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ABSTRACT

This paper is an attempt to understand the factors underlying the low take up and contract renewal rates frequently observed in insurance programs in poor countries. This is done on the basis of the experience of a microinsurance health program in India. We show that deficient information about the insurance product and the functioning of the scheme, poor understanding of the insurance concept, and the resulting low use of the insurance products by eligible households are the major causes of the low contract renewal rate among the households which has previously enrolled into the program. A particularly interesting finding is that, when a household has received a negative payout during the preceding year (the cost of the premium has exceeded the insurance benefits), it is more inclined to renew its participation if it has a better understanding of what insurance exactly means (a redistribution between lucky and unlucky individuals). Such a finding strongly suggests that the understanding failure is a key problem in attempts to provide insurance to poor people, and this problem is obviously more difficult to overcome than the largely supply-driven information failure. That economists have neglected the role of the understanding failure is apparent from the lack of attention to this aspect in recent theories aimed at improving our knowledge of human behavior toward risk. Another central, policy-relevant finding of the study is that participation in previously constituted self-help groups has the effect of enhancing both the insurance take up and contract renewal rates. This points to the essential role of non-governmental organizations that operate at the grassroots level.

1. INTRODUCTION

Health risks pose dangerous threats to the lives and livelihoods of the poor. In developing countries, many low income individuals cannot afford medical treatments, or finance the purchase of medicines. These events have often been recognized as one of the main causes of poverty (see, e.g., Leatherman et.al., 2010). Because governments in most developing countries have not been able to meet the health care needs of their poor population, many community-based health insurance programs (CBHI) have emerged during the last decade to provide financial protection against costly health care for the poor. In general, a CBHI program is a local healthcare financing option for the poor that provides a defined set of health benefits and services, such as hospitalization or inpatient benefits.

Ensuring universal health coverage through public or PPP (public-private partnership) initiatives in low income countries has become a central objective of the international donor community. Microinsurance, or CBHI programs are increasingly considered as one of the ways available to build health coverage initiatives. Revealingly, health insurance for low income households, admittedly consisting of basic products that provide minimal coverage, has expanded exponentially over the past few years. More comprehensive products that provide higher value to low-income households are still rare. One such scheme, which goes beyond basic in-patient cover, is the CBHI program recently implemented in India by Swayam Shikshan Prayog (SSP) and Swasth India Services (SIS) and underwritten by a local insurance company. Aimed at reducing out-of-pocket health expenditures incurred by low income households, both urban and rural, in two districts of Maharashtra state, this program offers a hybrid health insurance product. Against a fixed annual premium that varies with the size of the household, households are granted (i) free access to in-patient care provided in empanelled hospitals, up to an annual benefit of US$667 for the whole family, and (ii) a reduction in out-patient health costs through a 50% discount on consultation fees and a 40-70% discount on the retail price of medicines. Another key feature of the program is that outpatient discounts are provided only through a specific network of community health workers, physicians, diagnostic centers and pharmacies (coordinated by a Community Health Trust).

It may appear surprising that many of these microinsurance programs have shown disappointing performances as measured by take up and contract renewal rates (see de Bock and Gelade, 2012, for a recent survey). Indeed, it is rather exceptional to see take up rates above 30% and quite frequent to observe rates below 15-20%. As for renewal rates, available data suggest that they may be even smaller: 7% in Nicaragua (Fitzpatrick et al., 2011), 4% in India (Stein, 2011), but 54% in Burkina Faso (Dong et al., 2009), for example. In the SSP program, the average rate of subscription in 2010 was only 1.6% with just a few villages exhibiting rates higher than 5%. As for

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contract renewal, more than two-thirds of the (few) subscribers decided to drop out of the program as their contract expired. We are thus provided with a unique opportunity to draw lessons from a challenging experience by looking systematically into the main causes behind low participation. Note that, even though the study design allows for an impact assessment evaluation (with comparisons between treatment and control villages), the exercise is not worth undertaking: impact is bound to be very disappointing owing to low enrolment rates and low rates of use of the insurance by subscribers.

It is common in the literature on microinsurance to distinguish between supply and demand factors. Supply-side factors that may cause problems in microinsurance programs include low quality of the services provided (for example, medical services or drugs), inappropriate characteristics of the insurance product or the contract design, ineffective marketing, etc. Demand arising from poor, risk-averse villagers is normally expected to be high but may be hampered by liquidity constraints, lack of people's trust in the insurer or in certain characteristics of the product, or else a weak understanding of the notion of insurance. One of the original features of this paper is its focus on understanding and information failures that are arguably at the heart of the SSP program's low performance. The information failure explains why many subscribers have not actually used their insurance in spite of having reported at least one health event whereas the understanding failure, a poor grasp of the notion of insurance points to an additional reason why subscribers have not renewed their contract, especially when their net insurance payout has been negative. The two kinds of failures also account for the very low rate of (new) subscriptions (around 3%) among the households which did not initially enroll into the program but had the opportunity to do so one year later inside the treatment villages.

Since SSP has been previously active in the study area through the formation of so-called self-help groups, we will also be able to test whether membership in such groups actually helps people not only to enroll into the microinsurance program but also to renew their contract. Our positive answer to that question suggests that complementarities exist between grassroot-level activities and initiatives in the field of microinsurance. In addition, because SSP has carefully selected the health providers (the centers where the discounts can be obtained), the problem of clients' mistrust of low-quality health delivery services, which is frequently encountered in India, does not seem to have motivated households to end their participation in the program.

The structure of the paper is as follows. In Section 2, our approach to sample design is explained and statistics are provided that describe the sample households in terms of their socio-economic and health characteristics. Section 3 proceeds in three steps. First, we present a simple conceptual framework that will help us specify the econometric models to be estimated. We then explain what we mean by a correct or incorrect understanding of the insurance concept and by a good or bad information regarding the SSP microinsurance health program, and how we measure these two key dimensions. Finally, we supply key descriptive evidence about the importance of these two problems and the way they are related to (i) the use of the insured services, (ii) satisfaction levels and (iii) contract renewal. Section 4 also consists of three consecutive parts since, using a multivariate framework, we attempt to explain inter-household variations in the three above variables, with special attention to the role of our understanding and information measures. Section 5 summarizes the main lessons from the microinsurance program concerned, and discusses some policy implications.

2. SAMPLE DESIGN AND CHARACTERISTICS

The health microinsurance program supported by SSP was initiated in year 2010 in two districts of Maharashtra state (Solapur and Osmanabad). A total number of 535 subscriber households, spread over 54 villages, were initially registered, 415 of them in Solapur (in 34 villages) and 120 in Osmanabad (in 20 villages of Tuljapur council). This amounts to a low average subscription rate of 1.6%. The frequency distribution of the subscribers is negatively asymmetric with only 5 villages exhibiting a subscription rate above 5%. The initial plan was to interview 600 households in the villages in which SSP introduced the insurance microinsurance program (the treated villages), 300 subscribers and 300 non-subscribers.[3] Assuming that there would be at least 5% of the population subscribing, we intended to interview 15 households of each type in each of 20 randomly selected treatment villages. When we realized that this assumption was over-optimistic, we had to change strategy.

The option of concentrating exclusively on villages where a sufficient number of households had subscribed was considered inappropriate, since it would cause an obvious selection bias. The alternative of concentrating on broader areas covering a sufficiently high number of villages to yield enough subscribers was also discarded. Because a very limited number of individuals would then be coming from the

[3] On the other hand, 450 households were to be interviewed in control villages.

Table 1: Sample of treated households as per their participation in the scheme (2010, 2011)

Subscriber households			Non-subscriber households		
Renewed contract in 2011	Dropped out in 2011	Total number	Enrolled in 2011	Stayed out in 2011	Total number
100	206	306	9	239	248

low subscription villages, the selection problem would not be satisfactorily solved. Finally, a stratification strategy based on the total population of the village, which might be correlated with the total number of subscribers in the village but exogenous to the behavior under scrutiny, proved to be unfeasible: there is, indeed, no correlation between the village population and the number of subscribers (0.026).

