time Doctor	0.00797***	-0.0112**	0.00987***	0.0123**
	(0.00292)	(0.00552)	(0.00310)	(0.00561)
Travel Time Hospital	0.000650	0.0156**	-0.00171	0.00999*
	(0.00158)	(0.00649)	(0.00122)	(0.00516)
Travel Time Pharmacy	-0.000119	0.00100	-0.000139	0.00135
	(0.000442)	(0.00172)	(0.000471)	(0.00279)
Short Term Illnesses	-0.0167	0.0477	-0.0494	-0.0454
	(0.0257)	(0.0516)	(0.0372)	(0.0441)
Long Term Illness (Dummy)	0.00286	-0.0160	0.0122	0.0197
	(0.0234)	(0.0380)	(0.0439)	(0.0426)
Number of Pregnancies	-0.0405*	-0.0182	-0.0565*	-0.0541
	(0.0223)	(0.0389)	(0.0317)	(0.0396)
Number of Hospital Visits	0.000613	0.0426	-0.00254	-0.0226
	(0.0246)	(0.0588)	(0.0344)	(0.0439)
Health Expenditure	2.20e-06	-6.27e-06	4.31e-06	1.37e-06
	(1.77e-06)	(5.86e-06)	(3.04e-06)	(1.86e-06)
Kanpur Dehat	-0.117***	-	-	-
	(0.0320)			

Vaishali	0.0275	-	-	-
	(0.0277)			
Constant	0.284***	0.205	0.121	0.351***
	(0.0642)	(0.128)	(0.0838)	(0.115)
Observations	1,230	368	349	513
R-squared	0.071	0.065	0.115	0.081

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3.1. Results of Socioeconomic Parameters

4.3.1.1Age

Age was found to decrease affiliation to CBHI in all three locations at the individual level. For a one-year increase in age, the probability of enrolment decreases by 0.18 percentage points, for all locations pooled together, keeping all else constant. For example, an adult aged 20 is 30.8 percentage points more likely to be enrolled than an adult aged 60 in Kanpur Dehat. Results indicated that younger people are more likely to be enrolled in CBHI schemes. This result is not explained by education or income, which are analyzed separately. A possible explanation for the result is that younger women are more likely to attend the microfinance self-help groups (SHGs), through which insurance products are offered.

This negative result provides evidence that individuals are not displaying behaviours consistent with adverse selection. As individuals age, they face higher probabilities of low states of the world and will value the ability to transfer income from high states to low states. The data does not show this trend, indicating that individuals facing higher probabilities of low states of the world are not more likely to insure.

At the household level, the age of the household head was not significant in Pratapgarh and Vaishali. In Kanpur Dehat, the sign-on age was negative. The implication that younger people are more likely to be enrolled in CBHI schemes is that they may have a higher WTP for such insurance products.

These enrolment findings are consistent with the WTP literature. Previous studies found non-significant results (Aseno-Okyere et al., 1997; Dong et al., 2003; Mathiyazhagan, 1998; Onwujekwe et al., 2010) or a negative relationship (Gustafsson-Wright et al., 2010; Dror et al., 2007) between age and WTP. Based on these results, there does not appear to be a difference in stated versus actual WTP based on the age of the respondent. When modifying premiums and pricing initial packages in other locations, age should be a factor considered when offering enrolment at the individual level. Locations with younger populations can set higher pricing points for premiums, while still attracting high enrolment rates. The effects of specific education on age as a factor should be determined, as there is no intuitive explanation for younger people's willingness to pay more.

4.3.1.2 Gender

In Vaishali, being male increased individual enrolment status by six percentage points, ceteris paribus. In Pratapgarh and Kanpur Dehat, gender was found to be insignificant. By the program design, gender is assumed to be extremely important. The insignificant results may indicate that the importance of gender is secondary to relationship to the SHG member. For example, it is possible that gender is insignificant in the two districts in Uttar Pradesh, because women attendees at SHGs are equally likely to enroll their spouses, which leads to similar rates of enrolment for men and women. This conjecture may not have robust applications for different projects where insurance is not only offered through SHGs. It should also be noted that 26 percent of the women in the sample were enrolled, compared with only 20 percent of males in a sample that was composed equally of males and females.

The same trend emerged for gender at the household level. In Vaishali, being male increased individual enrolment status, and in Pratapgarh and Kanpur Dehat, gender is insignificant. Overall, individual and household results indicate that enrolment is affected by gender; but this is influenced by regional differences, and gender is most likely secondary to the effect of position in the household.

The WTP literature is not directly applicable to this study, as insurance can only be purchased through the household's female SHG attendee, which does limit the generality of the findings. WTP elicitation and enrolment generally show the same trend, indicating that once again there is no difference between actual and stated WTP. Due to the small number of responses from female heads of household (only 20 percent of household heads are female in this data set and far fewer in the examined studies), it is difficult to examine the association between WTP and the gender of the household head. Further study in this area is required; but based on the findings, both WTP and enrolment are unlikely to differ by gender. High female enrolment is simply a result of the method of implementation.

4.3.1.3 Caste

Being a member of a scheduled tribe (ST) or a scheduled caste (SC) increases affiliation to the CBHI in Vaishali, but is statistically insignificant in the other two locations. ST and SC are two groups of economically and socially disadvantaged communities that make up a large portion of the population in three areas of study (Panda, et al., 2013). The results show that being a member of a lower caste may increase enrolment and at the very least will not be a barrier to enrolment. Individuals living in Vaishali have lower incomes, on average, compared to the other two locations. ST/SC castes' relatively high affiliation to the CBHI scheme in Vaishali indicates that this type of insurance is accessible to the poorest individuals in rural India. The same results are seen at the household and individual level because entire households fall into the same caste.

