Designing Community-Based Health Insurance among Rural Poor in India:

A novel time- and cost-effective method for data sourcing

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Ontwikkelen van collectieve ziektekostenverzekeringen voor arme plattelandsbewoners in India:
Een nieuwe tijds- en kosteneffectieve methode voor gegevensverzameling

Thesis

to obtain the degree of Doctor

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by command of the rector magnificus

Prof.dr. H.G. Schmidt

and in accordance with the decision of the Doctorate Board

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born in Benthuizen, The Netherlands

ERASMUS UNIVERSITEIT ROTTERDAM

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Chapter 1

Introduction

1.1 BACKGROUND

In developing countries, including India, the cost of healthcare is mainly paid out-of-pocket (OOP) at the point of service delivery. This fact persists despite the attempt to create publicly financed health centres as these health centres often do not provide proximate services, or indeed the expected level of quantity or quality of healthcare because of poor staffing, equipment or stock of medicines etc. (Dalal & Dawad 2009, GOI 2008, De Costa & Diwan 2007, Kotwani et al. 2007, NCMH 2005, Satpathy 2005, Kamat 1995). The OOP expenditures reach on average up to 50% of total health expenditures in low income countries; In India, more than 60% of total health expenditures is paid OOP (Figure 1.1) (World Bank 2012). Member States of the World Health Organization committed in 2005 to develop their health financing systems so that all people would have access to services and would not suffer financial hardship paying for them (World Health Assembly resolution 58.33). The preferred health financing policies to reduce OOP spending and achieve universal coverage have been risk pooling and health insurance mechanisms (James & Savedoff 2010, WHO 2010).

The Indian health insurance scenario is a mix of mandatory social health insurance (SHI) for a small minority of government employees, employer based schemes (mainly in multinational companies in the formal sector), voluntary private health insurance, state or central government sponsored schemes, and health micro insurance in the informal sector (mostly Community-Based Health Insurance - CBHI) (Reddy et al. 2011b, Devadasan 2006, WHO 2004a). This thesis focuses on the rural poor in India. These rural

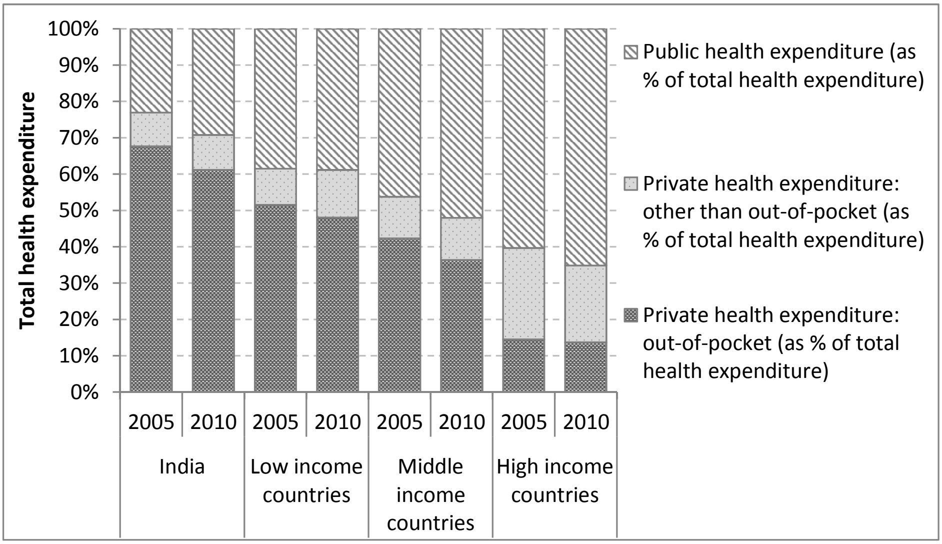

Figure 1.1 Public and private health expenditure as share of total health expenditure
Source: World DataBank – World Development Indicators (World Bank 2012)

poor have no access to SHI or employer based schemes, as the vast majority lives and works in the informal sector (Devadasan 2006, NCMH 2005). Private insurance companies and their agents are reluctant to offer policies in rural areas due to high transaction costs and lack of local information. Since 2007 some state governments have introduced insurance schemes targeting poor households and in 2008 central government started the Rashtriya Swasthya Bima Yojana (RSBY) scheme for the same target population. Most of these schemes cover only inpatient tertiary care; RSBY includes inpatient secondary care. In addition, the outreach is in most states still quite low, especially in rural areas (Reddy et al. 2011b). Thus, for the rural poor populations, the most viable option to get health insurance coverage is through CBHI (Bhat & Jain 2006, Ahuja 2005, Ahuja 2004, Gumber 2002).

In this thesis CBHI is defined as voluntary, group-based, self-help insurance schemes for which the group is involved at least in the design of the benefit package, and probably also in premium setting and in claims settlement (Dror In Press, Dror & Jacquier 1999). This definition departs from classical demand-driven market theory which views the individual as formulating demand, whereas here the group takes that role, and group demand reflects its aptitude to pool both risks and resources in order to provide protection to all members. This definition can be viewed as applying the subsidiarity principle (that decisions should be taken at the lowest level where they can be taken), which manifests itself in the following ways: the insurance is contextualized to local levels of willingness to pay, local needs and priorities of the specific community in question, and there is no competition among suppliers of health insurance, considering that people in the informal sector are unable to buy commercial forms of health insurance. The schemes are voluntary, with premiums suited to people with low incomes and designed to benefit the insured (Dror In Press).

As shown in Figure 1.2, four main models of delivery of health micro insurance can be identified: (i) the partner-agent model, (ii) the provider-driven model, (iii) the charitable insurance model and (iv) the mutual/community-based health insurance model (Radermacher & Dror 2006). All four models follow some of the principles described above, but only the mutual model follows all principles. Therefore the main focus of this thesis is on the design of CBHI according to the mutual model. In practice CBHI schemes can operate as mixtures of the different models and lessons learned in this thesis can also be useful in the other three models wherever appropriate.

In the partner-agent model any organization with close contacts to the rural and low-income target population is the intermediary (the agent) between the policyholder and an external insurance company (the partner). The insurance company is solely responsible for designing, pricing and underwriting of products, and for maintaining solvency in the long-term. In the provider-driven model a healthcare provider (e.g. hospital, clinic) launches an insurance scheme. Clients pay a premium to the healthcare provider, enabling them to consume health services, and often access is limited to that facility. In the charitable insurance model an external charitable organization acts as insurer (not-for-profit), performs all activities of the business process and is responsible for the long-term sustainability of the scheme usually by supplementing the payment of premiums through external donors (Radermacher & Dror 2006).

The mutual model operates on the basis that the risk of the insurance is borne by the insured. Such CBHI schemes usually operate with small, local groups formed as extensions of social ties developed in day-to-day interactions, mostly organized through Non-Government Organizations (NGOs) serving poorer segments of society. The clients or members play the central role; they are the owners of the scheme and are thus responsible for designing, pricing and underwriting, and for the long-term solvency of the insurance. The high degree of involvement of the members in this model has a few advantages: (i) multiple forms of information asymmetries that are typical of commercial health insurance can be reduced as readily available local knowledge can be used to streamline operational issues and (ii) a high degree of satisfaction with the product which is important in a context of voluntary insurance. But, this is conditional on fair and transparent management of the scheme, as well as on true and representative inclusion in the design process. The bottleneck of many mutual schemes however is that the management usually has little professional expertise in insurance and, the specialist knowledge that is necessary needs to be made available from the outside (Radermacher & Dror 2006).

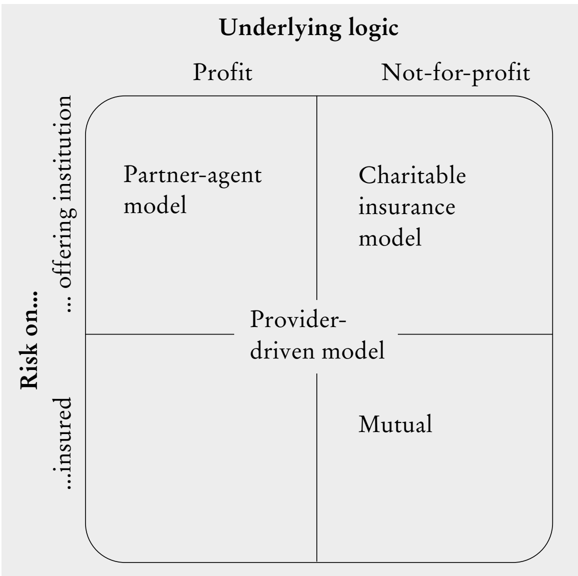

Figure 1.2 Types of health micro insurance provision
Source: Protecting the poor – A microinsurance compendium Volume 1, p402 **(Churchill & Matul 2012)**

As with every effort of insurance, launching a new CBHI scheme entails collecting and analysing the relevant information in order to design and price an insurance package; the main items of information in question include willingness-to-pay for health insurance, health status of the target population, its healthcare utilization, healthcare costs applying locally, and perceived priorities of the target population. Some information at high level can be obtained from official sources, e.g. the Indian National Sample Survey Organization (NSSO). However, NSSO data are available only at state level. As seen in previous studies (Dror et al. 2009b, Dror et al. 2008, Dror et al. 2007b, Dror 2007), differences across locations even within one and the same state can be significant and material, and therefore data is needed with much higher density for the purpose of relevant calculations for CBHI. The usual practice to collect such local data is to conduct a baseline household survey locally (Mwaura & Pongpanich 2012, Doyle et al. 2011, Onwujekwe et al. 2010b, De Allegri et al. 2008, Dong et al. 2004, AC Nielsen ORG-MARG Pvt Ltd. 2001). However, as a baseline study takes much time and is expensive, some NGOs proceed to implement CBHI without adequate data (with the obvious risks involved), and others are discouraged from attempting to launch altogether. Neither situation is very desirable.

1.2 PURPOSE AND RESEARCH QUESTIONS

The purpose of this thesis is to contribute to the knowledge that can facilitate pre-implementation activities aimed at upscaling penetration of health insurance among rural poor in India by developing a cost- and time-effective methodology to design health insurance products contextualized to the local situation.
The specific research questions addressed in this thesis are:

1. What are the financial consequences of the current situation, when the target population must pay for care out-of-pocket at the point of service delivery?
2. What are the morbidity patterns and healthcare seeking behaviour of the potential target population?
3. How can willingness-to-pay (WTP) for health insurance estimates be obtained quickly and at low cost?
4. How can relevant and reliable data be obtained for actuarial calculations of health insurance package design quickly and at low costs?
5. How can the preferences of prospective clients regarding the health insurance benefit package be established?

By answering these research questions, this thesis seeks to contribute to simplifying implementation of (community-based) health insurance among the rural poor in India, by showing that relevant data can be obtained through newly developed cost- and time-effective methodologies. The scientific significance of this thesis resides in the many issues related to health insurance that are analysed from novel angles, and in the development of several nonconventional methodologies.

1.3 OUTLINE OF THE THESIS

1.3.1 Short outline

Chapters 2, 3 and 4 of this thesis describe the situation prevailing among rural poor in India with respect to healthcare financing, healthcare needs and healthcare provision. This information sets the context for needs analysis of the target population, and for the design of the health insurance.

The second part of this thesis (Chapters 5 till 9) contains a detailed treatment of the development of new methodologies to collect or estimate the relevant data for the design and pricing of health insurance benefit packages. Specifically, the methods in question here relate to obtaining local estimates of WTP, morbidity and healthcare seeking behaviour, cost of healthcare, and perceived priorities for inclusion in insurance.

1.3.2 Financial consequences of OOP expenditures

When health insurance is implemented, the OOP expenditures (or at least part of it) are replaced by a premium. A first question that could arise is what is the extent of the problem presented by OOP payments in the first place? As OOP expenditures at the time and point of healthcare delivery are usually unexpected and the patient thus needs to have money at his disposal right away it is also important to investigate how the target population finances healthcare expenditures in the absence of health insurance. Another issue is that it is usually assumed that inpatient care is the main reason for catastrophic health expenditures (Peters et al. 2002), but is that indeed the case also in the informal sector and among rural poor? The subject of the second chapter of this thesis is the examination of what types of healthcare cause financial hardships. Novel criteria are used to analyse patterns of healthcare financing, giving full recognition, for the first time, that in addition to direct payments to healthcare providers, other costs, e.g. interest on borrowed money or losses due to the involuntary or suboptimal sale of (income-generating) assets, cause hardship for the rural poor. The reduction of such indirect additional costs could be viewed as a collateral benefit of the health insurance.

1.3.3 Healthcare needs and provision

In order to design a health insurance benefit package it is necessary to understand local healthcare needs and available provision. A lot of attention is given nowadays to the epidemiological transition in developing countries (WHO 2011a). Specifically, although infectious diseases are still highly present, there is an increasing prevalence of non-communicable diseases (NCDs) as well (WHO 2011b). The assumption is that one can observe a double burden of disease (both communicable and non-communicable) developing. In chapter 3 of this thesis the prevalence and financial burden of different types of NCDs is compared to communicable diseases (CDs), together with the health-care seeking patterns for the two classes of diseases.

The fourth chapter deals with the question of the preference of first contact for curative healthcare among rural communities. In India many different types of providers exist (public, private, charitable) practising different types of medicines (allopathic, Ayurveda, traditional, etc.). When designing health insurance it is important to know which providers the target population usually prefers to approach and why?

1.3.4 WTP for health insurance

An essential feature of mutual CBHI schemes is that affiliation is voluntary. These schemes usually operate without external funding and their expected costs (benefit cost plus administrative loading) must equal premium income. In that scenario, the estimate of WTP for health insurance determines the width and depth of the benefit package. Therefore an estimation of the WTP is the first step in designing the health insurance.

The target populations of CBHI schemes usually have no or very limited experience with health insurance or even insurance in general. In such a context the stated preference regarding the WTP can be queried during a survey amongst a representative sample of the target population using a Contingent Valuation technique. However, conducting such a survey takes time and is quite expensive. Also extended explanations are required because the target population has difficulty understanding the concept of WTP for health insurance and what they might get in return for the premiums. In the fifth chapter a new and simple way to obtain an anchor to estimate local WTP for health insurance is developed.