Therefore, to avoid a sample selection process based on the behavior of the households, a two-stage random sampling procedure was followed in order to complete the sample of 300 subscribers and 300 non subscribers in treatment villages. First, a treatment village was randomly selected from the list of 54 treatment villages. Then, in case the number of subscribers was small (lower than 20 subscribers), the entire population of subscribers was included in the sample. In case the number of subscribers was larger than this threshold, 20 subscribers were randomly selected and added to the sample. This procedure was pursued by adding new randomly selected villages till the set objective of 300 subscriber households was reached. In each of these treatment villages, the number of non subscribers surveyed was equal to the number of subscribers. Our village sample was eventually made of 35 units, instead of the 20 villages initially intended.

In practice, we slightly departed from the above procedure for the following reason. Given the central purpose of the study, which is to understand contract renewal behavior among subscriber households (and later enrollment of initially non-subscribing households), two successive survey rounds were planned. The first round took place in 2010 when the program started in the study area, and the same households were re-interviewed in 2011 after one year of experience had elapsed and the decision whether to renew the contract (or whether to enroll) had just been made. Because we wanted to have at least 300 subscriber households in the second round and the risk of attrition had to be taken into account, we increased the initial sample sizes beyond the aforementioned numbers (to 315 for subscribers and 315 for non-subscribers).[4] The number of households in the treatment villages that we could trace back in 2011 was 554 (corresponding to 2,629 individuals), consisting of 306 subscribers and 248 non-subscribers.[5] Clearly, attrition was more important among the latter than among the former households (21.3 % as against 2.9 %), a difference that arises from the weaker motivation of non-subscriber households to be re-interviewed rather than their higher mobility.[6] Note that the possible bias created by such a difference will not affect our results in so far as our basic econometric test will be based on the sample of initial subscriber households only. Finally, it is evident from Table 1 above that, out of the 306 initial subscribers whom we could re-interview in 2011, only 100 (less than one-third) chose to renew their insurance contract. On the other hand, only 9 out of 248 households which did not subscribe in 2010 (3.6 %) decided to enroll one year later.

We may now turn to presenting descriptive statistics of the sample households, distinguishing between subscribers and non-subscribers. These statistics relate to their socio-economic and health characteristics (see Table 2).

Most of the sample households have a male head (91%), and the average age of the head is 44 years. It is noteworthy that heads of subscriber households are significantly younger than non-subscriber households. Regarding education, the duration of schooling of the household head is 6 years on average, and 72 % of them can read and write. Households have an average of 5 members. To measure the wealth of the households, we follow two approaches depending on whether we use incomes or assets. The asset index is constructed by considering several binary asset ownership variables (the questions are reproduced in Appendix A). The index was obtained by applying Multiple Correspondence Analysis (MCA)[7]. Both measures of wealth describe a negative asymmetric shape, and display a linear correlation of 0.39. While the average income in the sample is 2,820 Rupees, the median income is only 708 Rupees. Subscriber households do not significantly differ from non-

4 Households interviewed in 2010 in the treatment villages thus numbered 630 while those interviewed in the control villages numbered 450, making up a total of 1,080 households.

5 The number of households interviewed in 2011 in the control villages was 387.

6 In a significant number of cases, indeed, non-subscribers gave us a wrong phone number so as to prevent us from contacting them again.

7 Note that MCA is a generalization of the classic Principal Component Analysis (PCA) where the variables to be analyzed are categorical, not continuous.

Table 2: Personal, health and socio-economic characteristics of the sample households

	Treatment villages	Subscriber households	Non-subscriber households	Difference in means
Gender of head	0.913	0.902	0.927	0.0255
	(0.282)	(0.298)	(0.260)	[1.06]
Age of head	44	42.68	45.63	2.957***
	(10.49)	(9.576)	(11.33)	[3.33]
Schooling of head	6.375	6.275	6.500	0.225
	(4.605)	(4.553)	(4.674)	[0.57]
Literacy	0.724	0.693	0.762	0.0693*
	(0.448)	(0.462)	(0.427)	[1.82]
Size of household (Nr of members)	4.749	4.650	4.871	0.221
	(1.721)	(1.551)	(1.907)	[1.50]
Monthly income	2.820	3.175	2.382	-0.793
	(10.07)	(12.84)	(4.805)	[-0.92]
Asset index	0.180	0.215	0.138	-0.0769
	(0.940)	(0.921)	(0.962)	[-0.96]
Sick member (2010-11)	0.892	0.908	0.871	-0.0375
	(0.311)	(0.289)	(0.336)	[-1.41]
Prevention index	0.0765	0.191	-0.064	-0.256***
	(0.943)	(0.924)	(0.948)	[-3.20]
Nr of households	554	306	248	554

Standar deviation in parentheses (), t-statistics in brackets [ ]
* p<0.10, ** p<0.05, *** p<0.01

subscriber households in terms of incomes and wealth. Table 2 also shows that health shocks affecting a family member are quite frequent in the sample: in 89% of the households, a sickness occurred during the year covered by our survey (2010-2011), testifying to the high incidence of health risks experienced in the study area. We cannot reject the null hypothesis that the probability of a health event is identical between the two subgroups of households.

The so-called prevention index is based on variables measuring the knowledge of households regarding basics in health care, personal hygiene, nutrition, sanitation, and water handling (the questions are reproduced in Appendix A). This information was combined through a MCA to form a single index. The resulting multimodal behavior expresses a strong heterogeneity in preventive behavior in the sample. The average value of this index is larger for subscribers (0.19) than for non-subscribers (-0.06), and the difference is statistically significant: households which enrolled into the program in 2010 were more health-and-hygiene conscious than others. It will therefore be important to control for this summary characteristics when we use the subsample of non-subscriber households in our econometric estimates.

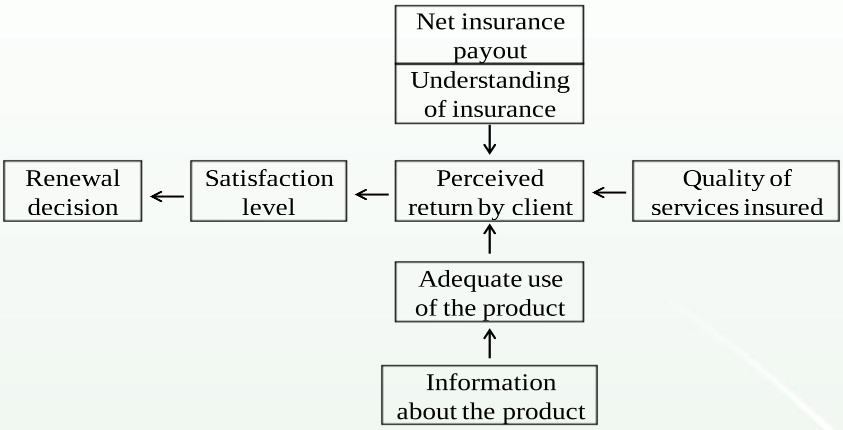
3. METHODOLOGICAL APPROACH AND KEY DESCRIPTIVE EVIDENCE

3.1. CONCEPTUAL FRAMEWORK

Figure 1 depicts the manner in which the contract renewal decision is determined. Users decide to renew their contract when they are satisfied with the product as they have experienced it in the (recent) past. Satisfaction depends on the perceived return which is itself influenced by three key factors. First, clients need to be well informed about the insurance product in order to be able to make an appropriate use of it when a (health) shock hits them. Second, they need to have a good understanding of the notion of insurance, particularly if the net insurance payout turns out to be negative. And, third, the quality of (health) services delivered must be of a sufficient quality.