Mathiyazhagan (1998) found that SC/ST castes had a positive WTP towards the CBHI, as compared to higher castes in the rural Indian state of Karnataka. A similar trend appears in the results found -- with the implication that lower castes may be more likely to join and pay for CBHI products, because they are the only risk-pooling options for these low-income individuals. Once again there does not appear to be a difference between stated and true WTP.

4.3.1.4 Education

Individual education was grouped into three dummy variable categories: primary, middle and secondary and above. Having some primary education, as opposed to being illiterate, increased enrolment in the CBHI in Pratapgarh and Kanpur Dehat. This result is to be expected, as literacy increases the ability to understand, evaluate and recognize the need for new financial products. Secondary education and above was found to be insignificant in Vaishali and Pratapgarh and to have a negative impact on enrolment in Kapur Dehat. Individuals with higher education are likely to have higher incomes, enabling the purchase of insurance through other risk-sharing methods, such as private health coverage. These households are also better equipped to deal with episodes of ill health due to their ability to pay out-of-pocket health expenses.

An unexpected result is that education of the most educated female in the household and the education of the household head were both found to be insignificant[8]. This is somewhat surprising, but can be explained by the education provided to SHG members: The most educated female in the household is most likely to be the SHG member and will value specific insurance education more than formal education when making enrolment decisions.

The literature (Dong et al., 2003; Mathiyazhagan, 1998; Onwujekwe et al., 2010; Aseno-Okyere et al., 1997; Gustafsson-Wright et al., 2010; Dror et al., 2007) has consistently found education to increase willingness to pay. This result did not translate to the enrolment results found. It is likely that differences are a result of specific insurance education, which is not captured by formal education, and is hypothesized to increase WTP. In the studies examined, prior to analyzing willingness to pay, the basics of insurance and premiums were explained to avoid confusing people with other savings products; however, this basic information does not provide the same in-depth understanding of the benefits of the insurance provided through microfinance groups (Dror et al., 2007). Furthermore, several studies were conducted at earlier dates when fewer microfinance projects were in place, further reducing the effects of specific education. For example, Aseno-Okyere et al. (1997) found that most of the study respondents were only aware of auto insurance and had no prior knowledge of health insurance. Thus, preparatory activities can explain the differences between stated and actual WTP. Preparatory activities prior to offering microinsurance products would be of value to all new projects, as they increase WTP and require minimal formal education.

[8] This result is seen both for education measured in years and for the three dummy variable groupings.

4.3.1.5 Household Size

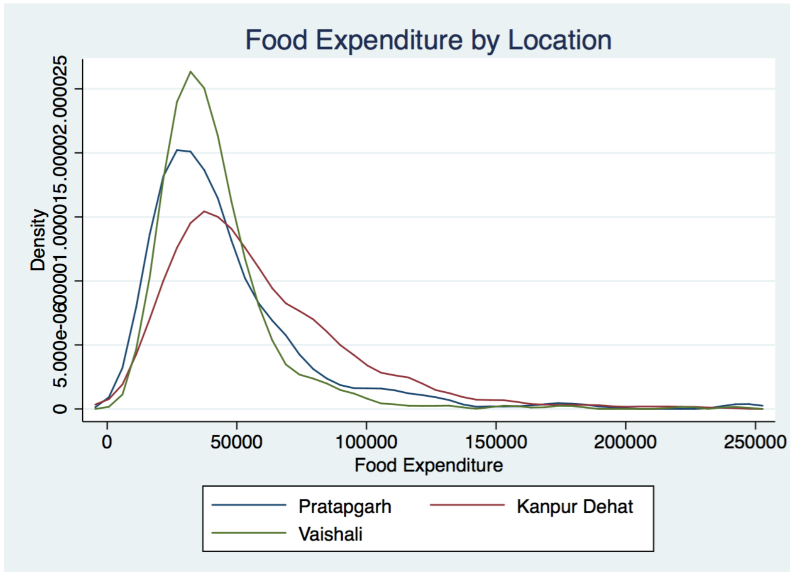
There is evidence that household size has a negative impact on CBHI uptake, when analyzing individual enrolment. Individual members of nuclear families are more likely to enroll than those of extended families in both Kapur Dehat and Vaishali, but this effect was statistically insignificant in Pratapgarh. Individual enrolment results are consistent with WTP results found by Dror et al. (2007) and Onwujekwe et al. (2010).

Household size is expected to play a smaller role when enrolment is not limited to entire households. Larger households will face financial limitations when required to enroll as a bloc. These households are not expected to enroll extended family members who do not earn income. The measurement of the enrolment ratio of the household is calculated using household size; therefore, it is not possible to examine the explanatory effects of size without creating an endogeneity problem in the model.

4.3.1.6 Income

Economic status of the household is measured through monthly household food expenditure per capita. Household monthly food expenditure is plotted and shown by location in figure two. Being in the second income quintile (20^{th} to 40^{th} income percentiles) increases enrolment probability, as compared to the base case of being in the bottom income quintile in Pratapgarh. In Kapur Dehat, being in income quintiles two through five all increased the probability of enrolment, compared to the base case. Income was insignificant for all quintiles in Vaishali. Income appears to be positively affiliated with enrolment, but this effect is confined to Pratapgarh and Kapur Dehat. Vaishali is the poorest of the three locations studied; therefore, the insignificance of income reaffirms the result that income is not a barrier to enrolment, even amongst the most disadvantaged population groups.

Figure 2: Household Food Expenditure



Income is divided into quintiles because sub-income groups are thought to differ in the portion of their incomes that they are willing to pay for health insurance. Studies (Dong et al., 2003; Barnighausen at al., 2007) indicate that willingness to pay increases at a lower rate than income; therefore, nominal WTP levels increase with income but decrease as a share of income (Dror and Koren, 2012). It is likely that the positive relationship between nominal WTP and income measured via proxies is only partly seen in the data, because the relationship between enrolment and income is secondary to that of the relationship to the household head and SHG member. Heads and spouses have higher enrolment, because income is prioritized to primary family members and income-earners. To investigate this postulate, relationship in the household effect on enrolment is tested.