1.3.5 Obtaining relevant and reliable data for the actuarial calculations of health insurance benefit packages

One of the hurdles to launching CBHI schemes is obtaining relevant information needed for informed choice when designing and pricing the insurance package. For these actuarial estimates, information is needed on the probability of healthcare utilized under the different insured benefits, and the cost of that utilization. Due to the large regional differences and lack of existing data, this information needs to be obtained locally (Dror et al. 2009b, Dror et al. 2008, Dror et al. 2007b, Dror 2007). The practice has hitherto been to collect this information at the relevant unit through household surveys (Mwaura & Pongpanich 2012, Doyle et al. 2011, Onwujekwe et al. 2010b, De Allegri et al. 2008, Dong et al. 2004, AC Nielsen ORG-MARG Pvt Ltd. 2001). As already mentioned, the difficulty with household surveys is that these are expensive and time consuming exercises. A very important question for the expansion of CBHI is whether it would be possible to obtain the same quality of data faster and cheaper.

In Chapter 6, a novel method to collect information on morbidity and healthcare utilization is developed. This novel method is called "Illness Mapping" and is a combined variation of two non-interactive consensus group methods (Delphi and Nominal Group Technique) operated as an interactive method. Stated differently, a qualitative approach is followed to derive quantitative estimates from "experts" in the target community.

The second key parameter, namely cost of healthcare, is discussed in Chapter 7 of this thesis. It is recalled that typically, CBHI schemes do not benefit from premium subsidy, and must therefore ensure that benefit expenditures would be within the limited premium income. The common way to ensure this is through the application of a threshold and/or a cap. A threshold is the predetermined amount above which the insurance reimburses the rest of the bill. A cap is the predetermined amount up to which the insurance reimburses the bill. The consequences of thresholds and/or caps on the expected average pay-outs of insurance can only be calculated when the distribution of healthcare costs is known. The question now is whether these full distributions of costs can be predicted for any location where one wants to implement CBHI based on some data points that could be obtained more easily than conducting a full household survey? The theoretical model that has been developed to simulate the distribution of cost of healthcare benefits, and enable the calculation of consequences of different caps and/or thresholds is discussed in chapter 7.

1.3.6 Revealing benefit package preferences of prospective clients

In the mutual model addressed in this thesis, the clients are the owners of the scheme and responsible for all its aspects, including benefit package design. However, how can this be accomplished among people that have no experience with insurance and are mostly illiterate and innumerate? And, when involved in a difficult process of priority setting of health insurance, how judicious are the choices they make? Chapters 8 and 9 describe a modified version of a tool originally developed and tested in the USA: Choosing Healthplans All Together, CHAT (Goold et al. 2005, Danis et al. 2004, Keefe & Goold 2004, Danis et al. 2002). CHAT is a simulation group exercise of choosing health insurance benefits under a limited budget, designed to make complex decisions more simple and familiar by incorporating complicated data such as actuarial costs into a simplified exercise board. The modified version is tailored to the reality of India and takes into account the illiteracy and innumeracy of the target population. Both chapters describe evidence of experiments during which the target groups made choices, and in chapter 9 it is analysed how judicious those choices were in terms of the actual expenditure patterns.

Chapter 2

Hardship financing of healthcare among rural poor in Odisha, India

Based on: Binnendijk, E., Koren, R., Dror, D.M.
Hardship financing of healthcare among rural poor in Odisha, India.
BMC Health Services Research 2012, 12:23.

ABSTRACT

Objective This study examines health-related "hardship financing" in order to get better insights on how poor households finance their out-of-pocket healthcare costs. We define hardship financing as having to borrow money with interest or to sell assets to pay out-of-pocket healthcare costs. ***Methods*** Using survey data of 5,383 low-income households in Odisha, one of the poorest states of India, we investigate factors influencing the risk of hardship financing with the use of a logistic regression. ***Results*** Overall, about 25% of the households (that had any healthcare cost) reported hardship financing during the year preceding the survey. Among households that experienced a hospitalization, this percentage was nearly 40%, but even among households with outpatient or maternity-related care around 25% experienced hardship financing. Hardship financing is explained not merely by the wealth of the household (measured by assets) or how much is spent out-of-pocket on healthcare costs, but also by when the payment occurs, its frequency and its duration (e.g. more severe in cases of chronic illnesses). The location where a household resides remains a major predictor of the likelihood to have hardship financing despite all other household features included in the model. ***Conclusions*** Rural poor households are subjected to considerable and protracted financial hardship due to the indirect and longer-term deleterious effects of how they cope with out-of-pocket healthcare costs. The social network that households can access influences exposure to hardship financing. Our findings point to the need to develop a policy solution that would limit that exposure both in quantum and in time. We therefore conclude that policy interventions aiming to ensure health-related financial protection would have to demonstrate that they have reduced the frequency and the volume of hardship financing.

2.1 BACKGROUND

While we know that the biggest part of health expenditures in India is paid by health-seekers themselves when getting care, we know much less about how those costs are met. Evidence confirms that out-of-pocket spending on healthcare absorb more than one quarter of household resources net of food costs in at least one-tenth of all households in India (Van Doorslaer et al. 2005). All over India, the level of out-of-pocket spending is 69.5% of total health expenditures (GOI 2009). This considerable burden warrants a better understanding of how poor households finance these out-of-pocket healthcare costs. This article focuses on this very question, using data from Odisha, where out-of-pocket spending represents nearly 80% of health expenditure (GOI 2009).

The literature dealing with financing of out-of-pocket healthcare cost includes definitions of "catastrophic" healthcare expenditures when spending exceeds an essentially arbitrary threshold. Xu et al. (2003) fix the threshold at 40% of disposable income net of subsistence needs; Russell (2004) and Van Doorslaer et al. (2005) use a threshold of 10% of total annual household income. However, these methods fail to recognize that a uniform threshold might represent varying levels of hardship. For example, spending 10% by a poor household could mean withdrawing a child from school or skipping a meal, while the same spending level would not entail any immediate consequence for a richer household (Kruk et al. 2009, Wagstaff 2008). Also the timing of the payment could cause different cash-flow problems. As most rural poor households in India have irregular flows of income, they would find it easier to pay during harvest season (when they have income from selling the crop or from work as agricultural labourers) than in other times of the year. Morduch and Rutherford (2003) reported this cash-flow pattern to hold true in most low-income countries.

We therefore assess the hardship a household faces as a consequence of health expenses not merely by the amount spent, but by the additional costs to the direct cost of healthcare related to how the out-of-pocket spending is financed. This is in line with notions put forward by Flores et al. (2008) and Kruk et al. (2009).

Three sources of financing out-of-pocket healthcare costs can be distinguished: paying from current income or savings; borrowing with zero interest (e.g. from family and friends), and borrowing with interest or selling assets. The first two categories may be regarded as less burdensome than the third (Asfaw et al. 2010, Kruk et al. 2009, Steinhardt et al. 2009), because selling assets or borrowing money with interest usually entails a cost. This cost is self-explanatory in the case of interest on loans (Krishna 2004). Selling assets also generates costs, such as losses when assets are sold at less than optimal price, or future income loss due to the sale of income-generating assets (like land or livestock). Thus, we say that households incur "hardship financing" when they are exposed to a less stable or worsened financial state brought about by additional costs/losses due to borrowing or selling assets. This definition follows Kruk et al. (2009), with the notable modification that we only consider borrowing with interest instead of any borrowing. Our adjustment is in agreement with previous findings (Kochar 1997) and with our investigations that confirmed that borrowing from family/friends for healthcare purposes is indeed mostly interest-free.

Many of the previous publications regarding the financing sources for out-of-pocket payments for healthcare in developing countries, and in India, are related to financing of care for specific diseases (Adhikari et al. 2009, Khun & Manderson 2008, Russell 2004, Van Damme et al. 2004, Wyss et al. 2004, Mock et al. 2003, Nahar & Costello 1998, Sauerborn et al. 1996) and mostly based on small-scale surveys. Some studies look at specific population segments (Asfaw et al. 2010, Bonu et al. 2005), others used data available on a whole country level (Kruk et al. 2009, Steinhardt et al. 2009, Flores et al. 2008, Leive & Xu 2008). Kruk et al. (2009), whom we follow in the definition of "hardship financing", looked at nationally representative household surveys of 40 low- and middle-income countries, whereas we look at rural (and largely tribal) poor in three districts of Odisha, one of the poorest states in India. By focusing on this target population, we examine hardship financing of out-of-pocket payments for healthcare expenditures among the most vulnerable segment of society in India. Our goal is to identify the parameters affecting households' risk to resort to hardship financing.

2.2 DATA AND METHODS

2.2.1 Setting and sampling

We used data from a household survey undertaken early in 2009 in the rural areas of Kalahandi, Khorda, and Malkangiri districts of the state of Odisha. Odisha, the eleventh largest state of India by population (41,947,358) with 83% of population being rural (GOI 2011b, GOI 2011a), is located on the Bay of Bengal at the east coast of India. The average monthly per capita consumer expenditure (MPCE) of INR 459 (PPP$ 30.6) for rural Odisha, is the lowest of all states (NSSO 2008). The household survey questionnaire was translated into Oriya (the local language), back translated for verification, and pretested among 80 households in the area. Surveyors who spoke local dialects fluently conducted the survey.

We followed a three-stage sampling procedure. (i) The sites in Odisha were selected due to a relationship with 11 NGOs[1] that invited the research team to conduct a baseline

1. The 11 grassroots NGOs linked with Madhyam Foundation, Bhubaneswar, Odisha included: (i) in Malkangiri: Parivartan, PUSPAC, SOMKS, SDS, ODC; (ii) in Kalahandi: Mahashakti Foundation, DAPTA, Lok Yojana, Sanginee; and (iii) in Khorda MVPS, DSS.

study (prior to launching a development project among their members). (ii) Within each district, villages were selected randomly from among those selected by the NGOs for the development project (27 villages in Kalahandi, 22 in Khorda, 31 in Malkangiri). (iii) Stage three entailed random sampling of two equal sub-cohorts in each village: 'member households' and 'non-member households' (comparator group). Member households (i.e. households that included at least one person who was a member of a Self-Help Group (SHG[2]) linked to one of the respective NGOs) were selected randomly out of the membership list. Non-member households were sampled randomly with the use of line sampling (from the centre of the village 4 lines were drawn in the four winds directions, "the four winds technique") (Som 1996).We interviewed a total of 5,383 households representing 25,606 individuals (with a similar number of member and non-member households in every village, totalling 2,688 member and 2,695 non-member households and with a similar number of households from each district, totalling 1820 households from Kalahandi, 1763 households from Khorda and 1800 households from Malkangiri). 100% of the sample interviewed was rural.

At the time of the rollout of the survey there was no local ethics committee in place in Odisha, India. We however held a two-day workshop in preparation of the study in which we discussed the ethical aspects of the study with scholars and senior scholars from India. Informed consent of the respondents was obtained at the beginning of the interviews and we kept participants' names confidential in data recording and analysis.

2.2.2 Data

The household survey questionnaire included questions on socioeconomic status: education of household head, occupation of household head, source of drinking water, toilet facility and caste. Under the Constitution of India, the government has "scheduled" certain backward Indian classes or groups [hence Scheduled Castes (GOI 1950a) or Scheduled Tribes (GOI 1950b), and "Other backward castes"], with the view to promoting their welfare. Scheduled Tribes (Tribals or Adivasis) are mostly not Hindu and thus out of the caste system and are considered the most disadvantaged economically. Scheduled Castes (Dalits and those sometimes labelled "Untouchable") are considered at the bottom of caste hierarchy. The list of Other Backward Castes is quite dynamic and changes from time to time in many states. All other castes are described here as General Caste.

For household income, we followed the method adopted by the Indian National Sample Survey Organization to obtain a proxy (monthly per capita consumer expenditure) through questions on many items of household expenditure (expenditures on

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2. SHGs represent a unique approach to financial intermediation in communities. The approach combines access to low-cost financial services with a process of self-management and development for the SHG members. SHGs are seen to confer many benefits, both economic and social.

food, clothing, fuel, etc.) (NSSO 2008). In our study, unlike the National Sample Survey Organization, we did not include health expenditure, because we seek to identify patterns of financing of healthcare (Wagstaff 2008, Flores et al. 2008). We label this proxy for socioeconomic status as "income-proxy".

We also developed an asset-index as proxy for socioeconomic status by performing a principal component analysis (PCA) on various aspects of household assets, following the guidelines of Vyas and Kumaranayake (Vyas & Kumaranayake 2006). PCA is a statistical technique used for data reduction. We included the following variables: house type, source of lighting, way of cooking, land ownership, various consumer durables (radio, motor cycle, telephone, etc.), possession of animals (cattle, sheep, chickens, etc.). Size of land and possession of animals were included as continuous variables, the other variables as binary (yes/no) variables. We then used the factor scores of each of the variables from the first principal component as weights and computed a total for each household: the household's socioeconomic score. Characteristic of this score is that it has a mean equal to zero and a standard deviation equal to one; the higher the score, the higher the implied socioeconomic status or wealth of that household. As we deal in this paper with health-related issues, source of drinking water and toilet facility were not included in the PCA given their possible direct relation with health status (Vyas & Kumaranayake 2006, Dunteman & Lewis-Beck 1989).

Besides indicators of socioeconomic status, the household survey questionnaire included questions on healthcare utilization and cost. The households were asked whether they had incurred expenditures for outpatient care, hospital admittances and maternity-related care in the year preceding the survey. Hospital admittances reflected cases with inpatient stay exceeding 24 hours. Stays in hospital of less than 24 hours were counted under outpatient care, together with consultations with a healthcare practitioner, and payment for medicines or tests in an outpatient setting. Maternity-related utilization included delivery and pre- and post-natal care. Respondents were asked to estimate total direct medical expenditures of the household in the year preceding the survey, as well as the expenditures for hospital admittances in the household in the year preceding the survey. More detailed information on outpatient care utilization and cost was queried for one month preceding the survey. Chronic illness in the household was identified by a set of questions related to symptoms, length of illness and regular medicine use.