To verify the role of the above determinants, we intend to test three relationships. The most important

Figure 1: Determinants of contract renewal behavior



one aims at explaining variations in contract renewal decisions, an objectively measurable outcome variable. The second, closely related relationship should explain variations in satisfaction levels, a subjective measure. Finally, we want to assess the influence of the level of subscribers' information on actual use of insured services. In the remainder of this section, we discuss the measures chosen for our three key independent variables: the degree of understanding of the notion of insurance, the degree of information regarding the insurance product and functioning of the scheme, and the net insurance payout. After we have presented each of these measures, we provide relevant descriptive statistics, and we end up by showing figures about how the variables under concern are interrelated. An original feature of our dataset is that it allows us to compare the (sign of the) net insurance payout as perceived by the insured households with the objectively measured payout.

a. Measures of key independent variables

UNDERSTANDING

The idea that people, especially in poor village societies, may not correctly grasp the concept of insurance has been first mentioned and elaborated by Platteau (1997). Based on anthropological evidence from mutual sea rescue groups in Senegalese fishing villages, he argues that people interpret insurance in terms of their traditional logic of balanced reciprocity. This implies, in particular, that the insurance premium (or the labor contribution toward helping a fellow fisherman) is conceived as a payment that must be compensated for within a reasonable span of time. If it is not, they think that they have the right to leave the insurance group and to have the (cash) premium returned to them. The most revealing finding in that paper is perhaps that, when confronted with such a demand, the other members of the group considered it legitimate. Using evidence from Uganda, another paper (Basaza et al., 2008) bears out the above hypothesis that insurance is perceived as a form of credit. This is reflected in the expressed belief that, if an individual has not received any payout during the past year, he (she) ought not to pay the (health insurance) premium for the subsequent year.

Clearly, such a view violates the prediction of expected utility theory which defines the insurance premium as a certain cost incurred today in order to prevent significant but uncertain future losses. An insurance transaction therefore implies that income is not only redistributed intertemporally (like in the case of credit) but also redistributed from lucky to unlucky members inside the risk-pooling scheme. A risk-averse individual is expected to be interested in protection against the *prospect* (and not the actual occurrence) of a shock and its damaging consequences. New theories of behavior toward risk have emerged during the last decades, such as the prospect theory (Kahneman and Tversky, 1979), regret theory (Loomes and Sugden, 1982), ambiguity aversion theory (Ellsberg, 1961), loss aversion theory (Stein, 2011), the "hot-hand effect" theory (Gilovich et al., 1985), or the "status-quo bias" theory (Cai et al., 2011).[8] None of them, however, can account for the behavior described above. If many of these new theories help explain why insurance take-up is possibly low among

[8] The "hot-hand effect" theory assumes that people's perception of risks is influenced by the frequency and intensity of past shocks. The prediction resulting from this theory is actually ambiguous. On the one hand, the experience of a shock can make the risk more salient and induce the individual to overestimate the true probability of a new shock. On the other hand, if he (she) believes that it is unlikely that several (independent) shocks will occur in a short period, the true probability of a new shock could also be underestimated (de Bock and Gelade, 2012).

risk-averse individuals, they do not provide a rationale for the fact that frustrated members of a risk-pooling group demand the reimbursement of the premium and that the other members comply with this request.

For example, regret theory assumes that the psychological experience of pleasure or displeasure associated with a particular result of an act of choice (assuming that the result is determined by the state of nature that is realized) will depend not only on the result itself but also on the alternative outcomes that would have arisen had other states of nature been realized. Thus, if it appears ex post that the individual has taken the best decision, he experiences rejoicing while in the opposite cases he is subject to regret feelings. Since people may be able to anticipate feelings of regret, they may decide to avoid entering into an insurance contract that seems attractive in terms of conventional expected utility theory. As pointed out by Thaler (1991), regret theory offers an intuitively plausible explanation of why people may well choose not to choose or to restrict the choice set in advance since this would suppress the possibility of experiencing regret and the associated painful feelings of guilt and responsibility (p. 16). But it does not explain why, once they have decided to subscribe to an insurance contract, they would require reimbursement of the premium if it has not brought any (sufficient) reward.

Likewise, the "hyperbolic discounting" component of prospect theory (time-inconsistent preferences) may explain why, when confronted with the request of an immediate payment of a premium, people may shun away from an actuarially fair insurance contract but, again, it does not explain why, if they have made that payment, they would ask for its return if the shock does not materialize. The same holds true of the ambiguity aversion theory according to which people dislike uncertainty about the likelihood with which events occur, and not only uncertainty about the events themselves. As a consequence, they tend to be pessimistic, assuming that the worst conceivable probability distribution is the true one when they evaluate their choice. This may limit their take up of insurance contracts (Bryan, 2010). Almost by definition, the status-quo theory predicts low insurance take-ups, and that is the end of the story.

Finally, loss aversion theory, which assumes that individuals experience more disutility from a loss than they experience utility from a gain of the same amount, is more directly relevant to our concern in this paper since it may explain why subscribers who obtain an insurance payout are more likely to renew their contract than those who do not. This is because they enjoy the feeling that a loss of a certain amount has been avoided, which makes the payment of the premium less painful.

In the light of the above discussion, we have gained a precise sense in which the concept of insurance can be deemed to be misunderstood. The three following questions, in particular, seem to be well-designed to capture people's understanding of an insurance contract:

(1) If the discounts obtained turn out to be smaller than the premium paid, should the insurer reimburse the premium?

(2) Is it unfair that everybody pays the same premium whether falling sick or not?

(3) Is it shocking that other people benefit from the premium that you have paid because they have been sick?

Understanding of the insurance concept is obviously reflected in negative answers to each question. It is striking that only 30% of the sample subscriber households answered no to either the first or the second question (29% for the first and 31% for the second). In addition, less than half of them (47%) answered negatively to the third question. On the basis of the answers to these three questions, we can construct three alternative binary measures of understanding: a dummy equal to one if the household has answered no to the three questions (UND_1), reflecting a very good understanding of what insurance is about; a dummy equal to one if the household has answered no to at least two questions (UND_2); a dummy equal to one if the household has answered no to at least one question (UND_3). From our dataset, it is evident that UND_1 = 1 for less than one-tenth of the subscriber households (7.52 %); UND_2 = 1 for about 35% (35.3%); and UND_3 = 1 for almost three-fourths (74.5%) of them.

INFORMATION

To measure the level of information, we use the following questions:

(1) Do you know the discounts provided by the insurance scheme?

(2) Do you know the health facilities in which you can obtain the discounts provided by the insurance?

(3) Do you know how to renew the contract?

Good information is reflected in positive answers to these questions. The data reveal that only one-fifth of the subscriber households could provide the correct details of the discounts offered by the SSP scheme. A little more than one-third of them (34%) knew that discounted prices can only be obtained in a limited number of health facilities, which they were able to identify. Finally, two-fifths of them knew how to renew their insurance contract. On the basis of answers to the above three questions, we construct three alternative binary measures of information: a dummy equal to one if the household has answered correctly to the three questions (INFO_1), reflecting very good information about the product and the functioning of the scheme; a dummy equal to one if the household has answered correctly to at least two questions (INFO_2); a dummy equal to one if the household has answered correctly to at least one question (INFO_3). From our dataset, it is evident that INFO_1 = 1 for less than one-tenth of the subscriber households (8.8%); INFO_2 = 1 for about 23% of them; and INFO_3 = 1 for about 62%.

Unsurprisingly, a significant correlation exists between understanding and information, yet this correlation is far from perfect. When we compare UND_3 with INFO_3, we have that:

- out of 228 households for which UND_3=1 (low level of understanding), 157 (68.9%) also have a low level of information (INFO_3=1);
- out of 108 households for which UND_2=1, 73 (67.5%) have an intermediate level of information (INFO_2=1);
- out of 23 households for which UND_1=1, 20 (86.9%) are well informed (INFO_1=1).