4.3.1.7 Relationship to the head of the household

Relationship to the head of the household is a highly significant factor in determining individual enrolment in each of the locations. The spouse of the head is four percentage points more likely to be enrolled than the head of the household, holding all else constant, for all the locations pooled together. All other household members, including children of the head, are less likely to be enrolled than the head. Other relatives and non-relatives were not included in the regression, as they perfectly predicted not being enrolled. When using the spouse of the head, who is most often female and an SHG member, as the base case[9], all others, including the head and children, are less likely to be enrolled than the spouse. By the program design, it is expected that spouses will account for the highest portion of individual enrolment. The trend shows that vertical relationships are given more weight than horizontal relationships, with the head and spouse being given the highest priority for enrolment.

Nuclear intergenerational family units will have a higher WTP than intragenerational extended families. In-laws, siblings and other relatives of the head will have the lowest WTP, which is confirmed by their low enrolment rates (see Table 5) and negative relationship seen in the regression results. This is a result of income distribution. The head of the household is likely to be earning the highest income and will have the highest food expenditure in households.

Table 5: Individual CBHI enrolment by relationship to household head

Relationship to Household Head	Not Enrolled	Enrolled	Total	Percentage Enrolled
Head	984	351	1,335	26.29213483
Spouse of head	700	384	1,084	35.42435424

[9] See appendix for all regression results with alternate bases of independent variables.

Child of head	2,783	869	3,652	23.79518072
Spouse of child of head	315	72	387	18.60465116
Grandchild of head	645	94	739	12.71989175
Parent of head	210	24	234	10.25641026
Sibling of head	138	6	144	4.166666667
In-law (father/mother)	81	6	87	6.896551724
Other relative	59	0	59	0
Non-relative	1	0	1	0
Total	5,916	1,806	7,722	100

4.3.1.8 Discussion of socioeconomic parameters

The main findings emerging from the socioeconomic group of explanatory variables are that WTP and enrolment are an individual decision; specific education may be more important than formal education as an explanatory factor; and income is not a barrier to enrolment, largely because of the way that microinsurance is designed and priced. WTP for health insurance appears to be an individual decision rather than a household one, as intra-household enrolment is highly stratified. Panda et al. (2013) found that it was rare for entire households to be enrolled, because households found that paying premiums for all members was burdensome. WTP will be much higher when CBHI is offered individually, as household heads and spouses are prioritized in income distribution, meaning that only primary family members will purchase insurance when given the opportunity to do so individually. Education is one of the few variables with a large disconnect between WTP and actual enrolment. This is likely because studies have not been looking at the effects of specific education. As long as individuals have at least primary education, information on risk-pooling will be more beneficial than more formal education for increasing WTP and enrolment. The caste and income variables show that economic status is not a limiting factor for enrolment, but are not useful for pricing premiums beyond this fact.

At the household level, many of the socioeconomic characteristics of the household head that were significant at the individual level are found to be insignificant. This provides further evidence that the decision to purchase insurance is more of an individual one than a household one.

4. 3. 2. Risk-Pooling Parameters Results and Discussion[10]

4.3 2.1 Rashtriya Swasthya Bima Yojana (RSBY) and Private Health Insurance

Household enrolment in the national health insurance program was highly insignificant in all locations in predicting individual or household enrolment. Having private[11] health insurance was found to produce a negative impact on individual enrolment; but this effect was restricted to Vaishali. This finding provides some evidence that private insurance and CBHI act as substitutes, while public insurance and CBHI act as complements. The services covered by RSBY are far more limited than those covered by CBHI. RSBY provides cashless insurance for hospital visits to public and private hospitals in all three locations, while the CBHI includes some transportation costs, wage losses and outpatient care (Panda et al., 2013). The difference in coverage provides evidence for the complementary nature of the insurance products. It is also important to note that, while private insurance did deter enrolment in Vaishali, such products are not affordable for the vast majority of the rural poor. There may also be a bias arising from the small number of participants who have private health insurance. Overall, CBHI is a

[10] It is not possible to compare this grouping of variables to WTP elicitation, as these variables were not examined by studies; but they are included because of their importance in determining enrolment.
[11] Private insurance is simply defined as any other insurance products other than CBHI or RSBY.

differentiated product; and having private or national insurance is unlikely to deter holders from enrolment.

Previous WTP studies did not analyze the effects of other insurance products on WTP. Based on the current findings, such insurance products will only affect WTP in their ability to provide experience with insurance. However, simply having other insurance products should not decrease WTP for CBHI, assuming that coverage remains differentiated. This result can be generalized to other low-income rural locations, but further study is needed for urban areas with greater access to other insurance products. It is likely in urban areas that private insurance companies may decrease willingness to pay for CBHI, because large population groups allow for low-cost operations.

4.3.2.2 Income Sharing

Households sharing income among their members are indicative of risk-pooling behaviour, as this reduces the dangers of future financial shocks by smoothing consumption patterns over time (Panda et al., 2013). Traditionally, households have relied on informal insurance mechanisms such as risk-pooling within the family or community. This method provides incomplete protection and is more cost-intensive than formal insurance.

Not pooling any income increases the probability of enrolment in Pratapgarh and Kanpur Dehat, compared with the base case of no pooling, holding all else constant. Similarly, when using no income-pooling as the base case, pooling all income decreases the probability of enrolment in Pratapgarh and Kanpur Dehat and is insignificant in Vaishali. Households that risk-pool on their own are less likely to require formal insurance. Risk-pooling within households acts as a substitute for CBHI. Households that pool income protect themselves against health expenditure shocks with savings and household assets. Small households and very low-income households should still exhibit a demand for CBHI, because intrahousehold risk-pooling is less feasible. Households in Vaishali are smaller and poorer, on average, compared with those in the two districts of Uttar Pradesh, which may explain why household income-sharing was insignificant in this region.