We asked households also what hospital they would go to in case of a hospitalization of more than 24 hours, what kind of hospital this is, and the distance (travel time in minutes) to this hospital. Similar questions were asked related to the practitioner for outpatient care.

Households that reported healthcare costs for hospitalizations, outpatient care, or maternity-related care during the year preceding the survey were asked how they financed each type of these cost. Sources of financing included using current income, money received as gift, savings, money obtained from selling assets, money obtained through borrowing (borrowing options included relatives, friends/neighbours, bank, moneylender, or microfinance e.g. local microfinance institution or SHG), health insurance, and other sources. Households could report as many sources of financing as relevant. With respect to borrowing we also queried how much was borrowed from each of these sources to pay for healthcare costs. In this paper we ignore three sources since they turned out to be negligible (e.g. 1.4% of households with any health expenditure reported gifts, 0.02% reported health insurance and 0.7% reported "other").

We categorized a combination of financing sources as hardship financing: selling assets or borrowing money with interest from bank, microfinance or moneylender. If a household had reported using at least one of these financing sources, this household was categorized as having had hardship financing. Households that reported using only current income and/or savings and/or borrowing from relatives or friends/neighbours were defined as having had no hardship financing.

2.2.3 Analysis

We investigated factors influencing the risk of households to need hardship financing when paying for healthcare costs with the use of a multivariate analysis. We applied a logistic regression (logit model) as the outcome variable is a binary variable (yes/no hardship financing). Only households that had healthcare costs in the year preceding the survey were included in the regression. The explanatory variables were included in the model in a stepwise inclusion procedure.

Data is analysed using STATA version 11. The unit of analysis is the household, reflecting the fact that in rural low-income countries, many decisions on paying for healthcare are taken at that level rather than by individuals (Sauerborn et al. 1995).

Statistical significance of difference has been shown at levels of 10%, 5% and 0.1% throughout the paper. When ANOVA is used we show significance with *, ** and *** respectively; when Pearson Chi-square is used we show significance with†, †† and††† respectively. In case of the logistic regression statistical significance of the coefficient (Z-test) is shown at levels of 5%, 1% and 0.1% with *, ** and *** respectively.

All amounts, reported in Indian Rupee (INR) during the survey, were converted into international dollars (Purchasing Power Parity, PPP$) using the exchange rate of PPP$ 1 = INR 16.389 for 2009 (IMF 2011).

2.3 RESULTS

2.3.1 Socio-economic profile

The socioeconomic profile of the sampled population is summarized in Table 2.1. The majority of the studied population is from Scheduled Caste or Tribe. The majority of the household heads have no or very little education and work as daily wage labourers or are self-employed in agriculture. The income of our sampled population in Odisha was on average below the extreme poverty anchor of PPP$ 1.08 per person and day (defined by the World Bank in 1993, equalling PPP$ 1.71 p.p.p.d. when adjusted to the survey year 2009 and to India) (Sillers 2005, OECD statistics). Most households have no toilet and get drinking water from a shared tap in the village or hand pump/well. The households consist on average of 4.8 persons of which 8% are infants (0-4 years old) and 8% are elderly (60 years and older).

The socioeconomic status indicators from the National Sample Survey Organization for rural Odisha show similar patterns as our aggregated total population (table 2.1): income-proxy PPP$ 28.9 p.p.p.m., household size 4.6 persons) (NSSO 2008).

2.3.2 Morbidity, healthcare availability, utilization and cost

Information on morbidity, availability of healthcare, utilization of healthcare and healthcare expenditures of the sampled population are summarized in Table 2.2.

Around 85% of the sampled households had health expenditures in the year preceding the survey, and almost 24% of households had to meet hospitalization costs in the same period. Around 10% of the sampled households have a chronically ill person in the household.

Average health expenditures represented about 9% of the average income-proxy for the sampled population (income-proxy p.p.p.m. and household size table 2.1, total health expenditure for the household last year table 2.2).

Households usually go to a public facility for hospitalizations of more than 24 hours. In about half of the cases they go to a public facility for outpatient care. To go to the facility where they would go to for a hospitalization takes a little bit more than 50 minutes travel time; the facility for outpatient care is on average 30 minutes away from their homes.

In Appendix 2.1 and 2.2 the same information of Table 2.1 and 2.2 is shown separate for the member and non-member sub-cohorts (defined in the methods section). The difference between SHG members and non-members in morbidity, healthcare utilization and cost is not significant for most indicators. The difference in socioeconomic profile between the member and non-member cohorts seems to be significant, pointing to a higher socioeconomic status for SHG members. However, for the indicators that are significantly different, this difference is rather small and probably immaterial. Therefore

Table 2.1 Demographics & socioeconomic status

	Mean (±SE[a])
Income-proxy p.p.p.m. (PPP$)[b]	32.41 (±0.29)
Asset-index[c]	0.00 (±0.03)
Household size	4.76 (±0.02)
Ratio infants (0-4) in household	0.082 (±0.002)
Ratio elderly (60 and older) in household	0.075 (±0.002)
	% of total
Caste[d]	
Scheduled Tribe	30.0%
Scheduled Caste	22.3%
Other Backward Caste	31.3%
General Caste	16.5%
Education level household head	
No education	51.4%
Class 1-5	22.2%
Class 6-10	23.8%
Class 11 and higher	2.7%
Occupation household head	
Self-employed agriculture	38.7%
Self-employed business/trade	16.1%
Regular Salaried employee	4.6%
Daily wage labourer	30.8%
Not working	9.9%
Source of drinking water	
Own tap	9.9%
Shared tap	53.9%
Hand-pump/well	36.2%
Toilet facility	
Own flush toilet	4.4%
Own pit toilet	4.9%
Shared toilet	1.0%
No toilet	89.7%

[a] SE = Standard Error.
[b] Income is proxied as monthly per capita consumer expenditure through questions on many items of household expenditure and expressed in Purchasing Power Parity International Dollar.
[c] Asset-index is a proxy for socioeconomic status based on various aspects of household assets. The index is calculated using a principal component analysis (PCA).
[d] Caste is a proxy for socioeconomic status in India. Scheduled Castes (Dalits and those sometimes labelled "untouchable") are considered at the bottom of caste hierarchy. The list of Other Backward Castes is quite dynamic and changes from time to time in many states. All other castes are described here as General Caste.

we aggregated the two sub-cohorts for the descriptive statistics, but included the membership variable in the regression analysis.

2.3.3 Healthcare financing

We asked respondents how they financed their healthcare costs (Figure 2.1). The majority of the households reported to have used at least (some) of their current income and savings to pay for their health expenditures. However, the multiplicity of sources shows that households were often unable to fund all their health expenditures from their current income and savings alone.

Households selling assets or borrowing money with interest in order to finance their healthcare were defined as households with hardship financing. Households that were able to finance their healthcare costs solely from current income, savings and/or borrowing without interest (from relatives or friends/neighbours) are defined as house-

Table 2.2 Morbidity, healthcare availability, utilization and cost in the sampled population

	Mean (±SE[a])
Total health expenditure last year for household (PPP$)[b]	167.34 (±5.14)
Distance to preferred hospital (in minutes)	52.48 (±0.54)
Distance to preferred primary care practitioner (in minutes)	30.40 (±0.40)
	% of total
Household with chronic ill person	10.5%
Household with hospitalization costs last year	23.5%
Household with outpatient care costs last year	83.8%
Household with maternity costs last year	14.4%
Household with any healthcare costs last year	85.1%
Hospital household usually goes to	
Private	6.3%
Public	93.7%
Preferred primary care practitioner household usually goes to	
Traditional healer	36.6%
Government facility	50.4%
Unqualified private doctor (non-MBBS)[c]	7.6%
AYUSH practitioner[d]	3.2%
Qualified private doctor/specialist (MBBS)	2.2%

[a] SE = Standard Error.
[b] Total health expenditure last year for household expressed in Purchasing Power Parity International Dollar.
[c] Unqualified private doctor (non-MBBS) is a doctor practicing allopathic medicine without having a medical degree (Medical Bachelor and Bachelor of Surgery).
[d] AYUSH is the aggregate of all qualified systems of traditional medicines in India: Ayurveda, Yoga and Naturopathy, Unani, Siddha and Homeopathy.

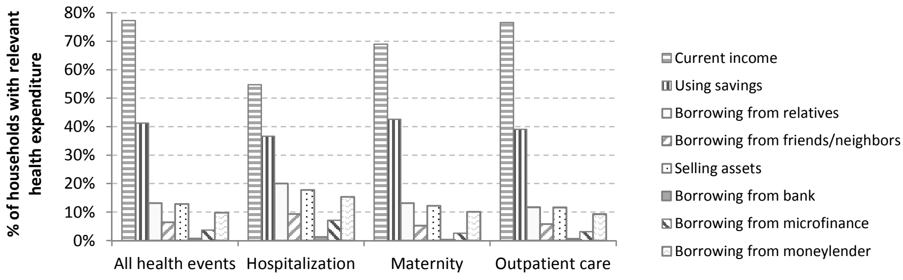

Figure 2.1 Healthcare financing

holds with no hardship financing. Figure 2.2 shows the shares of households paying healthcare costs with hardship financing versus households that did not have to use hardship financing.

Overall, about 25% of the households (with any healthcare cost) had hardship financing during the year preceding the survey. Among households that experienced a hospitalization this percentage is much higher, nearly 40% had hardship financing. Quite unexpectedly, 23% of household that incurred outpatient costs also reported that they had to use hardship financing sources to pay for this outpatient care, as well as 25% of the households that had a maternity case in the reference period.

2.3.4 Parameters influencing the risk of hardship financing

We explored with the use of a logistic regression the factors that could influence the risk of households to need hardship financing when paying for healthcare costs (Table 2.3).

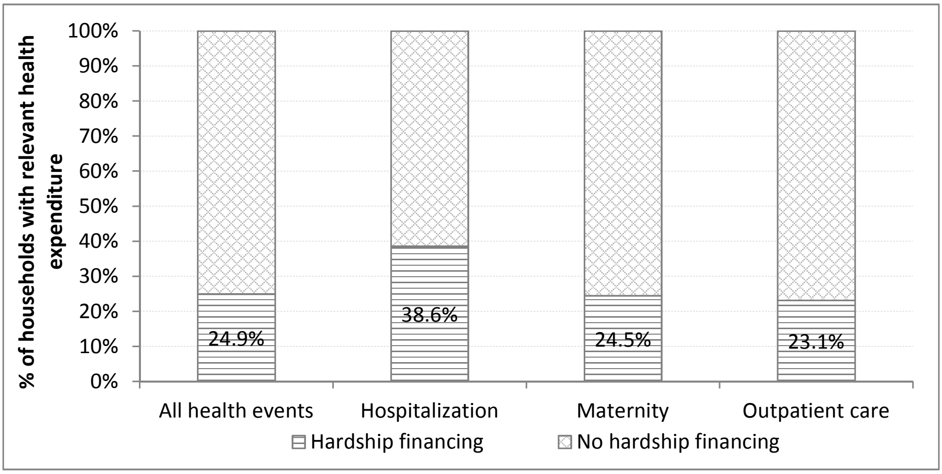

Figure 2.2 Hardship financing

Socioeconomic and demographic parameters

We found that, whereas the logarithm of the income-proxy was not a significant predictor of hardship financing, the asset-index was a highly significant and negative predictor (i.e. households with a lower asset-index have a higher propensity to have hardship financing). The education of the household head did not influence the probability to have hardship financing while his occupation did; households where the household head is self-employed in agriculture, self-employed in business, a daily wage labourer, or does not work due to any reason all have a significant higher likelihood to have hardship financing than households where the household head is a regular salaried employee. Caste, household size, the ratio of infants or the ratio of elderly in the household did not have a significant impact on hardship financing.

The minority (10%) of households with a better source of water are less likely to have hardship financing. The type of toilet used was not a significant explanatory variable.

Morbidity parameters & health expenditures

The logarithm of the total health expenditures during the year preceding the survey is a significant and positive predictor of hardship financing. Interestingly, having a chronically ill person in the household, or having experienced one or more events of hospitalization in the year preceding the survey are both significant independent predictors even after the overall health expenditures has been taken into account in the regression analysis.

2.3.5 Impact of SHG membership on hardship financing

The logistic regression (table 2.3) revealed that households where someone is a member of an SHG have a higher propensity to have hardship financing. This we found somewhat unexpected as we did not observe a big difference between the member and non-member sub-cohorts in demographics, socioeconomic status, morbidity, healthcare utilization and costs. Also the direction of the influence is somewhat unexpected. When looking at the demographics, SHG member households have a slightly higher asset-index, have more household heads that are salaried employees and more often have their own tap than non-member households (i.e. less poor households). And, from the logistic regression (table 2.3) it can be seen that, as expected, less poor households are less likely to have hardship financing. But, when controlled for these variables in the regression itself, it seems that SHG members are more likely to have hardship financing.

When looking at the financing sources used by members and non-members, we found that SHG members rely significantly more often on microfinance as a source of borrowing than non-members when paying for all health expenditures, hospital expenditures, or outpatient expenditures (4.4% vs. 2.3%, $p < .001$; 8.5% vs. 4.7%, $p < 0.01$; 3.7% vs. 2.1%, $p < .01$ respectively, Chi2). Non-members on the other hand make more frequently use of their savings in order to pay for hospital expenditures than members (23.8% vs. 17.0%, $p < .01$, Chi2).