NET INSURANCE PAYOUT

The net insurance payout is calculated over the one-year period covered by our study. It is obtained by subtracting the premium from the cost-savings realized in health expenditures as a result of the discounts provided by the insurance scheme. For almost 86% of the subscriber households in our sample, the net insurance payout has been negative during the 2010-2011 period. The mean value of the net payout is -227 Rs while the median value is -450 Rs. (The gross payout is 1,227 Rs, on an average, for those households which actually used the insurance services, while the median value is 660 Rs). When we ask the subscriber households whether they perceive that their net payout has been positive or negative, we find that 85% of them believe that they have incurred a loss from participating in the insurance scheme. Comparing perceptions with actual facts gives an idea about the degree of distortion of these perceptions. The outcome of such a comparison is presented in Table 3.

It is apparent that the great majority of subscribers (86.6%) have a correct perception about the sign of the net insurance payout. The remaining 13.4% are either too optimistic (they think that the net insurance payout has been positive while it has been actually negative) or too pessimistic (in the converse case). The degree of distortion in the subscribers' perception is therefore rather low, much smaller than we could have expected. Yet, the fact that so many subscribers incurred a net loss over the first year of the program begs an explanation, especially so because we know that more than 90% of them have had a health shock during that year. The clue behind this puzzle lies in a low use of the insurance by many subscribers. It is thus noticeable that, out of 278 households which suffered some health problem during the period 2010-2011, as many as 216 households (77%) did not actually make use of their insurance! In other words, the net insurance payout reaches its maximum negative value not only for the few households which did not need to call for health services but also for those numerous households which needed the insurance but could not take advantage of it. It is revealing that nine-tenths of the subscribers who believe that their net insurance payout has been negative did not make use of the insurance services.

ADDITIONAL KEY DESCRIPTIVES STATISTICS

The main factor behind the low rate of use of insurance is poor information. Thus, we find that, among the subscribers who did not use the insurance services while being sick, the fraction of those ignoring the discounts offered by the SSP program was considerably higher (90%) than among the subscribers who did use their insurance (42%). Albeit somewhat less marked, the contrast is also observed when we compare the proportions of subscribers

Table 3: Comparison between perceptions and facts regarding the sign of the net insurance payout (sample subscribers)

	Freq.	Percent
Think correctly that the net insurance payout has been negative	247	80.72
Think correctly that the net insurance payout has been positive	18	5.88
Think incorrectly that the net insurance payout has been negative while it has been actually positive (pessimistic belief)	26	8.5
Think incorrectly that the net insurance payout has been positive while it has been actually negative (optimistic belief)	15	4.9
Total	306	100

Table 4: Understanding of the insurance concept by contract renewal status

	Unfair		Must be reimbursed		Problem others benefit		
	no	yes	no	yes	no	yes	Total
Dropped out	46	160	49	157	99	107	206
	(22.3%)	(77.7%)	(23.8%)	(76.2%)	(48.0%)	(52.0%)	(100%)
Renewed	50	50	39	61	63	37	100
	(50.0%)	(50.0%)	(39.0%)	(61.0%)	(63.0%)	(37.0%)	(100%)
Total	96	210	88	218	162	144	306
	(31.4%)	(68.6%)	(28.7%)	(71.2%)	(52.9%)	(47.1%)	(100%)
Chi square test (p-value)	0.00		0.00		0.01		

who ignored that discounts are only provided in a limited number of health facilities: 70% for those who did not use their insurance as against 53% for those who did use it.

It is noteworthy that a large majority (74%) of the subscriber households expressed disappointment or strong disappointment with the SSP program (their number being equally shared among those disappointed and those strongly disappointed). By contrast, only 6% were very satisfied while the remaining 20% were satisfied. Even more relevant to our main concern is the fact that 56% of satisfied (or very satisfied) households chose to renew their contract compared to only 25% for the disappointed (or very disappointed) households. There is therefore a strong yet far from perfect correlation between satisfaction and the contract renewal decision. Also worth emphasizing is that 61% of the households which did actually use their insurance during the current period expressed satisfaction (or great satisfaction) whereas the proportion is only 16% for those which did not use it. Again, the contrast is marked but actual use does not fully explain satisfaction about the insurance scheme.

Our data also show that the quality of the services covered by the insurance, as well as the claiming and contract renewal procedures, are quite satisfactory so that they may not explain the low contract renewal rate in the SSP program. As a matter of fact, nine-tenths of the households which did use their insurance considered it useful and rather easy to handle. Moreover, among the households which perceived a negative return from the program, only 21% deemed the premium expensive and hard to finance. When queried about the rationale behind their decision not to renew their insurance contract, the majority of the households concerned mentioned either a lack of information about how and where to use the insurance and how to renew it (33%+15%), or the absence of benefits and the lack of need for an insurance given the non-occurrence of illness problems (28%+15%). Barely 9% of the households mentioned the level of the premium and less than ½% the low quality of the services covered.

Equally interesting is the evidence displayed in Table 4, which points to a correlation between the level of understanding of insurance and the renewal decision. We thus learn that 78% of the households which dropped out (as against 50% of the households which did not) consider it unfair to have paid the premium while they did not fall sick. Similarly, 76% of the households which dropped out (as against 60% of those which did not) believe that they must be reimbursed if their health expenditures turned out to be lower than the premium. Finally, 52% of them (as against 37% of the other households) see a problem in the fact that other households may have benefited from the premium they have themselves paid. All differences are statistically significant.

Likewise, Table 5 shows that renewal decisions are linked to the level of information about the insurance product and the functioning of the scheme. Thus, as many as 88% of the households which dropped out did not know the amount of the discount granted by the SSP scheme, while 69% of them did not know how to renew their contract, and 78% of them expected to receive discounts in any health facilty. By contrast, the proportions for households which did renew their insurance contract are 65%, 38%, and 42%, respectively. All differences are statistically significant.

Two last observations are worth reporting. First, while 48% of the households which renewed their insurance contract belonged to a self-help group, the proportion is only 30% among those which dropped out of the program. Second, while 71% of the households which renewed their insurance contract had a negative net insurance payout during the period 2010-2011, the proportion is as high as 92% among those which dropped out of the program. The average net insurance payout is +350 Rs for the former but only -509 Rs for the latter.

Table 5: Level of information by contract renewal status

	Ignore discount		Ignore facility limitation		Do not know how to renew		
	no	yes	no	yes	no	yes	Total
Dropped out	25	181	45	161	63	143	206
	(12.1%)	(87.9%)	(21.8%)	(78.2%)	(30.6%)	(69.4%)	(100%)
Renewed	35	65	58	42	62	38	100
	(35.0%)	(65.0%)	(58.0%)	(42.0%)	(62.0%)	(38.0%)	(100%)
Total	60	246	103	203	125	181	306
	(19.6%)	(80.4%)	(33.7%)	(66.3%)	(40.8%)	(59.2%)	(100%)
Chi square test (p-value)	0.00		0.00		0.00		

3. ECONOMETRIC EVIDENCE

We now want to check whether the above relationships continue to hold when we use a multivariate framework. Since some of our variables are significantly correlated, it is important to verify that they have a separate influence on the dependent variables. In particular, we want to know (1°) whether the level of understanding of the insurance concept influences contract renewal behavior (and satisfaction) once we control for the level of information about the insurance product, and for the value of the net insurance payout, and (2°) whether the level of understanding helps to mitigate the presumably negative impact of the net insurance payout. To answer the latter question, we will have to test for the impact of the corresponding interaction term.