4. 3. 3 Supply-Side Factors

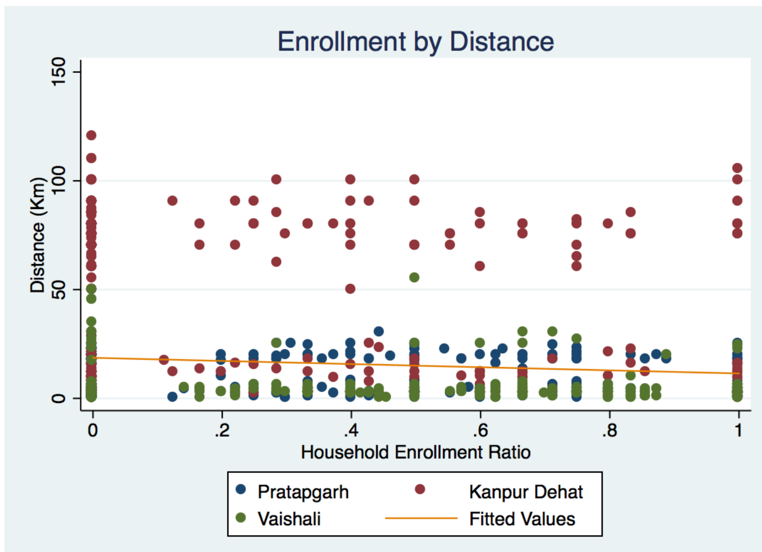
Health insurance is only relevant and desirable in regions with access to health facilities. All three regions have access to health care, but Kanpur Dehat has a relatively lower supply of health services. This can be seen in Figure 3, which shows distance to the nearest hospital broken down by location. From the fitted values, it can also be seen that the enrolment ratios decrease with distance to the nearest health-care facility. The distance and travel time from home to the nearest hospital, doctor and pharmacy are used to represent the accessibility of care[12]. It can be expected that individuals living within close proximity to health-care facilities will be more likely to join CBHI schemes and will have higher WTP for such schemes.

At the individual and household levels, there is mixed evidence of the impact of accessibility on enrolment. In Vaishali, increasing distance to the nearest pharmacy by one kilometre decreased individual affiliation to the CBHI by 1.6 percentage points. Distance to health-care facilities in the other two regions showed insignificant or positive impact on enrolment. This initially surprising result can be explained by the fact that health-care coverage plans in Pratapgarh and Kanpur Dehat covered transportation costs

[12] Only output for travel time is shown; however, both distance and travel time display similar results.

for each episode of hospitalization. This is assumed to reduce the negative effect that distance to health facilities has on enrolment. There is also the possibility that reduced accessibility will not affect enrolment, as long as services are available. In Vaishali, where transportation costs were not included as part of the coverage, travel time and distance to the nearest hospital were negative but statistically insignificant. This could indicate that as long as health care is available, reduced accessibility will not reduce enrolment.

Figure 3: Household enrolment ratio by distance to nearest health-care facility



The assumption that better accessibility of health care will increase WTP is generally upheld in the literature (Dror et al., 2007; Dong et al., 2003). The findings indicate that areas with less health-care accessibility should be charged lower premiums, unless transport costs are included in coverage. A direct comparison between the literature and enrolment rates cannot be made when transport fees are included as part of the coverage, as they are in Uttar Pradesh. The mixed results in Vaishali indicate that there is a disconnect between WTP and enrolment when it comes to accessibility. Reduced accessibility may not discourage enrolment to the extent that WTP studies suggest; but package design with respect to travel coverage must be incorporated in premium pricing.

4.3.4. Experience with Insurable Risk

Demand for microinsurance reflects an understanding that the inherent value of health insurance is that it should protect populations from financial shocks by covering health-related costs (Dror & Koren, 2012). The implication is that households experienced with the cost of care will be willing to pay more to prevent similar future expenditures, given bad states of the world. Previously conducted studies found mixed results concerning the most appropriate method to measure experience with risk; therefore, several proxies to measure the effect of past health risks are used. These proxies are short-term and long-term illnesses, hospital visits and pregnancies. Short-term and long-term health problems increase enrolment; but this effect is limited to Pratapgarh. For example, in Pratapgarh, having a long-term illness increased enrolment by four percentage points. Total household expenditure on these health events is found to be insignificant in all the locations at the individual level.

At the household level, all incidences of past illness have no impact on enrolment; however, total household expenditure to pay for these illnesses increased affiliation to the CBHI in Pratapgarh and Vaishali. The findings indicate that households that are more prone to ill health are more likely to seek out insurance, because they face greater health costs. Enrolling in CBHI schemes due to past experiences with insurable risk is consistent with adverse selection. By only allowing enrolment through the SHG members, adverse selection is somewhat reduced; however, allowing individual enrolment opens up the opportunity for increased adverse selection, if individuals with pre-existing health conditions self-select into enrolment.

The literature confirms through a variety of proxies that households and individuals that have faced recent ill-health experiences should be willing to pay more to prevent them in the future (Dror & Koren, 2012). Findings show that there is little difference between actual and stated WTP when it comes to experience with insurable risk. Experience with ill health and insurable risk increases understanding of the benefits of risk-pooling. Preliminary awareness-building may capture some of the same information that experience does and explains some of the insignificant results. The implication is that education and awareness can act as a substitute for experiences with insurable risks and will increase WTP.