Table 2.3 Factors that influence the risk of hardship financing for households with healthcare costs (logistic regression)

	Coefficient		95% Confidence interval	
Socioeconomic and demographic parameters				
Log income-proxy[a]	0.1197		-0.0694	0.3089
Asset-index[b]	-0.1176	***	-0.1698	-0.0655
Employment household head				
Salaried employee	*Reference*			
Self-employed in agriculture	0.8420	**	0.3307	1.3533
Self-employed in business/trade	0.7521	**	0.2176	1.2866
Daily wage labourer	0.9204	**	0.4005	1.4404
Not working	0.7824	**	0.2145	1.3503
Education household head				
No education	*Reference*			
Class 1-5	-0.0831		-0.2991	0.1329
Class 6-10	-0.1719		-0.3930	0.0492
Class 11 and higher	-0.0340		-0.6023	0.5343
Caste[c]				
Scheduled Caste	-0.1293		-0.4347	0.1761
Scheduled Tribe	0.2173		-0.0632	0.4978
Other Backward Caste	-0.1570		-0.4255	0.1116
General Caste	*Reference*			
Household size	0.0370		-0.0135	0.0876
Ratio infants (0-4) in household	0.2015		-0.4490	0.8520
Ratio elderly (60+) in household	0.1851		-0.3583	0.7284
Source of water				
Own tap	*Reference*			
Shared tap	0.4873	**	0.1733	0.8013
Hand pump / Well	0.3540	*	0.0286	0.6794
Type of toilet				
Own flush toilet	*Reference*			
Own pit toilet	0.0556		-0.5192	0.6305
Shared toilet	0.7037		-0.2623	1.6697
No toilet	-0.0607		-0.4942	0.3728
Morbidity parameters and health expenditures				
Log health expenditures last year	0.7232	***	0.6365	0.8099
Chronic illness in household				
No chronic ill	*Reference*			
Chronic ill	0.3779	**	0.1301	0.6257
Hospitalization in household last year				
No hospitalization	*Reference*			

Table 2.3 (Continued)

	Coefficient		95% Confidence interval	
Hospitalization	0.7225	***	0.5335	0.9116
<u>*SHG membership in household*</u>				
No SHG member	*Reference*			
SHG member[d]	0.2184	**	0.0536	0.3833
<u>*Location of residence*</u>				
Khorda district	*Reference*			
Kalahandi district	1.3776	***	1.1376	1.6176
Malkangiri district	0.1739		-0.0947	0.4424
Constant	-9.5496	***	-11.1226	-7.9766
N	4121			
Likelihood ratio test:				
LR chi2(27)	1025.76			
Prob > chi2	0.00			
Pearson goodness-of-fit test:				
Pearson chi2(4091)	3930.87			
Prob > chi2	0.96			

* Significance of coefficient p<0.05 (Z-test)
** Significance of coefficient p<0.01 (Z-test)
*** Significance of coefficient p<0.001 (Z-test)

[a] Income is proxied as monthly per capita consumer expenditure through questions on many items of household expenditure and expressed in Purchasing Power Parity International Dollar.

[b] Asset-index is a proxy for socioeconomic status based on various aspects of household assets. The index is calculated using a principal component analysis (PCA).

[c] Caste is a proxy for socioeconomic status in India. Scheduled Castes (Dalits and those sometimes labelled "untouchable") are considered at the bottom of caste hierarchy. The list of Other Backward Castes is quite dynamic and changes from time to time in many states. All other castes are described here as General Caste.

[d] A household was defined as SHG member if at least one person in the household was a member of a Self-Help Group (SHG) linked to one of the related NGOs.

2.3.6 Impact of location on hardship financing

When controlled for all features of individual households as variables included in the logistic regression, still the district in which a household resides remains a major predictor of the likelihood to have hardship financing (table 2.3). Therefore we explored this further. Figure 2.3 shows the difference in hardship financing between the districts.

By using a step-by-step inclusion procedure for the different variables in the regression, we found that the healthcare costs explained the difference in hardship financing between households in Malkangiri and Khorda districts. No other variable had this effect. The difference between Kalahandi on the one hand and Khorda and Malkangiri on the other hand remained unexplained with the current set of variables.

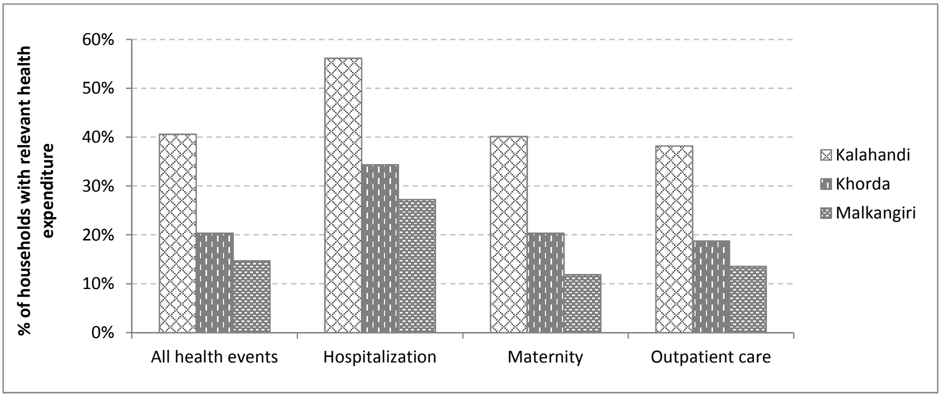

Figure 2.3 Hardship financing in the three districts

In the course of the examination we also checked other variables (e.g. preferred type of hospital, preferred practitioner for outpatient care, and distance (in minutes of travel time) to both preferred hospital and preferred outpatient practitioner) which were eliminated from the model as they did not proof to be statistically significant and weakened the overall model.

In order to find an explanation for the difference across the districts, we looked at alternative morbidity-related parameters. From our household survey we also have information on illness episodes and related costs for last month that cannot be annualized at the level of the single household. Therefore these parameters can serve to estimate morbidity of the district, but cannot be included in the regression analysis (Table 2.4).

In both Kalahandi and Khorda around 62% of the households reported an illness last month and around 60% had outpatient treatment (in the form of consultation, medicines and/or tests) for that illness. In Malkangiri this percentage is lower: 51% of the households reported an illness last month and 49% had some form of outpatient treatment for that illness. The average cost of the outpatient treatment is the highest in Khorda (PPP$ 71.74), a bit lower in Kalahandi (PPP$ 56.65) and much lower in Malkangiri (PPP$ 34.78).

Although the parameters of the socioeconomic status of individual households were included in the regression, we wondered whether the average socioeconomic status of the district is associated with the risk of hardship financing. Therefore we also show the average socioeconomic status (income-proxy and asset-index) for each of the three districts in table 2.4. We found that the sampled population in Khorda is on average wealthier than the other two districts which are similar to each other.

Finally we examined whether the access of households to a social network of family and/or friends that can provide interest-free loans is different in the three districts. We checked this through the share of households with health expenditures that borrowed from family and/or friends (table 2.4). We found that households in Khorda had a better access to such a social network than households in Kalahandi and Malkangiri. It is interesting to note that a higher average asset-index is positively associated with higher interest-free borrowing from family/friends.

Table 2.4 Additional explanatory variables across the three districts

Parameter	Kalahandi	Khorda	Malkangiri
% of sampled household that reported illness last month	62.3%	61.6%	51.3% [†††d]
% of sampled household that had outpatient treatment last month	60.7%	59.8%	49.1% [†††d]
Outpatient cost of household that reported illness last month (±SE) (PPP$)[a]	56.65 (±2.21)	71.74 (±3.39)	34.78 (±1.77) *** [e]
Income-proxy p.p.p.m. (±SE) (PPP$)[b]	29.94 (±0.48)	36.16 (±0.54)	31.35 (±0.46) ***
Asset-index (±SE)[c]	-0.70 (±0.04)	1.36 (±0.06)	-0.62 (±0.05) *** [f]
% of household with healthcare expenditures that reported borrowing from relatives and/or friends	15.6%	23.7%	14.2% [†††g]

*** Significance of overall difference across the three districts p<0.001 (ANOVA)
[†††] Significance of overall difference across the three districts p<0.001 (Pearson Chi-square)
[a] Average outpatient costs ± Standard Error, expressed in Purchasing Power Parity International Dollar.
[b] Income is proxied as monthly per capita consumer expenditure through questions on many items of household expenditure and expressed in Purchasing Power Parity International Dollar. SE = Standard Error.
[c] Asset-index is a proxy for socioeconomic status based on various aspects of household assets. The index is calculated using a principal component analysis (PCA). SE = Standard Error.
[d] The difference between Kalahandi and Khorda is not significant for both indicators, p=.687 and p=.593 respectively Chi2
[e] For each of the three districts the average cost is significantly different from any other district, p<.001 ANOVA
[f] The difference in average asset-index between Kalahandi and Malkangiri is not significant (p=.163 ANOVA)
[g] The difference in share between Kalahandi and Malkangiri is not significant, p=.282 Chi2

2.4 DISCUSSION

In this study we found that many households experienced hardship financing. We defined hardship financing as being exposed to a less stable or worsened financial state brought about by additional costs/losses due to borrowing or selling assets. Based on the information in our household survey we cannot quantify losses due to selling assets. However, using the amounts borrowed from different sources as reported in our household survey and assuming a standard period of 12 months for all loans, an equal monthly repayment regime, and the following interest rates per annum (48% - money-lenders, 24% - microfinance 12.5% - banks (Basu 2006, Kochar 1997)), we can estimate the additional cost of the interest payment on the loans. Households that borrowed with interest from a bank, moneylender or microfinance paid, under the above assumptions, a mean interest amount of PPP$ 64. This adds almost 24% to their healthcare costs, and represents on average nearly 5% of overall annual household expenditure excluding health expenditure. Unlike common economic theory that borrowing or selling assets would have immediate welfare in the sense that the ill person could be treated, that welfare gain comes at a cost of welfare loss that extends over a much longer period of time. The added welfare comes at varying prices, which reflects not the value of the additional consumption (in this case the cost of care) but the varying cost of financing, which is more expensive for those that resort to moneylenders than those that can resort to cheaper sources of borrowing or do not have to borrow at all.

Hardship financing occurs not only when facing the high cost of inpatient care (nearly 40%) but also outpatient care (23%). This finding is in line with a previous study where it was found that the aggregated costs of outpatient care can exceed those of inpatient care among low-income households in India (Dror et al. 2008). Interestingly our results reveal that maternity-related expenditures also cause hardship financing for a quarter of the households, although these events are known in advance and theoretically the household could save money and prepare for them. When considering the entire target population, the impact of hardship financing of outpatient care can be considered more severe than of inpatient care since 84% of the sampled households reported expenses due to outpatient care and only 24% had expenses due to inpatient care. Berman et al. (2010) have reached a similar conclusion using a different methodology. These authors compared the number of households below poverty line before and after healthcare payment as a definition of impoverishment and found that outpatient care was more impoverishing than inpatient care for households in India.

Peters (2002) reported that 40% of hospitalized patients (all-India average) had to sell assets or borrow money to pay for hospital costs. Duggal (2004) found that among the poorest quintile in India, this percentage was 50%. One would expect our result for the rural poor communities of Odisha to be similar to the percentage found for the lowest quintile. The discrepancy however could be due to the difference in definition, as we considered as hardship financing only borrowing with interest. According to these and other results (Kruk et al. 2009) it is reasonable to assume that poorer households have a higher risk to experience hardship financing. We wondered whether this difference still holds within our study-population, all of which is poor. We addressed this issue in our multivariate logistic regression by including two measures for wealth (income-proxy and asset-index). Interestingly we found that whereas a lower asset-index was associated with a higher risk of hardship financing, the association with income-proxy was not significant. This may well reflect the situation that in the informal economy many transactions are not monetized and the possession of assets is a more reliable indicator of socioeconomic status (Moser & Felton 2007). The negative association between asset-index and hardship financing could be due to asset-rich households for instance having a better chance of accessing social networks that would be more likely to give interest-free loans (non-hardship financing). It cannot be excluded though that the lower asset-index may be a result of, rather than the cause for, hardship financing, as we measure the asset-index after the health event.

Households where the household head is a salaried employee were least likely to need hardship financing compared to households where the head was self-employed in business or in agriculture, was a daily-wage labourer or did not work. As income was included in the regression as a separate parameter, the reason for the correlation with employment cannot be attributed solely to a difference in income. Perhaps the difference is due to having a steady rather than erratic flow of income. This finding would then be in agreement with our hypothesis that hardship financing can sometimes be caused by a time gap between the inflow of income and outflow of health expenses.

From our logistic regression it turned out, as could be intuitively expected, that health expenditures in the last year were significantly associated with the risk for hardship financing. However, interestingly, having had a chronic illness or hospitalization in the household in the last year were also independent significant indicators for hardship financing. This means that the presence of chronic illness or hospitalization affected the risk of hardship financing in a way which was independent of the related expenses. Both chronic illness and hospitalization generate many indirect costs (loss of income of the chronic ill patient, loss of income of the hospitalized patient and/or caretaker and transportation costs) which could independently aggravate the situation leading to hardship financing. The recurring nature of outpatient expenditures related to a chronic illness could cause depletion of savings and attrition of goodwill of others to give interest-free loans and thus increase the need for hardship financing. In the case of hospitalizations one should note that poor households usually have to pay (some) costs upfront before admission to or treatment in hospital (Duggal 2004). Therefore the unpredictable timing of hospital care and immediate need for large funds associated with such an event could increase the risk of hardship financing.

SHG membership surprisingly reported increased likelihood to have hardship financing, even though we have seen that SHG members are slightly better off than non-members (Appendix 2.1) and that better off households need less hardship financing. The explanation for this phenomenon might be that members have their savings tied up in the scheme and can therefore not liquefy those savings when needed. On the other hand, SHG members have an easier access to low-interest loans while non-members cannot easily access microfinance and low-interest loans. Therefore it is possible that SHG members would prefer this low-interest loan over borrowing from relatives/friends who may not be able to spare the money for a long time.

Finally it becomes very clear from the regression that the difference in hardship financing across the three districts could not be fully explained by the many household features included in the model. We found that the district where the household resides has a big significant independent effect on the risk of hardship financing. Using the stepwise regression method we found that when healthcare costs are introduced into the model, the difference in the risk of hardship financing between Malkangiri and Khorda became insignificant. The difference in hardship financing between Kalahandi on the one hand and Khorda and Malkangiri on the other hand remained unexplained with the current set of variables: living in Kalahandi could be associated with increased likelihood of hardship financing, because of higher utilization and costs of outpatient care compared to Malkangiri. In Khorda, both utilization and costs of outpatient care were similar to those observed in Kalahandi, yet the risk of hardship financing was significantly lower. This could be linked to the related finding that average income-proxy and asset-index in Khorda are higher than in Kalahandi (the asset index introduced in the regression takes into account the wealth of the individual household but the average asset index in the district reflects the wealth of the social network). This difference could suggest that households in Khorda have access to richer family/friends (better social network) that can provide more interest-free loans. This assumption gains credibility from the finding that a higher percentage of households in Khorda borrowed from relatives/friends, compared to Kalahandi (table 2.4).