In estimating regression equations to explain variations in the actual use of insurance services, satisfaction levels and contract renewal decisions, we use two different econometric models and two different datasets. The first model is a simple linear probability model based on data related to subscriber households only. The second model is a Heckman Probit model that includes a first-stage selection equation to determine entry into the microinsurance program. It therefore uses the complete sample of households interviewed in the treatment villages, whether subscribers or not. The advantage of estimating this second model is not only that it provides a robustness check for the results obtained with the standard OLS model, but also that it sheds light on the determinants of the subscription decision in addition to those of the renewal decision. A natural concern is related to the normality assumption of the error term that characterizes the Heckman selection model. To address this aspect, we also applied the semi-nonparametric selection model of Gabler et al. (1993), which relaxes the Gaussian distributional assumption by specifying the likelihood function semi-parametrically. The results obtained (not shown), which are similar to those found with the Heckman model, suggest that our findings are not influenced by distributional assumptions.

In the following, we first present the models that we estimate to find out the determinants of actual use of the insurance, we define the variables included in the regressions, discuss the related methodological issues, show the results and comment on them. Then, we repeat the same procedure for the regressions used to explain variations in satisfaction levels and contract renewal decisions.

a. Determinants of actual use of insurance services

The first model used to explain variations in actual use of insurance services is the following linear probability model:

$$Use_{iv} = \propto + \beta Info_{iv} + \gamma SHG_{iv} + \delta Controls_{iv} + \mu Villages + \varepsilon$$

The dependent variable Use_{iv} is a dummy with value one when household *i* of village *v* has actually used its insurance during the period 2010-2011. The first independent variable, $Info_{iv}$, is our measure of the household's level of information, whether INFO_1, INFO_2, or INFO_3. The second independent variable, SHG_{iv}, is a dummy with value one if the household belonged to a self-help group before the start of the microinsurance program. We also have a set of controls, $Controls_{iv}$, which includes the age, gender and education level of the household, its size, its income, wealth, health status during the current year and level of health-consciousness. Age (labeled *age*) is measured continuously while *gender* is a dummy with value one when the household head is a man. The size of the household (*hholdsize*) corresponds to the number of members of all ages in the household. Education is measured in two different ways. We use a dummy (*literacy*) equal to one if the household can read and write, and a continuous variable (*schooling*) that indicates the number of years of schooling at any level (primary, secondary, and higher). To test for the concavity of the schooling variable, we add a square term, *schooling2*. Health status (denoted by *sick_2010-11*) is a dummy indicating whether any member in the household was sick during the period 2010-2011. The household's level of health-consciousness, or awareness about the importance of prevention, is measured by a composite index that we have explained earlier and named prevention index (henceforth labeled *prevention_index*). Finally, *lnincome* is income measured in logarithmic terms while wealth is captured by a composite index denoted by *asset_index* (see Section 2).

Endogeneity of information to actual use is hardly a possibility. It is, indeed, difficult to believe that a household did not want to use services covered by an insurance to which it subscribed (at a positive cost) and, therefore, chose not to acquire the necessary information. Much more realistic is the possibility that the occurrence of a health event influences effort to obtain such information. Because these two variables figure out on the RHS of the above equation, we should observe multicollinearity. Our data nevertheless show that this correlation does not actually exist: households which had a sick member during the period 2010-2011 are not better informed than the other households. This is an important finding since it strongly suggests that information failures arise from the supply rather than the demand side. Such a conclusion is borne out when we consider the correlation between the health prevention index and information, based on the idea that people who are more health conscious should strive to get more information about the insurance scheme if they have subscribed. What we find is that this correlation is surprisingly low (0.11), much smaller than the correlation between the prevention index and income (0.23), or between the prevention index and education measured by the number of years of schooling (0.24) or the literacy dummy (0.18).

The second model is the selection model. It has the following form:

$$Use_{iv}^{*} = \propto + \beta Info_{iv} + \gamma SHG_{iv} + \delta Controls_{iv} + \mu Villages + \varepsilon$$
$$S_{iv}^{*} = \theta P_{iv} + \gamma' SHG_{iv} + \delta' Controls_{iv} + \mu' Villages + \eta$$
$$Use_{iv}^{*} = \begin{cases} Use_{iv} & \text{if } S_{iv}^{*} = 1 \\ NA & \text{if } S_{iv}^{*} = 0 \end{cases}$$

The selection equation explains the unobservable propensity to subscribe to an insurance, S_{iv}^{*}, as a function of a set of instruments, P_{iv}^{*}, and the independent variables included in the second-stage equation. The dependent variable Use_{iv} is observed only when $S_{iv}^{*}=1$. The two instruments that we use are the health status of the household prior to the start of the SSP program (labeled *Sick_2009-2010*), and a dummy (labeled *aware*) indicating whether the household was aware of the existence of the SSP program when it was launched or before. The exclusion restriction is obviously satisfied for the first instrument since actual use of the insurance is expected to be influenced by the household's health status during the year 2010-2011 and not by the same status in the previous year which should have influenced the subscription decision instead.[9] In other words, it is reasonable to assume that health status prior to the start of the program influences actual use of insurance services only through the channel of the subscription decision. Regarding the second instrument, we cannot be entirely certain that the exclusion restriction is theoretically satisfied, yet this is quite likely because we control for information. It is noteworthy that removing it from the selection equation does not affect our results at all.

Finally, we need to mention that, in both the LP and the selection models, the standard errors are clustered at the village level.

In Table 6, results of the LP model and the Heckman probit selection model (with average marginal effects) are displayed, successively. In this table, the estimates of six different regressions are shown, depending on which information variable we use and on whether we add village fixed effects or not. The first-stage selection equation is reported in the last column of the table. What we see is that whichever is the information variable used the impact on actual use is positive and statistically significant at 99% confidence level. Moreover, the size of the coefficient decreases monotonously as the intensity of information declines (being the highest for *Info=INFO_1* and the lowest for *Info=INFO_3*). Two additional results deserve to be singled out. First, the household is more likely to actually use the insurance services when at least one of its members has fallen sick during the current period (2010-2011). Second, membership in a self-help group also increases the likelihood that these services are taken advantage of.

Regarding the selection equation, the results are as follows. First note that the two instruments are strongly significant with a positive sign: enrolment into the program is more likely if at least one of the members of the household has fallen sick prior to the start of the SSP program, and if it was aware about the existence of the SSP program beforehand. When we test for the validity of the instruments by re-estimating the second-stage equation with the instruments included on the RHS, we find that none of them turns out to be

[9] This implies that our set of controls is not exactly identical between the first and the second stage equations. Indeed, the health status variable, which is present in both equations, refers to the state of health pertaining to two different periods of time (2009-2010 or 2010-2011) depending on which equation is considered.