4.3.5 Discussion of Findings

The results of the empirical analysis show several key insights that can be applied when pricing premiums. First, results suggest that the distinction in the level of WTP and enrolment by gender is negligible. Premiums should be similar for both genders, once taking into account the different costs associated with gender-specific health risks like pregnancy; but the methodology of introducing microinsurance projects through pre-existing microfinance community groups and institutions that are focused on women has proven itself effective. Further, caste and income are not barriers to enrolment when premiums are priced appropriately to meet target populations’ ability and willingness to pay. Finally, differences in enrolment and WTP based on socioeconomic, risk-pooling and health characteristics suggest a need for multiple plans offered through a single CBHI scheme.

Another interesting insight is that higher levels of formal education are not a necessity when determining communities for which CBHI is appropriate, as preparatory information is far more important. Specific education is enhanced when recipients are literate, with at least some primary education. National and private health insurance had minimal effects on enrolment, because products were differentiated, while informal risk-pooling within households did decrease enrolment, because households saw CBHI as a substitute for income-pooling. This highlights the need for differentiated CBHI schemes that offer products that are complementary to existing mechanisms.

A final key point is that WTP based on accessibility of health-care services is dependent on features of coverage plans. The inclusion of travel costs allows for higher premiums to be charged. There is some evidence that regardless of travel costs, enrolment is not deterred by less health infrastructure. Rural households appear to be willing to travel long distances in order to access health care. The implication is that as long as health services are available, willingness to pay premiums will not be affected by the location of villages.

4.4 Cost Value Analysis of Premium Pricing:

Premiums in microinsurance markets must be priced to be sufficiently large enough to cover future losses, but not so high as to discourage enrolment of low-income populations in CBHI schemes. The standard actuarial approach to pricing premiums involves estimating the mean and standard deviations of the total random loss from an insured risk in advance (Biener, 2013). Insurance providers can control for insolvency risks by adding a fee that is dependent on the distribution of the losses from the insurance risk (Biener, 2013). In traditional insurance markets, risk of insolvency can be reduced by increasing the fee or increasing the number of persons insured; however, in microinsurance markets the number of persons insured is limited, and risk of insolvency can only be decreased by increasing the fee (Biener, 2013). As a result, microinsurance markets will face higher technical premiums than standard insurance markets. When high premiums are combined with low ability to pay and high price sensitivity, insurance without unsustainable subsidies can be overpriced for low-income populations or put insurers at risk of insolvency (Biener, 2013)

Premium pricing in microinsurance markets moves away from the standard actuarial approach and instead uses WTP as a proxy for premiums. Providers set premiums above minimum cost requirements, but below maximum WTP (Biener, 2013). Willingness to pay can be calculated in many ways. The studies reviewed all conducted extensive household surveys with complex elicitation methods, the most common of which was the bidding game method (Dror & Koren, 2012)[13]. The common factor in all WTP elicitation methods is that they are time-consuming and expensive. Further, it has been found that estimates differ significantly across locations, even within states or regions of a single country; therefore, it is not possible to rely on previously conducted surveys when estimating premiums and WTP (Binnendijk et al., 2013).

A novel alternative approach that expresses WTP as a percentage of income has recently been developed by the Micro Insurance Academy. WTP can be calculated in three ways: as a percentage of income; as a percentage of food expenditure; and as a

[13] Other methods include dichotomous choice technique, where demand curves are estimated from specific commodity estimation questions; the 'take it or leave it' approach, where econometric tools are used to combine large pools of respondents answering the single question; and the payment card method, where respondents state their maximum willingness to pay (Dror & Koren, 2012).

percentage of discretionary income (Binnendijk et al., 2013). For the purposes of this study, the food expenditure method has particular merit. For six states across rural India, Binnendijk et al. (2013) found that WTP for insurance products accounts for approximately 4.5 percent of total household expenditure on food.

The food expenditure method is given further accreditation from the results of a two-year CBHI operation in rural Nepal that was successfully conducted without premium subsidies or subsidized health-care costs (Dror et al., 2014). The study estimated WTP using the bidding game and food expenditure methods. Premium levels were bounded by the two estimates and chosen closer to the food expenditure level by community groups (Dror et al., 2014). Based on the success of the food expenditure elicitation method, the 4.5 percent results will be tested for this dataset. Further study into WTP as a percentage of food expenditure across different locations is required before results can be generalized.

4.4.1 Food Expenditure Predictions and Household Survey Predictions

Food expenditure is calculated from monthly household spending on food consumption and the monetary value of homegrown products consumed. Household spending on purchased cereals, vegetables, meats, fish, eggs, dairy and other food items are calculated on a yearly basis by extrapolating one month of survey data. The monetary value of food produced at home was also calculated on a yearly basis using 2010 food prices across the three locations. Calculations were done separately for each target location, because of the differences in premiums[14] and food expenditure. First, households are divided into quintiles based on their food expenditure data. A dummy

[14] Annual CBHI premiums per person per year in Indian rupees differed in each of the locations and were 176 in Pratapgarh, 192 in Kanpur Dehat and 197 in Vaishali.

variable is given a value of one if 4.5 percent monthly food expenditure per capita is greater than or equal to the premium divided by 12. As expected, the percentage of households that meet this cutoff is significantly different for each quintile. This dummy variable is then checked against enrolment rates. If the dummy and enrolment have the same value, the model has predicted correctly. Only results from the final stage are shown in Table 6.