While this study can play an important role in advancing the notion of hardship financing as a measure of the effectiveness of health financing policy alternative to the catastrophic spending method, there are some limitations to this study. Without adequate data one cannot conclude that the same findings would apply elsewhere. And, as the source of data is interviews with respondents, the regular limitations of self-reporting of incidence of illness and cost of care apply.

2.5 CONCLUSIONS

Our study sheds light on a hitherto understudied dimension of hardship of very poor rural groups occasioned by the need to raise funds to pay for healthcare out-of-pocket. We defined "hardship financing" as borrowing with interest or selling assets. The extra cost due to the interest payable on money borrowed with interest is far from negligible. We estimated the additional costs due to interest on loans to pay for illness-related costs at 24% of the health expenditure, a cost that represented nearly 5% of households' annual overall expenditure. The monetary value of the loss due to selling assets is also not zero, but hard to estimate. The hardship associated with these costs extends well beyond the duration of the health event.

This analysis has shown that hardship financing occurs not only in cases of expensive hospitalizations (40%) but also in many cases of expenditures for outpatient (23%) and maternity care (25%). Taking into account that the frequency of outpatient utilization is much higher, many more people actually face hardship financing due to outpatient care than due to inpatient care.

We have shown that possession of assets and having regular income-flow are predictors of lower expected hardship financing, and better predictors than the income-proxy of the household used in this study. The first parameter indicates the aggregate financial strength of the household in an environment where many economical transactions are not monetary. The second parameter is self-explanatory, as regular income makes it easier to plan future expenses based on stable future income. Interestingly, not only the assets of the households with out-of-pocket healthcare costs were negatively associated with hardship financing, but also the average wealth in the community in which the households resides. This indicates that hardship financing is also influenced by attributes of the social network the household can access; better access to a wealthier social network seems to increase the likelihood of obtaining interest-free loans.

Our study adds a qualitative dimension to understanding health-related financial exposure among rural poor households. Hardship financing is explained not only by how much is spent out-of-pocket on healthcare in nominal terms or relative to income or assets, but also by when the payment occurs, and, as is the case with chronic illness, its frequency and duration. This important finding that rural poor households are subjected to considerable and protracted financial hardship due to the indirect and longer-term deleterious effects of how they cope with out-of-pocket healthcare costs points to the need to develop a policy solution that would limit that exposure both in quantum and in time. We therefore conclude that policy interventions aiming to ensure health-related financial protection would have to demonstrate that they have reduced the frequency and the volume of hardship financing.

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Appendix 2.1 Demographics & socioeconomic status disaggregated for members and non-members

	Non-member sub-cohort[a]	Member sub-cohort[a]
	Mean (±SE[b])	Mean (±SE[b])
Income-proxy p.p.p.m (PPP$)[c]	31.98 (±0.42)	32.84 (±0.39) [NS]
Asset-index[d]	-0.16 (±0.04)	0.16 (±0.05)***
Household size	4.66 (±0.04)	4.86 (±0.03)***
Ratio infants (0-4) in household	0.085 (±0.003)	0.078 (±0.002)*
Ratio elderly (60 and older) in household	0.080 (±0.003)	0.070 (±0.003)**
Caste[e]	% of total	% of total
Scheduled Tribe	30.8%	29.2%
Scheduled Caste	21.8%	22.8%
Other Backward Caste	29.8%	32.7%
General Caste	17.6%	15.3% ††
Education level household head		
No education	52.8%	49.9%
Class 1-5	20.7%	23.7%
Class 6-10	23.6%	23.9%
Class 11 and higher	2.9%	2.5% ††
Occupation household head		
Self-employed agriculture	38.5%	38.9%
Self-employed business/trade	14.6%	17.6%
Regular Salaried employee	3.9%	5.3%
Daily wage labourer	33.0%	28.5%
Not working	10.0%	9.7% †††
Source of drinking water		
Own tap	8.7%	11.0%
Shared tap	54.9%	52.9%
Hand pump/well	36.4%	36.1% ††
Toilet facility		
Own flush toilet	4.0%	4.8%
Own pit toilet	4.2%	5.7%
Shared toilet	1.1%	1.0%
No toilet	90.7%	88.6% ††

NS = non-significant difference between member and non-member sub-cohorts
* Significance of difference between member and non-member sub-cohorts $p<0.1$ (ANOVA)
** Significance of difference between member and non-member sub-cohorts $p<0.05$ (ANOVA)
*** Significance of difference between member and non-member sub-cohorts $p<0.001$ (ANOVA)
[††] Significance of difference in distribution between member and non-member sub-cohorts $p<0.05$ (Pearson Chi-square)
[†††] Significance of difference in distribution between member and non-member sub-cohorts $p<0.001$ (Pearson Chi-square)
[a] Comparison of the two sub-cohorts in our dataset: households where at least one person in the household was member of a Self-Help Group (SHG) linked to one of the related NGOs (member sub-cohort) and households where no one in the household was member of a Self-Help Group (SHG) linked to one of the related NGOs (non-member sub-cohort).
[b] SE = Standard Error.
[c] Income is proxied as monthly per capita consumer expenditure through questions on many items of household expenditure and expressed in Purchasing Power Parity International Dollar.
[d] Asset-index is a proxy for socioeconomic status based on various aspects of household assets. The index is calculated using a principal component analysis (PCA).
[e] Caste is a proxy for socioeconomic status in India. Scheduled Castes (Dalits and those sometimes labelled "untouchable") are considered at the bottom of caste hierarchy. The list of Other Backward Castes is quite dynamic and changes from time to time in many states. All other castes are described here as General Caste.

Appendix 2.2 Morbidity, healthcare availability, utilization and cost disaggregated for members and non-members

	Non-member sub-cohort[a]	Member sub-cohort[a]
	Mean (±SE[b])	Mean (±SE[b])
Total health expenditure last year for household (PPP$)[c]	159.32 (±7.62)	175.33 (±6.89)[NS]
Distance to preferred hospital (in minutes)	51.93 (±0.76)	53.03 (±0.76)[NS]
Distance to preferred primary care practitioner (in minutes)	30.37 (±0.56)	30.43 (±0.56)[NS]
	% of total	% of total
Household with chronic ill person	9.7%	11.3% †
Household with hospitalization costs last year	22.3%	24.7% ††
Household with outpatient care costs last year	82.9%	84.7% †
Household with maternity costs last year	15.3%	13.5% †
Household with any healthcare costs last year	84.2%	85.9% †
Hospital household usually goes to		
Private	6.5%	6.0%
Public	93.5%	94.0% [NS]
Preferred primary care practitioner household usually goes to		
Traditional healer	35.6%	37.5%
Government facility	51.4%	49.5%
Unqualified private doctor (non-MBBS)[d]	7.8%	07.4%
AYUSH practitioner[e]	3.4%	0 3.0%
Qualified private doctor/specialist (MBBS)	1.7%	2.7% †

NS = non-significant difference between member and non-member sub-cohorts

† Significance of difference in distribution between member and non-member sub-cohorts $p<0.1$ (Pearson Chi-square)

†† Significance of difference in distribution between member and non-member sub-cohorts $p<0.05$ (Pearson Chi-square)

[a] Comparison of the two sub-cohorts in our dataset: households where at least one person in the household was member of a Self-Help Group (SHG) linked to one of the related NGOs (member sub-cohort) and households where no one in the household was member of a Self-Help Group (SHG) linked to one of the related NGOs (non-member sub-cohort).

[b] SE = Standard Error.

[c] Total health expenditure last year for household expressed in Purchasing Power Parity International Dollar.

[d] Unqualified private doctor (non-MBBS) is a doctor practicing allopathic medicine without having a medical degree (Medical Bachelor and Bachelor of Surgery).

[e] AYUSH is the aggregate of all qualified systems of traditional medicines in India: Ayurveda, Yoga and Naturopathy, Unani, Siddha and Homeopathy.

Chapter 3

Can the rural poor in India afford to treat non-communicable diseases?

Based on: Binnendijk, E., Koren, R., Dror, D.M.
Can the rural poor in India afford to treat non-communicable diseases?
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ABSTRACT

Objective Non-communicable diseases (NCDs) are on the increase in low-income countries, where healthcare costs are paid mostly out-of-pocket. We investigate the financial burden of NCDs vs. communicable diseases (CDs) among rural poor in India and assess whether they can afford to treat NCDs. ***Methods*** We used data from two household surveys undertaken in 2009–2010 among 7389 rural poor households (39 205 individuals) in Odisha and Bihar. All persons from the sampled households, irrespective of age and gender, were included in the analysis. We classify self-reported illnesses as NCDs, CDs or 'other morbidities' following the WHO classification. ***Results*** Non-communicable diseases accounted for around 20% of the diseases in the month preceding the survey in Odisha and 30% in Bihar. The most prevalent NCDs, representing the highest share in outpatient costs, were musculoskeletal, digestive and cardiovascular diseases. Cardiovascular and digestive problems also generated the highest inpatient costs. Women, older persons and less-poor households reported higher prevalence of NCDs. Outpatient costs (consultations, medicines, laboratory tests and imaging) represented a bigger share of income for NCDs than for CDs. Patients with NCDs were more likely to report a hospitalisation. ***Conclusions*** Patients with NCDs in rural poor settings in India pay considerably more than patients with CDs. For NCD cases that are chronic, with recurring costs, this would be aggravated. The cost of NCDs care consumes a big part of the per person share of household income, obliging patients with NCDs to rely on informal intra-family cross-subsidisation. An alternative solution to finance NCD care for rural poor patients is needed.

3.1 BACKGROUND

Non-communicable diseases (NCDs) are leading causes of death globally, but nearly 80% of NCD deaths occurred in low- and middle-income countries (WHO 2011a). In 2004, nearly 60% of deaths worldwide were because of NCDs, and around 23% because of communicable diseases (CDs) (WHO 2008). In India, these percentages were 50% and 28%, respectively (WHO 2004b). NCDs are also responsible for the biggest part of disease burden as assessed by disability-adjusted life-years (DALYs[3]), both worldwide and in the south-east Asian region (48% and 44%, respectively, in 2004) (WHO 2008). NCD deaths are projected to increase by 15% globally between 2010 and 2020; in south-east Asia, this increase could even be more than 20% and is a major barrier to the development (WHO 2011a).

In India, around 70% of total health expenditure is paid out-of-pocket (WHO 2011a) and caused some 7% of rural households to drop below poverty line in 1 year (Berman et al. 2010). Any intervention aiming to reduce financial shocks because of illness needs information on prevalence and cost. As a higher burden of NCDs is unavoidable, better insights are needed on the morbidity of NCDs and the changing implications for out-of-pocket healthcare expenditures.

Most of the literature on NCDs deals with reducing the impact of NCDs by addressing a number of risk factors underlying most high-burden NCDs (e.g. tobacco use, physical inactivity, unhealthy diet, alcohol abuse). The aim of this literature is to have countries address these risk factors in prevention programs and reduce the burden of these NCDs. The burden is investigated mainly through mortality (premature death) and disability (DALY) because of NCDs (WHO 2011a, Beaglehole et al. 2011, Dans et al. 2011, Kinra et al. 2010, Lopez et al. 2006, Boutayeb & Boutayeb 2005, Murray & Lopez 1997). However, the information about the number of patients afflicted with NCDs and the financial consequence of NCDs is sorely rare. Some information is available about the prevalence of certain NCDs but not all. The rare studies that deal with the financial burden, also deal with specific NCDs. We found one study looking at cost implications of NCDs for all India (Engelgau et al. 2012), based on data from 1995 to 1996 and 2004 of the National Sample Survey Organization that provides important insights. For example, in 2004, almost 50% of out-of-pocket health expenses were on NCDs and medicines represented 46% of total out-of-pocket health spending (Engelgau et al. 2012). To the best of our knowledge, no study examined the financial implications of NCDs amongst the most vulnerable segment of society in India: the rural poor.

3. Quantification of the burden of disease which simultaneously considers both premature death (number of years of life lost due to premature death) as well as the non-fatal health consequences of disease and injury (number of years lived with a disability) (Murray 1994).

The purpose of this article is to examine the financial implications of NCDs relative to CDs among rural poor communities in two states of India (Odisha and Bihar), taking into account the prevalence of illness categories, and age and income of the ill persons.

3.2 DATA AND METHODS

3.2.1 Setting and sampling

We used data from two household surveys conducted in rural areas of Odisha (Kalahandi, Khorda and Malkangiri districts, January 2009) and Bihar (Gaya district, May–June 2010). Average monthly per capita consumer expenditure for rural Odisha (INR 559, PPP$ 35.5) is lowest of all states in India; average expenditure for rural Bihar (INR 598, PPP$ 38.0) is fourth lowest (after Odisha, Chhattisgarh and Jharkhand) (NSSO 2010b). These studies formed part of a baseline study to initiate rural micro-health insurance programmes, and the locations were selected in agreement with implementing local non-government organizations (NGOs[4]).

We followed a two-stage sampling procedure in each state. In stage 1, 130 villages (27 in Kalahandi, 22 in Khorda, 31 in Malkangiri and 50 in Gaya) were selected randomly from lists that local NGOs provided where they organised self-help groups (SHGs[5]); in Gaya, 50 additional villages were selected randomly from Census 2001 registry. In stage 2, households in each village were sampled randomly by applying the 'four winds' (or 'line sampling') technique (Som 1996). Only households where an adult was available at the time of the survey were sampled[6]. Households were sampled in two cohorts of equal size: member (if at least one person participated in an SHG linked to partner-NGOs) and non-member households. Sample size was 5383 households in Odisha (25 885 individuals) and 2006 households in Bihar (13 320 individuals). Hundred percentage of the sample was rural.