Table 6: Determinants of actual use of insurance services

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) Heckman	(8) Heckman	(9) Heckman	(10) Probit
Gender	0.08	0.12	0.05	0.09	0.09	0.10	0.06	0.05	0.06	-0.04*
	(0.09)	(0.10)	(0.09)	(0.10)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.02)
Age	-0.01**	-0.01*	-0.01**	-0.01*	-0.00*	-0.00	-0.01***	-0.01**	-0.00*	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Schooling	-0.03	-0.04	-0.03	-0.03	-0.03*	-0.04*	-0.02	-0.03	-0.03	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Schooling2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Literacy	0.05	0.06	0.08	0.08	0.08	0.09	0.03	0.05	0.06	-0.02
	(0.06)	(0.07)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.02)
Hholdsize	0.01	0.01	0.02	0.02	0.02	0.02*	0.01	0.01	0.02*	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
lnIncome	0.02	0.02	0.03	0.04*	0.04**	0.04**	0.02	0.03	0.05**	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Asset_index	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0.01	0.01	0.01
	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)
Sick_2010-11	0.25***	0.23***	0.27***	0.25***	0.25***	0.21***	0.23***	0.24***	0.23***	
	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)	(0.06)	(0.08)	(0.06)	(0.01)	
SHG	0.16***	0.19***	0.16***	0.18***	0.14***	0.16***	0.15***	0.15***	0.12***	0.12***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)
Prevention_index	-0.00	-0.00	-0.00	0.00	0.01	0.01	-0.00	-0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
INFO_1	0.51***	0.45***					0.41***			
	(0.07)	(0.07)					(0.07)			
INFO_2			0.34***	0.29***				0.26***		
			(0.06)	(0.05)				(0.04)		
INFO_3					0.25***	0.21***			0.27***	
					(0.05)	(0.06)			(0.06)	
Sick_2009-10										0.03**
										(0.02)
Aware										0.87***
										(0.02)
Village dummies		Yes		Yes		Yes				
Constant	-0.15	-0.28	-0.29	-0.48**	-0.42*	-0.61***				
	(0.18)	(0.19)	(0.20)	(0.21)	(0.21)	(0.22)				
Observations	306	306	306	306	306	306	947	947	947	947
R-squared	0.24	0.34	0.24	0.34	0.20	0.31				

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

statistically significant. No other test is available because the endogenous explanatory variables are constant for the observed values of the dependent variable in the second-stage equation.

Second, turning to the other results, we find that a household is more likely to have subscribed to the insurance scheme if its head is a woman, and if it participated in a self-help group prior to the start of the program. Perhaps surprisingly, the effects of the literacy and schooling variables are not statistically significant, nor are those of the continuously measured income and asset variables. Yet, if instead of measuring incomes and assets continuously, we use the tertile distributions, we find that the households belonging to the lowest tertiles are less likely to have enrolled into the insurance program, testifying to its exclusionary character vis-à-vis the poorest households (the effects are significant at the 95 percent confidence level —results not shown). Excluded households turn out to be very poor since the threshold marking the lowest tertile of the distribution (median value = 260 Rs) is significantly smaller than the poverty line in India (equal to 673 Rs).[10] Belonging to the intermediate or upper tertile, whether in terms of incomes or assets, does not make a difference regarding participation. It is worth noticing that using tertile dummies instead of continuous measures of incomes and assets in the selection equation does not affect the estimates obtained in the second stage at all (in terms of neither statistical significance of the coefficients of the various regressors nor their size). This holds true not only for the present but also for the following regression estimates (in Tables 7 and 8 —results not shown).

b. Determinants of contract renewal and satisfaction level

In this subsection, since the list of the independent variables is identical in both cases, we discuss the regressions intended to explain variations in satisfaction level and contract renewal together. The first model that we estimate to explain such variations is the following linear probability model:

$$Dependent_{iv} = \propto + \beta Info_{iv} + \lambda Und_{iv} + \sigma Payout_{iv} + \omega Und_{iv} x Payout_{iv} + \gamma SHG_{iv} + \delta Controls_{iv} + \mu Villages + \varepsilon$$

The dependent variable is either *renewal*$_{iv}$, a dummy equal to one if the household has chosen to renew its insurance contract, or *satisfaction*$_{iv}$, another dummy equal to one if the household has expressed (strong) satisfaction about the program and to zero if it has expressed (strong) disappointment. Compared to the model presented in the previous subsection, three new independent variables appear in the above model. The first one is *Und*$_{iv}$, our measure of the household's level of understanding of the insurance concept, whether UND_1, UND_2, or UND_3. The second variable is *NetPayout*$_{iv}$, which measures the amount of the net insurance payout accrued to the household at the end of the period 2010-2011. We use different versions of this variable, such as a continuous variable constructed in such a way that all values equal to or higher than zero are set to zero (to prevent the mixing up of positive and negative values that complicates the interpretation of the interaction term mentioned below), a binary variable with value one if the net insurance payout has been negative (and zero if it has been positive or nil), a binary variable with value one if the net payout has been lower than the median value (equal to -450 Rs), and value zero if it has been higher, or similar variables in which the threshold is different from the median (for example, a critical value corresponding to the first tercile of the distribution so that value one is assigned to any household belonging to the one-third of households exhibiting the lowest values of the negative net payout). Finally, the third new independent variable is the interaction between *Und*$_{iv}$ and *NetPayout*$_{iv}$, which provides a critical test of the hypothesis at the core of this paper. We expect that the signs of β, λ, and ω are positive, and the sign of σ is negative.

In an alternative specification of the above model, we test whether the contract renewal decision or satisfaction with the program is influenced by a peer effect. Toward that purpose, we define a new independent (binary) variable indicating the presence of a relative or friend who has opted out of the program, denoted by *peer_effect*$_{iv}$. In a manner analogous to that mentioned above, we then also add an interaction term between *Und*$_{iv}$ and *peer_effect*$_{iv}$. We expect the sign of *peer_effect*$_{iv}$ to be negative and that of the new interaction term to be positive.

We do not believe that endogeneity of the information and understanding variables is a real problem in the context of this study. It is, indeed, difficult to imagine that households which are expected to renew their insurance contract would more actively seek information about the product and the scheme or make efforts to better understand the notion of insurance. It is conceivable that such households would have put in more efforts to improve their state of knowledge and understanding when making their decision about whether to subscribe or not to the insurance contract, but it is hard to see why they would do so once they have subscribed and they consider whether to renew that contract. Moreover, we have pointed out earlier that information failures seem to be essentially driven by problems on the supply side. In particular, there is no correlation between health status and information. What we may add now is that there is no correlation between health status and understanding either. Thus, for example, the proportion of households with at least one health event during the year 2010-2011 for which UND_2=1 does not significantly differ from the proportion of those with no health event.[11]

Finally, we estimate a Heckman selection model and the first-stage equation is identical to the one used for explaining variations in the use of insurance. This model is therefore the same as the second model presented in Subsection 4.1, except for the fact that there are now three additional independent variables in the second-stage equation. In both the LP and the selection models, the standard errors are clustered at the village level.

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[10] Since the median income in our sample is around 500 Rs, the implication is that at least half of the sample population can be considered as poor, by Indian standard.

[11] In the absence of reliable instruments, we have tested for the endogeneity bias by using as excluded restrictions a set of internally generated instruments, following the approach recently proposed by Lewbel (2012). The results obtained are similar in size and significance to those presented in this section.

Table 7: Determinants of contract renewal

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) Heckman	(8) Heckman	(9) Heckman
Gender	0.15**	0.19**	0.15**	0.19***	0.18***	0.19**	0.17***	0.17***	0.19***
	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.06)	(0.06)
Age	-0.00	0.00	0.00	0.00	-0.00	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Schooling	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***	-0.05***	-0.06***	-0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Schooling2	0.00**	0.00**	0.00**	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Literacy	0.25***	0.16***	0.28***	0.19***	0.26***	0.17***	0.24***	0.27***	0.25***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Hholdsize	-0.02**	-0.01	-0.02*	-0.01	-0.02*	-0.01	-0.03*	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
lnIncome	0.00	-0.01	0.01	-0.01	0.01	-0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Asset_index	-0.08***	-0.04*	-0.07***	-0.04	-0.07***	-0.05**	-0.07***	-0.07***	-0.07***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Sick_2010-11	0.09	0.05	0.11*	0.08	0.07	0.06	0.09	0.12*	0.09
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)
SHG	0.14**	0.06	0.13**	0.06	0.13**	0.08	0.14***	0.13**	0.12**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Prevention_index	0.05**	0.05**	0.05**	0.06**	0.05**	0.05**	0.04**	0.05**	0.04**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
INFO_2	0.38***	0.32***	0.39***	0.33***	0.37***	0.32***	0.30***	0.31***	0.29***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)	(0.04)	(0.04)
UND_2	0.20***	0.17***	0.10**	0.08**	0.15***	0.14***	0.19***	0.09**	0.14***
	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)
Payout			-0.13**	-0.09*				-0.11**	
			(0.06)	(0.05)				(0.05)	
Payout x UND_2			0.23**	0.19**				0.23**	
			(0.11)	(0.09)				(0.09)	
Peer_effect					-0.23***	-0.20**			-0.35***
					(0.07)	(0.08)			(0.13)
Peer_effect x UND_2					0.26**	0.19*			0.39***
					(0.10)	(0.10)			(0.14)
Village dummies		yes		yes		yes			
Observations	306	306	306	306	306	306	947	947	947