For example, in Pratapgarh the calculation for the bottom income quintile is:

$$Premium\ cutoff = 0.045 * Monthly\ per\ capita\ food\ expenditure = 4.5\% * 285.3094$$
$$Predicted = 1\ if\ premium\ cutoff\ (4.5\% * 285.3094) \geq \frac{176}{12} = 4.62\ \%$$
$$Correct\ Prediction = 1\ if\ Enrolment\ rate = Prediction = 58.89\ \%$$

Predictions from the household survey methodology are calculated from the results of the individual probit regressions (Regression 1 presented Table 2). The dependent variable can only take on one possible value; therefore Stata[15] can predict the number of correct predictions of the model. The same calculation is done in Stata that is done manually for food expenditure, that is, the success in forecasting enrolment using different models is predicted by comparing estimates with actual enrolment rates. For each individual in the dataset, the probability of enrolment is given a score between zero and one based on the regression coefficients. For example, for a male head of household, age 20, in an ST caste, a score is given using the following formula:

$$enrolment = F(age\ (20) * \beta_{age}(-0.00168) + Gender(Male = 0) * \beta_{gender}(0.313)$$
$$+Caste\ (ST = 1) * \beta_{caste} + Household\ Position\ (Head = 1) * \beta_{realtionship}(-0.0497)$$
$$\ldots. +RP * \beta_{RP} + SS * \beta_{SS} + HE * \beta_{HE}) = Score\ (0 - 1)$$

[15] The *estat classification* Stata 13 command was then used to produce a cross tabulation of observed and predicted outcomes.

The estimated score is then compared to enrolment status. A positive outcome is predicted when the probability is 0.5 or more and a negative outcome otherwise (StataCorp, 2013).

Table 6: Predictions of the Models

	Pratapgrah	Kanpur Dehat	Vaishali
Food Expenditure Method			
Correct Prediction Quintile 1	58.89%	68.25%	53.44%
Correct Prediction Quintile 2	59.12%	59.52%	52.86%
Correct Prediction Quintile 3	57.97%	66.14%	53.63%
Correct Prediction Quintile 4	54.50%	64.29%	50.19%
Correct Prediction Quintile 5	53.12%	63.76%	49.43%
Average	**56.72%**	**64.392%**	**51.91%**
Household Survey Method			
Individual Enrolment Quintile 1	75.19%	75.86%	75.71%
Individual Enrolment Quintile 2	71.44%	73.92%	73.49%
Individual Enrolment Quintile 3	69.49%	71.21%	71.54%
Individual Enrolment Quintile 4	72.37%	76.89%	77.29%
Individual Enrolment Quintile 5	76.70%	76.88%	76.74%
Average	**73.2%**	**74.90%**	**75.01%**

The results presented in Table 6 show the predictability of both models. For all locations and income groups pooled together, the predictability of the food expenditure model was 57 percent and the predictability increased for the household survey model to 74 percent. It should be noted that the predictability of the food expenditure model is seven percentage points above the average locations in Kanpur Dehat, because households in these locations have higher incomes on average; therefore, a higher percentage of households meet the premium cutoff calculation. Using the household survey method, estimations remained similar across locations due to the fact that all socioeconomic, risk-pooling and supply-side variables are included.

The food expenditure method results show that the predictability of the model decreases as income increases. The result is of particular magnitude because the number of people who meet the 4.5 percent cutoff increases with income[16]; therefore, the overall decreasing predictability indicates that this method is far less accurate at making predictions for higher-income groups. Studies have shown that nominal levels of WTP increase with income but decrease significantly when measured as a share of income (Dror & Koren, 2012). This explains why the higher-income quintiles have less accurate predictions. The 4.5 percent anchor is an average estimate for all income groups; but higher-income groups should be willing to pay less than 4.5 percent of their income for insurance and lower-income groups should be willing to pay more than 4.5 percent. This same trend is not seen in the household survey method. Predictabilities remain constant between quintiles because income is only one of the many significant explanatory variables used to forecast enrolment.

A major limitation of the approach used is that monthly per capita numbers were calculated by simply dividing household monthly food expenditure by household size. This calculation does not take into account any intrahousehold income dynamics, including the possibility that extended non-income-earning family members will not be given an equal share of income earned. This is of particular importance when insurance is offered on an individual basis as well as on a household basis. The household survey methodology captures this dynamic; and position in the household was found to be one of the most important determinants of enrolment.

[16] Only 4.62 percent of the bottom quintile meet the stage one cutoff, while 100 percent of the top quintile meet the stage one cutoff.

4.4.2 Costs and Benefits

The food expenditure method has been developed with the aim of reducing the time and cost associated with extensive surveys, because the only data required are average food expenditure (Binnendijk et al., 2013). The necessary data can be obtained from pre-existing sources, such as government census surveys, microfinance focus groups or basic household surveys querying only income (Binnendijk et al, 2013). In meeting this aim it is very successful, but it does come at the cost of lost enrolment.

Table 7: Lost Enrolment Estimates

	Pratapgrah	Kanpur Dehat	Vaishali
Lost Enrolment (%)	16.48%	10.51%	23.10%
Lost Enrolment (INR)- Wave 1	223975.0656	155794.1299	351405.054
Lost Enrolment (INR)- Wave 2 and 3	352210.56	224576.98	493693.20

Estimates of losses incurred are calculated using the differences in predictabilities of the two models multiplied by premiums and enrolment rates. Results are shown in Table 7 in Indian rupees per year. Results show that losses are significant for low-budget projects with narrow profit margins. The development nature of CBHI provides further evidence of the harm caused by inaccurate premium estimates. Lost enrolment estimates are highest for Vaishali, the most economically disadvantaged of the three locations, and lowest in Kanpur Dehat, the least economically disadvantaged. Less accurate estimates of premiums not only reduce profits but increase income shocks for the most vulnerable populations.

The household survey methodology is better able to predict premiums that will encourage enrolment; however, the data required must be obtained with expensive household surveys. The costs of administering such a survey is estimated based on time, distance travelled and number of surveys conducted[17]. Rough estimates are presented in Table 8. These do not include time and costs taken to construct surveys, data entry costs and research expenses. These are not included, because research costs are typically subsidized for such projects. For example, the European Commission Framework Program and local partner NGOs subsidized the Micro Insurance Academy's research and implementation costs for the dataset at hand (Doyle et al., 2013)

Table 8: Partial Cost Estimates of Household Surveys

Time to complete survey	2.15 hr* 1335 surveys= 2870 hr.
Cost to complete survey	2,870 hr.* 800 INR/hour= 2296000 INR
Travel Time	120 days, 350 miles= 76800 INR
Total	237200 INR

Based on the results, it can be concluded that food expenditure serves as an excellent anchoring point for premiums, but is not sufficient on its own. Due to its less precise nature, it should be combined with community focus groups that set benefit packages, premiums and claim processes with insurance providers, for the best chances of success. It reduces some of the critical need for baseline surveys, but at the moment does not provide sufficient information to price premiums. As more research and household surveys are conducted, there will be a decreased need for baseline surveys.