The survey questionnaire was translated from English into local languages (Oriya and Hindi), back translated for verification, and pre-tested in each state among 80 households. Surveyors fluent in local dialects conducted the interviews. In principle,

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4. In Odisha the Madhyam Foundation [comprising 11 grassroots NGOs: Parivartan, PUSPAC, SOMKS, SDS, ODC (Malkangiri); Mahashakti Foundation, DAPTA, Lok Yojana, Sanginee (Kalahandi); MVPS, DSS (Khorda)] and in Bihar BASIX.

5. SHGs represent a unique approach to financial intermediation in communities. The approach combines access to low-cost financial services with a process of self-management and development for the SHG members. SHGs are seen to confer many benefits, both economic and social.

6. In rural India most of the time an adult is in the house or can be found near the house, and is willing to participate in an interview.

one household member reported for all household members, but usually more persons were present to help. We obtained informed consent of the respondents and kept confidential participants' names in data recording and analysis. This research project met all the requirements of the funding agency (NWO-WOTRO) on ethical issues arising in social science research.

3.2.2 Data

The data collected included general demographics of household members (age, gender, education, and economic activity), distance to their habitual primary care practitioner (min) and information on household expenditures. We obtained an income-proxy through questions on many items of household expenditure, following the method of the Indian National Sample Survey Organization (2008). Our 'income-proxy' is the monthly per capita consumer expenditure excluding healthcare costs, because we seek to identify patterns of financing healthcare (Flores et al. 2008, Wagstaff 2008).

The household survey also included questions on illness episodes and illness-related outpatient expenditures of household members during 1 month preceding the survey, and hospitalisations (exceeding 24 h) with related costs during 1 year preceding the survey. Information about the episodes was queried through open questions on the illness or symptoms that caused the episode. Illnesses that were clearly different or occurred at different periods were treated as separate episodes. Information about per-episode outpatient expenditures was collected, including consultation fees of qualified allopathic practitioners, and expenditures for medicines, laboratory and imaging tests. The self-reported illnesses or symptoms were categorised, following the WHO classifications (WHO 2008), as specific categories of NCDs, CDs and 'other morbidities' (injuries, maternal, perinatal or nutritional conditions). Ailments that could not be well defined based on the reported symptoms were categorized as 'missing'. This classification of illnesses was carried out by two of the authors with some medical background, in consultation with a clinician who practiced in rural India.

3.2.3 Analysis

All persons from the sampled households, irrespective of age and gender, were included in the analysis. The significance of difference between means was tested by a two-tailed t-test and the significance of difference of frequencies was established by chi-square tests. We aggregated the member and non-member sub-cohorts in each state for the purpose of the analysis reported here as we found no significant difference in frequency of reported illness episodes.

We measured the inequality of reported illness episodes by income proxy, using concentration indices. An index of zero indicates there is no inequality, a negative (positive) index a disproportionate concentration of the health indicator among the poor (rich)

(O'Donnell et al. 2008). We show two versions of the index: the index as described by O'Donnell et al. (2008) and a corrected index as suggested by Erreygers (2009). We used STATA version 11.1 (StataCorp, Texas, USA) for all the analyses.

All amounts, reported in Indian rupee (INR), were converted into international dollars (purchasing power parity, PPP$) using the exchange rate of PPP$ 1 = INR 16.692 for 2009 and 18.073 for 2010. The amounts from the National Sample Survey Organization report of 2009/2010 were converted using the average exchange rate for the 2 years (17.383). For the report of 2007/2008, this rate was 15.727 (15.323 + 16.13/2) (IMF 2012).

3.3 RESULTS

3.3.1 Socio-economic status of studied populations

In both populations, the income proxy is on average around the poverty line: about PPP$ 1 per person per day in Odisha and PPP$ 1.5 in Bihar. Considering the relevant data from the Indian National Sample Survey Organization (NNSO), we found that our sampled populations were comparable to the rural averages of their states. Most people depend on hard physical labour for their income as daily wage labourers (e.g. in agriculture, load carrying, construction) or self-employment in agriculture (39.5% in Odisha and 45.3% in Bihar). A minority (12.8% in Odisha and 6.5% in Bihar) is employed in what can be considered sedentary work (salaried employee or self-employed in business/trade, mainly shopkeepers, teachers). In both locations, 46% of the adult population did not have any education. In Bihar, 41% of the adult population have finished class 6 and higher compared to 36% in Odisha. This information is shown in Table 3.1.

Around 17% of the surveyed individuals in Odisha and 31% in Bihar reported an illness episode in the month preceding the survey. Nearly 5.5% of the sampled population in Odisha and 2.5% in Bihar incurred a hospitalization in the year preceding the survey. Respondents in Bihar reported that they needed 18 min on average to reach their preferred primary practitioner and in Odisha, 30 min.

3.3.2 Prevalence and classification of self-reported illness episodes

In rural Odisha or Bihar, there are no official records about illness or treatment in the population. Our source of information on morbidity to classify illnesses as 'NCD', 'CD' or 'other morbidity' (Table 3.2) has therefore been the self-reported symptoms from our surveys.

Non-communicable diseases accounted for around 20% of all diseases in Odisha and 30% in Bihar. CDs were responsible for most of the illness episodes. The three most prevalent categories of NCDs in both locations were musculoskeletal, digestive and cardiovascular problems. The population reporting NCDs was significantly older than

Table 3.1 Socio-economic and demographic status of studied populations

	Odisha (N=25,885)	NSSO[a] Rural Odisha	Bihar (N=13,320)	NSSO[a] Rural Bihar
	% of sampled population			
Gender				
Male	50.6%		51.0%	
Female	49.4%		49.0%	
Missing	0.05%		0.0%	
Age distribution				
Infant (under 5)	8.9%	9.3%	11.8%	11.7%
Child (5-14 yrs. old)	22.7%	21.9%	28.5%	28.8%
Young Adult (15-29 yrs. old)	26.0%	25.8%	25.3%	23.1%
Adult (30-44 yrs. old)	22.0%	21.3%	17.5%	20.4%
Midlife (45-59 yrs. old)	13.0%	14.2%	9.5%	10.6%
Old Age (over 60)	7.3%	7.4%	7.5%	5.3%
Missing	0.2%	0.0%	0.0%	0.0%
Education of adult population (15 yrs. and older)[b]				
No education	45.7%		45.8%	
Class 1-5	17.0%		12.2%	
Class 6-10	29.3%		32.6%	
Class 11 and higher	6.5%		8.3%	
Missing	1.5%		1.1%	
Economic activity of adult population (15 yrs. and older)[b]				
Daily wage labourer	20.7%		32.7%	
Self-employed in agriculture	18.2%		12.2%	
Self-employed in business/trade	9.4%		3.6%	
Regular salaried employee	3.2%		2.8%	
Domestic duties	32.2%		28.1%	
Other[c]	14.6%		19.7%	
Missing	1.8%		1.0%	
Illness episode in month preceding survey	17.0%		31.0%	
Hospitalized (for more than 24 hours) in year preceding survey	5.6%		2.5%	
	Mean (±SE[d])			
Distance to preferred primary care practitioner (in minutes)	29.95 (±0.18) (1.2% missing)		18.21 (±0.16) (0.0% missing)	
Income-proxy p.p.p.m. (PPP$)[e]	30.09 (±0.13) (4.7% missing)	35.54	43.84 (±0.28) (0.5% missing)	44.87

[a] National statistics data from National Sample Survey Organization of India (NSSO). Information shown for rural Odisha is from 2007/2008 (NSSO 2010a, NSSO 2010b) and for rural Bihar from 2009/2010 (NSSO 2011a, NSSO 2011b), periods that correspond best to the time when our data was collected.
[b] Adult population: N=17,716 in Odisha; N=7,954 in Bihar.
[c] Other can mean going to school, being unemployed, disabled or pensioned.
[d] SE = Standard Error.
[e] Income is proxied as monthly per capita consumer expenditure through questions on many items of household expenditure and expressed in Purchasing Power Parity International Dollar.

the population experiencing CDs (P < 0.001, t-test, both locations). The average age of patients with NCDs was 42.1 (±0.6) and 37.9 (±0.6) years old, while the average age of patients with CDs was 27.2 (±0.4) and 21.1 (±0.4) years in Odisha and Bihar, respectively.

Women were more afflicted with an illness (P < 0.05 in Odisha, P < 0.001 in Bihar, chi-square test). However, this effect was more pronounced for the prevalence of NCDs than CDs (P < 0.001, chi-square test, both locations): in Odisha, of those who reported NCDs last month, 59.0% were women and of those who reported CDs last month 51.1% were women. In Bihar, respectively, 65.3% and 53.9% were women.

Table 3.2 Classification of self-reported illness episodes

	% of illness episodes		% of NCDs	
	Odisha (N=4443)	Bihar (N=4217)	Odisha (N=917)	Bihar (N=1253)
NCDs	20.64%	29.71%		
(Malignant) Neoplasms			*0.87%*	*1.92%*
Diabetes Mellitus			*2.73%*	*1.44%*
Endocrine disorders			*0.22%*	*0.32%*
Neuropsychiatric conditions			*6.22%*	*3.27%*
Sense organ diseases			*0.11%*	*1.20%*
Cardiovascular diseases			*20.72%*	*10.45%*
Respiratory diseases			*5.67%*	*4.39%*
Digestive diseases			*23.45%*	*35.12%*
Genitourinary diseases			*2.07%*	*2.47%*
Skin diseases			*5.02%*	*4.31%*
Musculoskeletal diseases			*28.14%*	*32.16%*
Congenital anomalies			*0.44%*	*0.00%*
Oral conditions			*2.73%*	*2.47%*
Rest			*1.64%*	*0.48%*
CDs	73.73%	51.93%		
Other morbidities[a]	5.25%	18.36%		
Missing[b]	0.38%	0.00%		

[a] The group 'other morbidities' is comprised of injuries, maternal, perinatal or nutritional conditions.

[b] Ailments that could not be well defined based on the reported symptoms were categorized as 'missing'.

3.3.3 Outpatient health-seeking and expenses by illness types

We explored health-seeking behaviour and costs with three types of healthcare providers: government health facility, private general practitioner (GP) and private specialist (Table 3.3).

Table 3.3 Frequency of access and costs of consultations

	% of ill cases where treatment was sought[a]		Average cost per visit (±SE[b]) (PPP$[c])	
Treatment sought with:	Odisha	Bihar	Odisha	Bihar
Government health facility				
NCDs	68.9%	10.0%†††	1.43 (±0.40) (3.7% missing)	1.22 (±0.41) (0.0% missing)
CDs	69.3%	6.0%	1.41 (±0.11) (4.8% missing)	0.86 (±0.23) (0.0% missing)
Private GP				
NCDs	15.9%††	21.6%†††	5.09 (±0.67) (1.5% missing)	6.19 (±0.51) (0.4% missing)
CDs	11.6%	13.6%	5.19 (±0.50) (3.9% missing)	5.81 (±0.65) (0.0% missing)
Private specialist				
NCDs	20.8%†††	9.6%†††	8.00 (±1.06)** (4.5% missing)	11.08 (±1.50)* (0.0% missing)*
CDs	6.8%	3.8%	4.66 (±0.56) (1.0% missing)	6.52 (±0.78) (0.0% missing)

[a] N=917 NCD cases and 3276 CD cases in Odisha; N=1253 NCD cases and 2190 CD cases in Bihar. Information on treatment was missing for 23 of the CD cases in Odisha (0.7%); no information was missing for the NCD cases in Odisha or CD and NCD cases in Bihar.
[b] SE = Standard Error.
[c] PPP$ = Purchasing Power Parity International Dollar.
†† Significance of difference in percentage of people that sought treatment with one of the listed providers out of the persons who reported either NCD or CD last month $p<0.01$ (Chi-square)
†††Significance of difference in percentage of people that sought treatment with one of the listed providers out of the persons who reported either NCD or CD last month $p<0.001$ (Chi-square)
*Significance of difference in cost between NCDs and CDs $p<0.05$ (t-test)
**Significance of difference in cost between NCDs and CDs $p<0.01$ (t-test)

Patients with NCDs accessed healthcare providers more frequently (except government facility in Odisha). This more frequent health seeking is most manifested in consultations with private specialists. Both in government facilities and at private GPs, patients with NCDs paid about the same per visit as patients with CDs, but private specialists were costlier per visit for patients with NCDs.

Outpatient costs often include medicines, laboratory and imaging tests. The average costs for these services are shown in Table 3.4. Two main findings emerge clearly: outpatient costs were lower in Bihar than in Odisha and patients with NCDs had higher costs than patients with CDs for all treatment categories. Aggregating all outpatient costs, patients with NCDs reported about double the costs of patients with CDs, in both locations. Medicines were the costliest item in all cases.

Table 3.4 Outpatient expenditures

	Average cost last month (±SE[a]) (PPP$[b])	
	Odisha	Bihar
Consultations with qualified practitioners		
NCDs	4.86 (±0.52)†††	3.30 (±0.30)†††
CDs	2.31 (±0.13)	1.55 (±0.15)
Medicines		
NCDs	45.24 (±2.52)†††	12.71(±1.10)†††
CDs	26.31 (±0.87)	6.52 (±0.68)
Lab tests		
NCDs	2.56 (±0.38)††	0.76 (±0.19)†
CDs	1.92 (±0.09)	0.34 (±0.05)
Imaging		
NCDs	1.64 (±0.26)†††	0.94 (±0.16)†††
CDs	0.37 (±0.06)	0.14 (±0.04)
Total outpatient expenditures		
NCDs	53.49 (±2.86)††† (2.18% missing)	17.27 (±1.28)††† (0.9% missing)
CDs	30.51 (±0.94) (2.0% missing)	8.45 (±0.75) (0.4% missing)

[a] SE = Standard Error.
[b] PPP$ = Purchasing Power Parity International Dollar.
†Significance of difference in cost between NCDs and CDs p<0.05 (t-test)
††Significance of difference in cost between NCDs and CDs p<0.01 (t-test)
†††Significance of difference in cost between NCDs and CDs p<0.001 (t-test)

3.3.4 Income and the frequency of disease and its cost

We examined the association between income proxy and reported prevalence of NCDs and CDs (Table 3.5). The positive concentration indices describing NCDs show a significant 'pro-rich' distribution: NCDs were reported more frequently by higher income segments of the study populations, more so than CDs. This trend was consistent when calculated according to O'Donnell et al. (2008) and according to Erreygers (2009).