Robust and clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In Table 7, we show the results of the LP and the selection models when the dependent variable is *renewal* and, in Table 8, when the dependent variable is *satisfaction*. Each table contains ten columns corresponding to different specifications. In column (1) and (2), we show the results for the LP model without and with village fixed effects when the *Payout* variable and the corresponding interaction term are omitted. In columns (3) and (4), the same exercise is repeated but we now add these two variables. In columns (5) and (6), instead of *Payout*, we use the *peer_effect* variable and the corresponding interaction, again without and with village fixed effects. In columns (7), (8), and (9), we follow the same procedure in estimating the selection model but give the results only when village fixed effects are omitted. Note, finally, that all the results are based on the following definitions for the information and understanding variables: *Info=INFO_2*, and *Und=UND_2*, implying that the reference category consists of households which answered incorrectly to two or three questions raised to them. (Using the highest, rather than the intermediate, levels of understanding and information is not a good option because the corresponding subscribers are quite few and the interaction term would therefore concern an even smaller group). Estimates based on alternative definitions of these variables have been run but are not shown.

The rationale behind the choice of *UND_2* in the regressions displayed in Table 7 (and Table 8) is as follows. Let us re-define our measure of understanding by using three dummy variables that must be used simultaneously: *UND_A=1* if the household has answered correctly to one question, *UND_B=1*, if it has answered correctly to two questions, and *UND_C=1*, if it has answered correctly to the three questions (so that *UND_C* is identical to *UND_1*), so that the reference category consists of households which wrongly answered the three questions. When we analyze the effects of these variables on contract renewal (without *Payout* and the interaction term), we find that the coefficient of *UND_A* is not statistically different from zero while the coefficients of both *UND_B* and *UND_C* are strongly significant. Moreover, and as expected, the coefficient of *UND_C* is much higher than the coefficient of *UND_B* (see Appendix B, columns (3), (4), and (6), depending on which estimating model is used and whether village fixed effects are added or not).[12] In words, the households which answered correctly to only one of the three questions do not behave differently from those which incorrectly answered to all three questions. We are therefore justified in clubbing together the households for which *UND_B=1* and *UND_C=1*, which is done when using *UND_2*. Note that we find exactly the same results for the information variable, thus justifying our use of *INFO_2* (see Appendix B, columns (1), (2), and (5)).

We first consider the results in Table 7. The central assumptions behind this paper stand confirmed. Better information about the insurance product and the scheme, as well as better understanding of the insurance concept, have a positive impact on the probability of renewing the contract. The effects are strongly significant regardless of the specification used. When the *Payout* or the *peer_effect* variables are omitted, based on the LP model, we find that the probability of renewal is increased by 38% if the household improves its level of information (from ignoring the correct answers to all three key questions or knowing the correct answer to only one question to knowing the correct answers to at least two questions), and by 20% if it improves its level of understanding (with improvement defined in the same manner as for the information variable). It is important to stress that the effect of a reasonably good understanding of the insurance notion remains even after controlling for the measure of information. It is noteworthy that the significance of the effects of *Info* and *Und* persists when we change the definitions of these two variables using almost all conceivable combinations. Moreover, when we use *INFO_3*, which corresponds to the lowest level of information (except for complete ignorance), the size of the coefficient β decreases (0.14) whereas if we use *INFO_1*, corresponding to the highest level of information, the effect is larger (0.60). Similar results are obtained when we change the definition of the understanding variable.

The next results appear in columns (3) to (6) and concern the effect of *Payout* and the interaction terms. The variable *Payout*, as measured here by the median dummy (equal to one for households with a net payout smaller than the median), has a significant negative effect on the renewal probability even when we control for the levels of information and understanding. In other words, having had a comparatively low net insurance payout during the current period (2010-2011) reduces the likelihood of contract renewal. Interestingly, the threshold (median) value used, equal to -450 Rs, is not very different from the average or median value of the insurance premium paid by the sample households (average: 582 Rs; median: 600 Rs). This means that a significant number of households which experienced what we consider as a large net negative payout are households which paid the premium but did not get any service (because, as we have learned earlier, they did not actually use their insurance contract due to bad information).[13]

Second, the effect of the interaction between net payout and understanding is also statistically significant and is positive. This means that the negative influence of having had a net negative payout (below the median value) on the probability of contract renewal is dampened when the household has a better understanding of the insurance concept. Both the significance and the size of the coefficients of *Payout* and *PayoutxUnd* are barely affected when we use *INFO_1* (the highest level of information) instead of *INFO_2* as our measure of the household's information level. When the definition of either *Payout* or *Und* is modified, the effect of the interaction term ceases to be significant in many cases, yet it is worth emphasizing that the sign of coefficient ω always remains positive. Note, in particular, that when the net insurance payout is measured subjectively (using a dummy equal to one when the household perceives to

[12] With the LP model and village fixed effects, the coefficient of *UND_C* is 0.46 compared to 0.16 for *UND_B*.

[13] As a matter of fact, we did not use a measure of actual use of the insurance contract as a regressor because it would be too much correlated with the net payout variable. The correlation between the dummy measuring whether the insurance was actually used and the *Payout* variable measured by the median dummy is quite strong since 51.6 percent of the households which did not actually use the insurance received a net payout smaller than the median. By contrast, 72.6 percent of those which used it received a net payout higher than the median.

have earned a negative net payout), the effect of the interaction term is not significant, yet is positive. The message of all these estimates is therefore double. For one thing, households respond differently to a negative net payout depending on the size of the loss: when the negative payout is not too large, they do not give much importance to the loss incurred in their insurance transaction. For another thing, the negative impact (on contract renewal) of the loss is mitigated when the household head has a better understanding of the insurance concept.

Third, the coefficient of *peer_effect* is significant and negative, indicating that households are influenced by the dropping-out behavior of close acquaintances. Interestingly, the interaction between *peer_effect* and *Und* is also significant and the sign of the coefficient is positive. Again, the negative influence of peers on contract renewal decision is mitigated when the level of understanding of the household is improved. Notice that if we estimate the model by including both *Payout* and *peer_effect* together with their respective interaction terms, all the results stand except for the fact that the coefficient of the understanding variable (λ) is no more significant. From columns (7) to (9), it is evident that the same results are obtained with the selection model.[14]

There are other interesting results coming out of Table 7. To begin with, belonging to a self-help group before the start of the SSP program has a positive effect not only on the probability to enter into that program (see Subsection 4.1) but also on the probability to renew the insurance contract. Yet, this effect is not observed when village fixed effects are added, indicating that villages differ with respect to the presence of self-help groups. The effect of participation to self-help groups on both subscription to the SSP scheme and renewal is a priori ambiguous. This is because the informal-sharing mechanism possibly offered by such groups may be either a substitute for, or a complement to, the more formal insurance products provided in the SSP program. The complementary effect exists not only if the two schemes supply insurance against different risks, but also if the household wants to diversify its insurance portfolio. On another plane, there is the possibility that the people who have self-selected into self-help groups are also more keen to take their life into their own hands rather than passively submitting to their fate. An experience with these groups can also give them more self-confidence in their ability to deal with external agents and claim their due. Our results show that the second type of effects predominate.