4.5 Recommendations

Based on the findings of the empirical analysis, two recommendations can be made to reduce costs and risks of insolvency. The first is to offer multiple coverage plans through a single CBHI scheme. Empirical analysis shows that enrolment rates differ by

[17] The average time for a household to complete the survey was 129 minutes, with 1,335 households completing the survey for a total of 2,870 hours for all households. Sixty-seven different interviewers conducted the surveys over a period of two months from March, 2010, to May, 2010.

socioeconomic factors, health status, risk preferences and proximity to health infrastructure. This suggests a demand for a wider variety of coverage options. As previously mentioned, administrative costs and lack of adequate financial information make the introduction of deductibles and coinsurance options undesirable; however, offering multiple coverage plans can be done at the community level through the same microfinance institutions currently utilized.

The main benefit of increasing the number of coverage options is their ability to alleviate the need for baseline household surveys altogether when used in combination with initial pricing estimates and community focus groups. To start, premiums should be estimated using food expenditure data from government census surveys. Next, several coverage options can be designed in collaboration with community groups. During preparatory education activities, the specific benefits of each package should be explained. For example, individuals with high past health expenditures should be encouraged to purchase higher coverage options than those with low previous health expenditures. Packages should offer not only different levels of coverage but also different features, like the inclusion of travel costs or reimbursement of lost wages. Furthermore, multiple packages in combination with adequate financial information allow for self-selection based on risk types. The market can form a separating equilibrium, where low-risk types will only partially insure themselves and high-risk types will fully insure. Most importantly, all coverage options must be tailored to individual communities' needs and must be appropriate for the level of health infrastructure in each area.

The second recommendation is to financially combine CBHI schemes. Providers can merge CBHI offerings to form a diversified portfolio that faces less risk of insolvency, moral hazard and adverse selection. Currently, schemes are confined to small neighborhoods, which poses insolvency threats. Regional non-systemic health problems, such as malaria outbreaks, should not affect different schemes operating in different regions at the same time; therefore, combining schemes can allow for funds to be loaned to those plans facing liquidity constraints from high claim rates. This will protect the insurer against insolvency risks because of the larger pool of persons among whom to spread, pool and transfer risk and provide communities with funds in times of need. Having a larger pool of insured persons also reduces the risk of adverse selection and moral hazard problems through the law of large numbers. It should be noted that the implementation of this recommendation is complicated due to co-operation issues between providers and community groups. Operations must remain transparent to encourage trust in the CBHI schemes; therefore, introducing a financial merging plan must be done at the community level.

5. Conclusion

The purpose of this study was to examine the determinants of demand for micro health insurance. A better understanding of parameters that govern enrolment and willingness to pay can be extremely helpful to insurance providers and policymakers when designing an insurance product that suits target populations (Dror and Koren, 2012). When examining the parameters that determine enrolment, it was found that supply-side and socioeconomic factors differed from previously conducted studies (Dong et al., 2003; Mathiyazhagan, 1998; Onwujekwe et al., 2010; Aseno-Okyere et al., 1997;

Gustafsson-Wright et al., 2010; Dror et al., 2007), while risk-pooling factors and health events were similar. Distance traveled to health-care facilities, as well as gender and education are of less importance in determining enrolment in CBHI schemes than past research suggests. These results are promising, as they indicate that schemes are appropriate for a wider variety of communities. For example, isolated communities with low levels of education can now be considered suitable targets for new CBHI schemes.

When comparing models to price premiums and forecast enrolment, it was discovered that there is still an important role for household surveys, even as new, innovative techniques of pricing premiums are developed. With further development that allows for more precise pricing, the need for baseline surveys will be alleviated when community focus discussion groups are used in combination with anchoring WTP methods and multiple coverage plans. Some similarities between the determinants of enrolment and WTP (health status and risk-pooling factors) indicate that with time, findings from previous WTP studies will be applicable in pricing premiums, especially as financial literacy and insurance awareness increase.

Reduced costs and the ability to better predict demand needs will improve health-care services in emerging markets. This innovative and developing market is of particular importance for rural areas, because they will otherwise have no access to health care or preventative medicine and no social safety net if their own health collapses.

References:

Akerlof, G., (1970), The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84 (3), pp: 488-500.

Asenso-Okyere, W. K., Osei-Akoto, I. Anum, A. & Appiah, E. N. (1997). Willingness to pay for health insurance in a developing economy: A pilot study of the informal sector of Ghana using contingent valuation. *Health Policy, 42(3),* pp: 223-227.

Bonan, J., Lemay-Boucher, P., & Tenikue, M., (2013). Household's willingness to pay for health microinsurance and its impact on actual take-up: results from a field experiment in Senegal. *CEPS Working Paper (2013-15)*.

Biener, C. (2013). Pricing in microinsurance markets. *World Development*, *41*, 132-144.

Biener, C., & Eling, M., (2014). Regulation in Microinsurance Markets: Principles, Practice, and Directions for Future Development. *World Development*, *58*, 21-40.

Binnendijk, E., Dror, D. M., Gerelle, E., & Koren, R., (2013) Estimating Willingness-to-Pay for Health Insurance Among Rural Poor in India By Reference to Engel's Law *Social Science & Medicine* 76, pp: 67-73.