Having found that the prevalence of NCDs was higher amongst the higher income segments of our sampled rural poor and that NCDs were costlier than CDs, we examined whether the two phenomena cancelled each other out. We therefore calculated out-patient costs (reported for last month) as percentage of income proxy (per person per month), both for NCD and CD cases. The percentage spent by NCDs was significantly and materially higher than by CDs, (P < 0.001, t-test, both locations). In Odisha, patients with CDs spent on average 125.6% (±4.8%) of income proxy while patients with NCDs spent on average 180.6% (±10.6%). In Bihar, these percentages were 21.1% (±1.5%) and 41.4% (±3.0%), respectively. Even though NCDs were more prevalent among higher income

Table 3.5 Association between income and prevalence of illness

	Concentration Index as described by O'Donnell et al. (2008) (±SE[a])		Concentration Index as described by Erreygers (2009) (±SE[a])	
	Odisha	Bihar	Odisha	Bihar
NCD	0.157 (±0.019)	0.115 (±0.016)	0.022 (±0.003)	0.044 (±0.007)
CD	0.022 (±0.010)	0.027 (±0.011)	0.011 (±0.005)	0.018 (±0.007)

[a] SE = Standard Error.

segments, the treatment costs for NCDs represented a bigger share of their income. It can be expected that in case of chronic NCDs, these expenses will be incurred again in other months during the year.

The percentages above also indicate that patients in Bihar (both CDs and NCDs) spent a much lower share of income on outpatient healthcare than in Odisha. The difference across locations seems to be because of two reasons: in Bihar (i) average income was higher and (ii) mean outpatient costs were lower.

3.3.5 Inpatient treatment and expenditure

We also examined the risk and cost of hospitalisations. Persons who reported an NCD (last month) were more likely to be hospitalised (last year) than the sampled population without NCDs: in Odisha 15.5% vs. 5.2%, in Bihar 5.0% vs. 2.2% ($P < 0.001$, chi-square test). The average cost of hospitalisation was comparable: in Odisha PPP$ 312 (±53) for patients with NCDs and PPP$ 197 (±9) for the sampled population without NCDs; in Bihar PPP$ 425 (±81) and PPP$ 380 (±40), respectively.

3.3.6 Share of NCD categories in outpatient and inpatient expenditures

Finally, we analysed which category of NCDs was the costliest with respect to overall outpatient and inpatient expenditures (Figure 3.1). The relative share of costs is determined by the frequency of an NCD category and its severity in terms of aggregated cost.

The two NCD categories that contributed most to overall outpatient expenditures (both locations) were digestive and musculoskeletal problems, followed by cardiovascular and neuropsychiatric conditions. With respect to overall inpatient expenditures, digestive and cardiovascular diseases were amongst the three costliest. Neuropsychiatric, genitourinary and musculoskeletal problems were also important contributors to the overall costs in both locations. The cost of malignancies in Odisha seems to be much higher than in Bihar but is probably due to a small number of outliers as only a modest percentage of hospitalisations was because of cancers (9% in Odisha, 6% in Bihar).

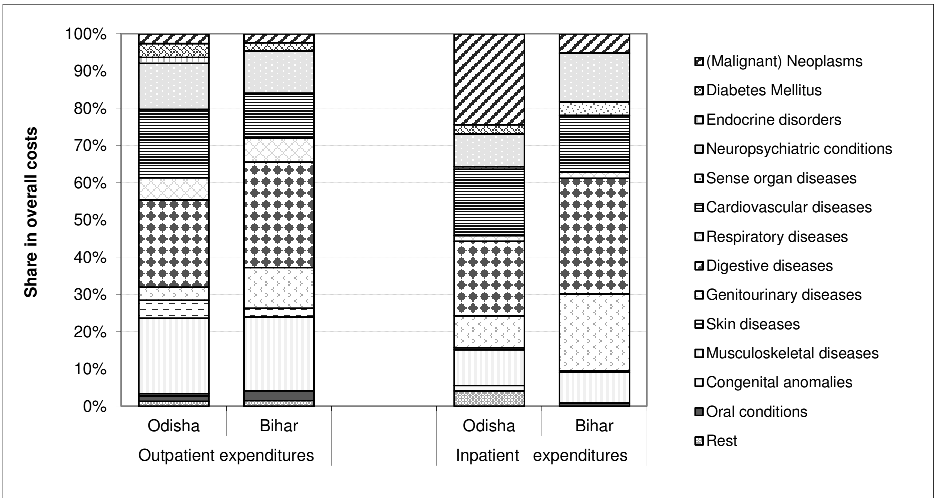

Figure 3.1 Share of non-communicable disease (NCD) categories in outpatient and inpatient expenditures

3.4 DISCUSSION

The analysis of the financial burden of NCDs on rural poor households in two states in India presented here differs from much of the literature on NCDs in that it considers the information on prevalence and treatment cost of NCDs, in general, and by the category of NCDs, rather than deaths or DALYs associated with NCDs. We found that, while CDs represent the major share of self-reported illnesses, the prevalence of NCDs is considerable, with about 20% of illness episodes in Odisha and 30% in Bihar. With increasing age (Lee & Mason 2011) and with a higher prevalence of NCDs amongst the elderly, this percentage is likely to increase in the future.

Amongst the NCDs, the three most prevalent in our study populations were musculoskeletal, digestive and cardiovascular diseases. These categories also represented the highest share of outpatient expenditures. Cardiovascular and digestive diseases generated the highest inpatient costs. The morbidity profile usually associated with NCDs (cardiovascular problems, diabetes, cancers and chronic long conditions) (WHO 2011a) is not replicated in our study. Instead, we see higher prevalence of NCDs related to lifestyle, occupational and nutritional conditions of the rural poor which are exposed simultaneously to (i) very hard physical labour as daily wage labourers (e.g. in agriculture, load carrying, construction) or self-employment in agriculture (Table 3.1), (ii) unstable and irregular nutrition because of poverty that can cause cardiovascular diseases (Van Abeelen et al. 2012, Vorster & Kruger 2007) and (iii) not very hygienic living conditions (ADB 2009, Khurana & Sen 2008, Nath 2003).

It is commonly claimed that poorer population segments are in worse health, also in low- and middle-income countries (Hosseinpoor et al. 2012). Our results showed, however, that self-reported illnesses, particularly NCDs, are more frequent among the wealthier segments of the studied populations. This finding is in accordance with a previous report of positive association between household income and self-reported incidence among poor in India (Dror et al. 2009b). Engelgau et al. (2012) also found that in India spending on NCDs as share of income increases by income. As we investigate the lowest income segments only, it is possible that members of the poorest households cannot afford to stop daily activities for illnesses perceived as minor, and therefore they do not report them.

Analysis of the expenditure patterns of NCDs revealed several important insights. First, patients with NCDs sought care with private practitioners (GP or specialist) more frequently than patients with CDs, even though these practitioners charge more than government facilities. In fact, patients with NCDs even reported higher fees per visit with specialists than patients with CDs. The public sector in India, especially the more peripheral facilities, commonly suffers from shortages in qualified staff and supply. The population therefore is sceptical about quality of public sector services (Reddy et al. 2011a, Peters et al. 2002, Berman 1998). Viewed in combination with the possibility that patients with NCDs consider their illness as requiring more serious diagnosis and treatment than CDs, they might decide, despite their poverty, to prefer costlier private care.

Second, patients with NCDs reported paying more for all types of outpatient care (consultations, medicines, tests) and medicines came out to be the costliest component of outpatient care. These findings are in line with those of Dror et al. (2008) that medicines were the largest component of healthcare costs for chronic care and of Engelgau et al. (2012) that patients with NCDs had to bear higher costs for consultations and medicines than other patients.

Third, despite the higher prevalence of NCDs among the less poor of our sampled rural poor, the cost for NCDs represented a bigger portion of the patient's share in household income than CDs. In this analysis, we looked at outpatient costs paid out-of-pocket during 1 month only. For chronic NCDs [many of the illnesses categorised as NCD can be considered chronic (WHO 2011a, Beaglehole et al. 2011, Dans et al. 2011)], clearly these costs can accumulate to a significant portion of the patient's share of income over the year. Such high costs we believe can only be met when considerable cross-subsidisation occurs within the household (other household members' share of income has to be used to pay the patient's treatment). When such informal cross-subsidisation is unavailable, access to care becomes unaffordable. This would presumably be more likely in small households composed of older persons only, or in poorer households. Indeed the higher reporting of NCDs by households with more financial resources strengthens the impression that the diagnosis of and treatment for NCDs strongly depends on intra-household cross-subsidisation.

Finally, patients with NCDs were more likely to be hospitalised than the population without an NCD. And, even though the cost of a hospitalisation was comparable for NCD and non-NCD cases, this higher incidence of hospitalisations places an additional financial burden on patients with NCDs.

At the time our surveys were conducted, the surveyed populations in Odisha and Bihar had practically no access to health insurance. The Government of India introduced hospitalisation insurance [Rashtriya Swasthya Bima Yojana (RSBY)] in 2008, which, however, was not implemented in the studied areas until much later (GOI 2012a). The information on enrolment, renewals and payment of claims is for the time being limited. Moreover, RSBY usually covers only the cost of care in an empanelled hospital. It has been shown here that most of the financial problems of patients with NCDs arise from financing outpatient care. As this paper goes to print, the Government of India is piloting the expansion of RSBY to include outpatient care; however, it is unclear whether this pilot will be generalised, or which services would be included under RSBY in the future (GOI 2012b, GOI 2011c).

The big differences across the two locations included in this study do not change the general conclusion regarding the unaffordability of NCD care, or regarding the reliance of chronic NCD cases on intra-household subsidization of their care costs. However, these big differences in reporting illnesses deserve some considerations. The higher income, better education and shorter travel time to primary care practitioners in Bihar, compared to Odisha (Table 3.1), may have contributed to the big difference in number of reported illness episodes; in Bihar, the sampled population had almost twice as many episodes compared to Odisha. On the other hand, the average treatment costs were higher in Odisha than in Bihar (Table 3.4) and several reasons could explain this: supply aspects (e.g. fewer providers), clinical aspects (e.g. morbidity that is more expensive to cure, or differences in seasonal morbidity).

This study offers a first estimation of the size of the problem of financing access to NCD-related care. On the basis of the results of this study, more qualitative questions could arise, such as, why is treatment sought with certain providers? Is there non-compliance of treatment and why (not)? These and similar questions could be addressed in a qualitative follow-up study.

A limitation of this study is that the data used for the analyses are self-reported. Reporting of the type, frequency, severity and cost can obviously suffer from recall bias and other biases, for example, underreporting of illnesses perceived as minor especially among the poorer households, or inaccurate reports by one household member of illnesses incurred by others.

3.5 CONCLUSIONS

Patients with NCDs in rural poor settings in India pay considerably more for the treatment than patients with CDs. This trend might be aggravated in the case of chronic NCDs because of the expected recurrence of outpatient expenditures, which in this study were analysed only for 1 month. It is self-explanatory that chronicity is less likely with CDs. This trend is likely to worsen over time because incidence, prevalence and chronicity are expected to increase with changes in lifestyle and extension of life-expectancy (WHO 2011a, WHO 2008, Lopez et al. 2006).

In the absence of any systemic solution (like insurance) to deal with the financing of access to care, we believe patients suffering from NCDs rely on intra-household cross-subsidisation to pay for their care. This cross-subsidisation can work for as long as the proportion of NCD cases in the overall household population remains relatively small; but this proportion is likely to increase because of expected decrease in household size (GOI 2001b) and increase in age. Consequently, the ability of households to continue funding family members requiring NCD care will decrease and could lead to lower drug and treatment compliance. This conclusion clearly points to the urgent need to develop suitable policy solutions which would allow rural poor populations to afford care for NCDs even as NCDs are expected to increase. Such policy choices would have to cover outpatient care in view of its major contribution to the financial burden of patients with NCDs.

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Chapter 4

'First we go to the small doctor': First contact for curative healthcare sought by rural communities in Andhra Pradesh & Odisha, India

Based on: Gautham, M., Binnendijk, E., Koren, R., Dror, D.M.
'First we go to the small doctor': First contact for curative healthcare sought by rural communities in Andhra Pradesh & Odisha, India.
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ABSTRACT

Objective Against the backdrop of insufficient public supply of primary care and reports of informal providers, the present study sought to collect descriptive evidence on 1st contact curative health care seeking choices among rural communities in two States of India - Andhra Pradesh (AP) and Odisha. ***Methods*** The cross-sectional study design combined a Household Survey (1,810 households in AP; 5,342 in Odisha), 48 Focus Group Discussions (19 in AP; 29 in Odisha), and 61 Key Informant Interviews with healthcare providers (22 in AP; 39 in Odisha). ***Results*** In AP, 69.5 per cent of respondents accessed non-degree allopathic practitioners (NDAPs) practicing in or near their village; in Odisha, 40.2 per cent chose first curative contact with NDAPs and 36.2 per cent with traditional healers. In AP, all NDAPs were private practitioners, in Odisha some pharmacists and nurses employed in health facilities, also practiced privately. Respondents explained their choice by proximity and providers' readiness to make house-calls when needed. Less than a quarter of respondents chose qualified doctors as their first point of call: mostly private practitioners in AP, and public practitioners in Odisha. Amongst those who chose a qualified practitioner, the most frequent reason was doctors' quality rather than proximity. ***Conclusions*** The results of this study show that most rural persons seek first level of curative healthcare close to home, and pay for a composite convenient service of consulting-cum-dispensing of medicines. NDAPs fill a huge demand for primary curative care which the public system does not satisfy, and are the de facto first level access in most cases.

4.1 BACKGROUND

Primary curative outpatient healthcare is in great demand in India. According to National Health Accounts (GOI 2005a), 88 per cent of households' health expenditure is spent on curative services, of which 48 per cent is towards primary curative care, also defined as "ambulatory or outpatient treatment of illness" (Berman 1998). Dror et al. (2008) investigated the cost of illness among the poor in five locations in India and reported that 33 per cent of the costs were attributed to consultations and 49 per cent to payment for drugs.