Another striking, and non-trivial result is the effect of education. On the one hand, being literate increases the propensity to renew. On the other hand, the effect of schooling measured continuously is non-monotonous: it is negative in the first years and becomes positive once a sufficient level of education has been achieved. There are thus two turning points in the relationship between education and contract renewal. When a household head becomes literate, he is more likely to understand the advantages of renewing participation in the insurance scheme than when he is illiterate. Once he is literate, however, attending to school first reduces the probability of renewal while beyond a point further years of schooling enhances that probability. Since insurance is a concept difficult to grasp, the above effect is not really surprising.

To complete our review of results, less wealthy households are more likely to renew their contract, which is also true of more health-conscious households (those with higher values of the prevention index). Regarding the impact of wealth, it is interesting to notice that, if we replace the continuous measure of the asset index by tertile dummies, we find that households belonging to the lowest tertile have a higher probability to renew their contract compared to the other two tertiles. This finding is especially relevant when put into the perspective of an earlier result derived from the selection equation: if the poorest households are less likely to enroll into the insurance program, they are more likely to stay on once they have experimented with it. Note, moreover, that when the lowest tertile dummy is interacted with our understanding variable (after removing the interaction term between the net payout and *UND_2*), the effect does not turn out to be significant. Lastly, when we replace the continuous measure of income (which has no significant effect on contract renewal) by the corresponding tertile dummies, no dummy appears with a coefficient statistically different from zero.

Inspection of Table 8 shows that the aforementioned results regarding the effects of information and understanding continue to hold when *satisfaction* instead of *renewal* is the dependent variable. In particular, better informed households, households with a better grasp of what insurance means, or households which participated to a SHG prior to the start of the program are more likely to be satisfied with their first year of experience. Differences between Tables 7 and 8 lie in the fact that the payout and peer effect variables, as well as the corresponding interaction terms, are no more statistically significant. Also insignificant are the effects

14 Bearing in mind that the marginal effect of a change in both interacted variables is not equal to the marginal effect of a change in the interacted term, we have estimated the marginal effects following the method proposed by Ai and Norton (2003). Thus computed as the cross derivative of the expected value of the dependent variable (instead of the derivative of the interaction), the marginal effects are 0.25** and 0.29** for columns (8) and (9), respectively.

Table 8: Determinants of satisfaction level

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) Heckman	(8) Heckman	(9) Heckman
Gender	-0.01	-0.01	-0.00	-0.01	-0.00	-0.01	0.00	0.01	0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Age	-0.00**	-0.01**	-0.01**	-0.01**	-0.00**	-0.01**	-0.00*	-0.01**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Schooling	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Schooling2	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Literacy	0.16**	0.17**	0.16**	0.17**	0.17**	0.17**	0.15***	0.16***	0.15***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)	(0.06)	(0.05)
Hholdsize	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lnIncome	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Asset_index	0.02	0.03	0.02	0.03	0.02	0.03	0.03	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sick_2010-11	-0.12*	-0.12	-0.13	-0.12	-0.12*	-0.12*	-0.11*	-0.11*	-0.11*
	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
SHG	0.13***	0.14***	0.14***	0.14***	0.13***	0.14***	0.12***	0.12***	0.12***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Prevention_index	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.02	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
INFO_2	0.16***	0.17***	0.16***	0.17***	0.16***	0.17***	0.12***	0.12***	0.12***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	(0.05)	(0.05)
UND_2	0.34***	0.31***	0.36***	0.30***	0.34***	0.30***	0.28***	0.29***	0.27***
	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.04)	(0.05)	(0.05)
Payout			0.03	-0.01				0.02	
			(0.05)	(0.07)				(0.06)	
Payout x UND_2			-0.03	0.01				-0.02	
			(0.10)	(0.12)				(0.08)	
Peer_effect					-0.01	-0.02			-0.04
					(0.06)	(0.06)			(0.08)
Peer_effect x UND_2					0.02	0.03			0.03
					(0.11)	(0.11)			(0.10)
Village dummies		yes		yes		yes			
Observations	306	306	306	306	306	306	947	947	947

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

of household wealth and health consciousness, and of the schooling level of the head. As for the influence of illness events, it cannot be established in a robust manner, yet the sign of the coefficient is consistently negative throughout all regression estimates.

5. CONCLUSION

In the Indian microinsurance health program examined in this paper, the take-up of the insurance has been extremely low and only a third of the subscribers have renewed their contract after one year of experience. We have shown that these disappointing performances can be ascribed to precisely defined understanding and information imperfections. Deficient information about the insurance product and the functioning of the scheme as well as poor understanding of the insurance concept, plus the fact of having received a significantly negative net payout, separately account for non-renewal decisions. Moreover, the interaction between the understanding dimension and the negative (net) payout significantly influences such decisions in the following sense: when incurring a current loss from the insurance transaction, a household is less inclined to opt out of the program if it has a better understanding of what insurance exactly means (a redistribution between lucky and unlucky individuals). The latter result strongly suggests that the understanding failure may be a key factor behind the low demand for insurance in poor and ill-educated communities.

The information failure could have been avoided because it is supply-driven. The information effort by the organization in charge should not only consist of explaining the program to willing subscribers at the time of its launching, but also of following up the actual insurees so as to guide them when they happen to need the insurance services. At least, such a continuous communication, which requires continuous physical presence on the field, ought to take place during the first, critical years of an insurance program. This is with a view to not only helping those who have subscribed to the insurance but also demonstrating its advantages to those who have not. As field observations revealed, efforts on both aspects were not sufficient: on the one hand, the awareness-building campaign was too short and superficial and, on the other hand, there was no continuous physical presence of the organization's agents on the field. This explains why subscribers with sick members have not succeeded in acquiring more information than other subscribers, and why many of them have even failed to actually use the services covered by the insurance. The good news is that this lacuna can be remedied if enough resources, both human and financial, are provided for the purpose. It is revealing in this regard that those households which have actually used the insurance are generally satisfied with the program and that very few households have complained about the price of entry into it.

Another encouraging result is the positive effect of participation in self-help groups on both subscription to the insurance and contract renewal. Since the same non-governmental organization has been involved in the formation of these groups and the implementation of the microinsurance health scheme, the conclusion seems to be that the latter responsibility could have received more attention. But past grassroots work with self-help groups has paid dividends and indicates an important way of promoting microinsurance in poor areas. Literacy is another important factor of success and, here too, the policy implication is easy to draw. The same can again be said about education concerning basic health care measures since more training on this subject increases the likelihood of renewal significantly.

Also worth emphasizing is the result regarding of the effect of wealth: poorest households are less likely to enroll into the micro-insurance program yet, once they have experimented with it and other things being equal (occurrence of sickness, understanding and information levels, etc.), they have a higher probability to renew their contract than other households. This is an encouraging finding suggesting that campaigning efforts ought to be concentrated on the poorest segment of the population since it appears to draw comparatively large benefits from health microinsurance when the circumstances are favourable.

The most difficult problem arguably arises from the understanding failure. In dealing with the issue of insurance, economists have almost completely neglected that aspect. Even the most recent theories aimed at improving our knowledge of human behavior toward risk do not pay attention to the possibility that people are frustrated by an insurance scheme from which they have not benefited during the current year. If these theories help to account for oft-observed low take-up rates, they are generally unable to explain low contract renewal rates. The reason why the understanding failure is a hard nut to crack is rather obvious: removing it requires a change in the people's perception of the very aim pursued by microinsurance programs. Through elaborate and sustained awareness campaigns, they must be made to understand that insurance is different from credit and that incurring a negative net payout during a period of time is no sign of the ineffectiveness of an insurance program. At the same time, the products must be conceived in such a way that people can most easily perceive the value of insurance for them, for example by including frequent risks in the insurance package (see Platteau, 1997, for a discussion).

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