Bhat, R., & Jain, N. (2006). Factoring affecting the demand for health insurance in a micro insurance scheme

Churchill, C., & McCord, M. J. (2012). Current trends in microinsurance. In C. Churchill, M. Matul, (Eds.), *Protecting the poor: A microinsurance compendium: Vol. II*. Geneva, Switzerland: International Labour Organization, pp :8-39

Dror, D. M. and Koren, R.(2012). The Elusive Quest for Estimates of Willingness to Pay for Health Microinsurance . *Protecting the Poor: A Microinsurance Compendium. Vol II. Edited by C. Churchill and M. Matul. Geneva, ILO, 2012*. Chapter 7. pp: 156-173.

Dror, D., & Jacquier, C. (1999). Micro-insurance: Extending health insurance to the excluded. *International Social Security Review*, *52(1*), pp: 71–98.

Dror, D., & Perker, A. Social Reinsurance: A New Approach to Sustainable Community Health Financing. *World Bank and ILO; 2002*

Dror, D. M., Radermacer, R., Koren, R., (2007) Willingness to pay for health insurance among rural and poor persons: field evidence from seven micro health insurance units in Inida. *Health Policy,* 82(1), pp: 12-27.

Dror, D. M., Majumdar, A., Panda, P., John, D., & Koren, R. (2014). Implementing a Participatory Model of Micro Health Insurance among Rural Poor with Evidence from Nepal. *The Geneva Papers on Risk and Insurance-Issues and Practice*, *39*(2), 280-303.

Dror, D. M., & Firth, L. A. (2014). The Demand for (Micro) Health Insurance in the Informal Sector. *The Geneva Papers on Risk and Insurance-Issues and Practice*.

Doyle, C., Panda, P., van de Poel, E., Radermacher R, & Dror, D. (2011) Reconciling research and implementation in micro health insurance experiments in India: study protocol for a randomized controlled trial. *Trials Journal,* 12 (224)pp:1-15.

Dong, H., Kouyate, B., Snow, R., Mugisha, R., Sauerborn, R., (2003). Gender's effect on willingness-to-pay for community-based insurance in Burkina Faso. *Health Policy*, 64 (2), pp: 153-162.

Giesbest, L., (2010), Uptake of Micro-Life Insurance in Rural Ghana. *Chronic Poverty Research Center*.

Gustafsson-Wright, E., Asfaw, A., & van der Gaag, J. (2009). Willingness to pay for health insurance: An analysis of the potential market for new low-cost health insurance *products* in Namibia. *Social Science & Medicine*, *69*(9), 1351-1359.

Kihaule, A. (2013). Determinants of rural household demand for micro health insurance plans in Tanzania. *Working Paper,* A6, pp: 1-40

McCord, M., & Churchill, C., (2005). Microinsurance. *Delta Life: Bangladesh*

Mathiyazaghan, K. (1998). Willingness to pay for rural health insurance through community participation in India. *The International journal of health planning and management*, *13*(1), 47-67.

Onwujekwe, O., Okereke, E., Onoka, C., Uzochukwu, B., Kirigia, J., & Petu, A. (2010). Willingness to pay for community-based health insurance in Nigeria: Do economic status and place of residence matter? *Health Policy Plan,* 25(2), pp: 155-161.

Panda, P., Chakraborty, A., Dror, D., & Bedi., A. (2013) Enrolment in community-based health insurance schemes in rural Bihar and Uttar Pradesh, India. *Health Policy and Planning,* 29(4)

Rothschild, M., & Stiglitz, J.E., (1976). Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information. *The Quarterly Journal of Economics,* 90(4), pp: 630-49.

StataCorp. 2013. *Stata Statistical Software: Release 13*. College Station, TX: StataCorp LP.

Von Neuman, J., & Morgenstern, O., (1944). *Theory of Games and Economic Behaviour*. Princeton, NJ, Princeton University Press.

WHO (2011). Report of the Commission on Macroeconomics and Health. *Geneva:* World *Health Organization*

Yao, Y., (2013), Development and Sustainability of Emerging Health Insurance Markets: Evidence from Microinsurance in Pakistan. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 38, (1), pp: 160-180.

Appendix

Table 9: Individual probit regressions using spouse of household head as base

	(1)	(2)	(3)	(4)
VARIABLES	All	Pratapgrah	Kanpur Dehat	Vaishali
Head	-0.0455*	-0.0481	-0.0259	-0.0546
	(0.0234)	(0.0445)	(0.0421)	(0.0364)
Child of Head	-0.133***	-0.153***	-0.159***	-0.107***
	(0.0259)	(0.0526)	(0.0410)	(0.0416)
Spouse of Child of Head	-0.186***	-0.143***	-0.168***	-0.262***
	(0.0287)	(0.0546)	(0.0484)	(0.0453)
Grandchild of Head	-0.243***	-0.255***	-0.220***	-0.281***
	(0.0275)	(0.0548)	(0.0415)	(0.0463)
Parent of Head	-0.226***	-0.238***	-0.168***	-0.247***
	(0.0301)	(0.0561)	(0.0499)	(0.0549)
Sibling of Head	-0.309***	-0.344***		-0.297***
	(0.0296)	(0.0574)		(0.0711)
In-Law of Head	-0.258***		-0.224***	-0.0944
	(0.0416)		(0.0515)	(0.113)
Observations	7,063	2,198	2,010	2,777

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Individual probit regressions using pooling all income as a base case

	(1)	(2)	(3)	(4)
VARIABLES	All	Pratapgrah	Kanpur Dehat	Vaishali
No Pooling	-0.0585***	-0.132***	-0.0852***	-0.0155
	(0.0140)	(0.0351)	(0.0265)	(0.0205)
Partial Pooling	-0.0758***	-0.00702	-0.0521	-0.0796**
	(0.0237)	(0.120)	(0.0440)	(0.0310)
Observations	7,063	2,198	2,010	2,777

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1