National surveys suggest that the proportion of persons falling sick and seeking curative care in rural and urban India is comparable: the National Sample Survey (60^{th} Round) reported 823/1000 ailments treated (in the 15 days preceding the survey) in rural vs. 893/1000 in urban areas (NSSO 2006); this difference is offset by the higher proportion of rural population (more than 70%) (GOI 2001a), so in absolute numbers, rural treatment-seekers outnumber urban ones.

Despite a larger demand for healthcare among rural persons, the quality and quantity of healthcare supply is relatively lower in rural than in urban areas (De Costa & Diwan 2007, GOI 2005d). For instance, a survey of all healthcare providers in the State of Madhya Pradesh (population 60.4 million) enumerated 24,807 qualified doctors, of whom, 75.6 per cent worked in the private sector, mostly (80%) in urban areas (De Costa & Diwan 2007).

Ambulatory outpatient care is supposed to be available in rural areas through the public delivery system at Primary Health Centres (PHCs). Each PHC serves on average 30,000 persons and is managed by a medical doctor. A PHC is linked to 6 sub-centres (SCs), each serving about 5,000 persons, and managed by an Auxiliary Nurse Midwife (ANM) who delivers family planning services, some maternity care and immunizations. Secondary level care is supposed to be delivered by Community Health Centres (CHCs), where four specialist doctors should offer specialized care to 120,000 persons (GOI 2008). A district hospital at the top provides tertiary referral care and supervision.

This basic 3-tier system has not changed since it was proposed by India's first Health Survey and Development Committee (Bhore 1946), but the Committee's recommended 'population norm' of one PHC per 10,000-20,000 population has never been achieved. With a current infrastructure of 23,458 PHCs and 4,276 CHCs, and with 18.8 per cent vacancies in PHC doctors' positions and 51.6 per cent vacancies in CHC specialists' positions (GOI 2008), the system suffers from inadequate infrastructure and doctor shortages (Satpathy 2005), while India's rural population has grown to more than 700 million (GOI 2001a). There is low utilization of primary outpatient care in public facilities because of long distances, inconvenient opening hours, lengthy waiting, staff absenteeism, poor availability of medicines, and poor quality of care (Dalal & Dawad 2009, Kotwani et al.

2007, Ager & Pepper 2005). One analysis showed that public facilities were utilized by people in low income States more than by people in high- and middle-income States (Purohit 2004).

Evidence suggests that rural people seek outpatient primary care from private providers for many conditions, including new-born/child illnesses (Deshmukh et al. 2009, Kaushal et al. 2005), malaria/febrile illnesses (Chaturvedi et al. 2009), TB (Fochsen et al. 2006) and women's health (Rani & Bonu 2003). People's choice of provider may reflect provider proximity, cost, reputation, perceived 'recovery', lack of faith in the public sector, and lay notions of aetiology (Dongre et al. 2008, Ager & Pepper 2005, Kamat 1995). The private health sector in rural India includes a heterogeneous mix of providers; some are professionally trained, but the majority are unqualified. A survey done in 2007 enumerated only about 28 per cent qualified doctors (De Costa & Diwan 2007). Almost all the 89,090 unqualified providers practiced as private rural practitioners. Different types of practitioners and systems have existed in rural India. Studies from the 1960s and 1970s reported that traditional healers or indigenous medical practitioners used both modern and traditional medicines (Bhatia et al. 1975). Later studies refer to "rural medical practitioners" (Rohde & Vishwanathan 1994) following mainly allopathic treatment practices. More recent studies have reported that in rural areas health-seekers approached traditional healers (Chaturvedi et al. 2009, Dongre et al. 2008) and also qualified practitioners of AYUSH (Ayurveda, Unani, Siddha and Homeopathy systems) (De Costa & Diwan 2007). However, only a minority (14%) utilize the pure traditional cures (Singh et al. 2005).

The Indian government launched its National Rural Health Mission (NRHM) in 2005 to increase access and quality of healthcare in rural areas (GOI 2005b). The present study conducted in 2008-2009, sought to investigate the post NRHM status of curative health care seeking at first contact among rural communities. Evidence collected from health care seekers (demand side) was juxtaposed with evidence collected from providers (supply side) on first contact healthcare, including the illnesses, patients' choices and providers' patient load, treatments, medicines, and referrals. This study embraces a horizontal approach in investigating first contact curative care, regardless of the cause, and by all providers participating de-facto in the health system.

4.2 DATA AND METHODS

This study was part of a larger baseline study to initiate rural micro health insurance programmes in two states – Andhra Pradesh (AP) and Odisha. Field work was conducted in AP during May-June 2008 and in Odisha during January-February 2009.

4.2.1 Quantitative methods

4.2.1.1 Household survey

Sampling: In the two districts in AP there were 2031villages with a total population of 5,359,959 spread across 1,257,235 households (GOI 2001a). In the three districts in Odisha (Kalahandi, Malkangiri and Khorda), there were 4436 villages, and a total population of 2,776,546 spread across 602,561households. For AP with a total of 1257,235 households and an assumed 10 per cent frequency of visiting qualified physicians (obtained by discussions with community leaders) the calculated sample size for an error of 2% and 99% confidence level was 1491 households. For Odisha, with a total of 602,561 households, the calculated sample size was 1489. The actual sample included 1,810 households in AP and 5,342 in Odisha.

The villages were selected purposively, where local organizations were involved in the micro health insurance project [Cooperative Development Foundation (CDF) in AP and the Madhyam Foundation in Odisha with its 11 affiliated NGOs]; 20 villages in AP (12 in Warangal and 8 in Karimnagar districts) and 80 villages in Odisha (27 in Kalahandi, 22 in Khorda, and 31 in Malkangiri districts). In every village, two cohorts were randomly sampled counting the same number of households: members of self-help groups (SHGs), and non-member households.

The SHGs were savings and borrowing societies that were already present at the two sites. The micro health insurance was intended only for existing SHG members, and we wanted to make sure that there was no difference in socio-economic status or education between the prospective insured and uninsured (to eliminate any confounding differences later on in our impact analysis).

Research tool and implementation: A structured questionnaire was developed in English, translated into Telugu and Oriya, and validated through back translation and cognitive pre-testing in 80 households each in AP and in Odisha, and modified as necessary. Project personnel trained local investigators to carry out the interviews. The questionnaire included close-ended questions on respondents' socio-demographic characteristics, healthcare utilization, providers approached first by household members for outpatient care when ill, and reasons for approaching these providers. In the Odisha survey, the inquiry was refined to confirm whether allopathic practitioners were degree vs. non-degree [which was inferred in AP by combining household survey and focus group discussion (FGD) data].

The method as adopted by the Indian National Sample Survey Organization (NSSO) was followed to obtain a proxy for income through questions on many items of household expenditures. Similar to NSSO, the monthly per capita expenditure (MPCE) served as proxy for income.

4.2.2 Qualitative methods

4.2.2.1 Focus group discussions (FGDs)

Sampling: A total of 19 FGDs (9 men's, 10 women's) in AP, and 29 FGDs (13 men's and 16 women's) were conducted in Odisha; 214 persons participated in FGDs in AP (96 men and 118 women), and 314 in Odisha (121 men, 193 women). Villages for FGDs were selected (5 in AP and 15 in Odisha) by location within districts, distance from towns and from medical facility (near, medium or far). Participants in FGDs were men and women aged 25 to 45 yr. Groups were gender- and income homogenous (proxy for income was land ownership). As far as possible, the same number of FGDs was conducted with males and females in each village.

Research tool and implementation: An FGD guide (pre-tested with 2 male and 2 female focus groups in each State) was developed and local persons (2 in AP, 4 in Odisha) were trained to facilitate discussions on morbidity and incidence, health seeking decisions, first providers approached, perceptions of how providers treated and what they charged. The facilitators were debriefed after every session. All FGDs were held in settings ensuring privacy and confidentiality to participants.

4.2.2.2 Key informant interviews (KII)

Sampling: KIIs were conducted with 9 village-based providers in AP and 20 in Odisha, plus solo general practitioners (GPs) and specialists in nearby towns, and hospital-based providers (13 in AP and 19 in Odisha). First popular providers were located and interviewed and then other providers were identified with their help.

Research tools and implementation: Semi-structured interview tools were developed per provider category (pre-tested with 4-6 providers in each State) to collect information on education and training of village providers, practice characteristics, services rendered, and types of patients. Interviews in health facilities or with GPs focused on listing services, staff, and basic information on patients.

4.2.3 Ethical compliance

This research project met all the requirements of the funding agency (NWO-WOTRO) on ethical issues arising in social science research. The research document for all the interventions (e.g. FGDs, household survey interviews, and KIIs) included an introductory section tantamount to a protocol of informed choice in which the researchers explained the purpose of the study, what would be done with the data, and sought and obtained verbal consent of participants to participate in the interviews and discussions, and to record the FGD meetings. Participants' names were kept confidential in data recording and analysis. All interviews were organized so as to ensure interviewees that confidentiality would be kept.

4.2.4 Analysis

SPSS v.17 was used to analyse household survey data. We organised the taped, transcribed and translated FGD data into matrices and explored similarities, differences, recurrent themes and categorizations within data driven sub themes, broadly covering perceptions of common diseases, hierarchy of care seeking, characteristics of and perceptions related to providers of first contact. KII data were entered in Excel, and simple frequencies for close-ended questions were calculated. Open-ended questions were entered verbatim and analysed qualitatively to determine common characteristics, relationship with communities, and treatment patterns.

4.3 RESULTS

4.3.1 Socio-economic status of studied populations

The study populations in the two States reported significantly different household incomes. Median MPCE in AP was INR 1,289, more than twice that of Odisha (INR 504). The proportion of Scheduled Tribes (STs) was significantly ($P<0.001$) higher in Odisha than in AP, while the proportion of OBCs was higher ($P<0.001$) in AP. Illiteracy was higher ($P<0.001$) in Odisha (Table 4.1). There were also differences in economic activity of household heads: in Odisha the largest group was that of self-employed small farmers, while the largest group in AP was composed of casual wage labourers. No significant differences were found between SHG members and non-members. Women formed the majority of household survey respondents in both States: 72.3 per cent in AP and 67.7 per cent in Odisha. Other available household members, if present, also contributed.

In AP as village sizes were bigger than in Odisha and there was sufficient representation of men and women from different socio-economic groups, four different FGDs were organized per village (2 men's and 2 women's) representing poor and better off households in each village. In most of the poorer groups, half or more of the participants were illiterate and a few only had completed 10 years of schooling. However, literacy differences were less pronounced in the women's groups where even the better off groups had more illiterate than literate members. Participants in the poorer groups were either landless and worked as "coolies" (daily wage farm labourers), or as other types of daily wage labourers (e.g. loaders), or had small farms less than 3 acres in size but also sometimes worked as "coolies" or ran small businesses (such as a small shop) to supplement their farm income. Participants in the better off groups usually owned medium sized (3-6 acres) farms and a few owned bigger ones (10-20 acres). These groups also had participants with less land but with bigger businesses (e.g. tailor) and some had salaried jobs (e.g. teacher, driver).

Table 4.1 Profile of the study communities in Andhra Pradesh (AP) and Orissa

	AP (n=1810	Orissa (n=5342)
Caste of household head		
Scheduled Tribe	2.3%	30.0%[††]
Scheduled Caste	18.6%	22.3%[†]
Other Backward Caste	61.9%	31.3%[††]
Other Caste	17.1%	16.5%
Literacy of household head		
Illiterate	44.8%	51.3%[††]
Activity of household head		
Casual wage labourer	42.1%	30.8%[††]
Self-employed in agriculture	26.2%	38.7%[††]
Self-employed in business/trade	15.7%	16.1%
Regular salaried employee	8.3%	4.6%[††]
Rest (non-income earning)	7.7%	9.8%
Median MPCE[a] (INR)	1289	504[*]

[a] MPCE = Monthly Per Capita Consumer Expenditure
[†] Significance of difference between Orissa and Bihar p<0.01 (Chi-square)
[††]Significance of difference between Orissa and Bihar p<0.001 (Chi-square)
[*]Significance of difference in cost between Orissa and Bihar p<0.001 (ANOVA)

In Odisha, villages were smaller and communities more homogenous with respect to occupations and land ownership. Thus only two FGDs could be organized per village, one male and one female. In general, there were more illiterate participants here than in AP. While in each district 1-2 FGDs comprised landless daily wage labourers (e.g. farm labour/constructions workers/small vendors), the majority were small farmers with 1-5 acres of land. As in AP the latter supplemented their income through daily wage activities, or through small businesses such as selling fruits, vegetables and also fish, and in those villages that were close to the capital city of Bhubaneswar, through salaried jobs (e.g. clerks and peons).

4.3.2 Providers of first health-seeking contact

In both States, FGD narratives suggested that the first response to an illness could be self-medication, with men more likely to buy an over-the-counter paracetamol or other medicine and the women more likely to rely on home remedies. When these were not effective, they sought care from available providers. In AP, 94.8 per cent household survey respondents usually approached an allopathic practitioner first (Figure 4.1); most (69.5%) approached private allopathic practitioners in the same village or nearby village and 22.1 per cent approached private practitioners in town. FGDs revealed that in villages, private 'allopathic' practitioners were informally trained and unlicensed, often called Registered Medical Practitioner (RMPs), a designation used in some States until the 1970s, and still included in some State Medical Councils (Madhya Pradesh Medical Council 1987), but currently synonymous with unregistered practitioners without formal qualifications in medicine. We refer to these as non-degree allopathic providers (NDAPs).

In Odisha 53.1 per cent of respondents had their first health-seeking contact was with an allopathic practitioner; of these 40.2 per cent approached NDAPs and 12.9 per cent consulted qualified physicians (Figure 4.2). In the FGDs, people referred to the NDAP as "choto doctor" (small doctor). Triangulation of the household survey, FGDs and KIIs showed that in Odisha, some NDAPs (e.g. pharmacists, nurses and compounders) were employed in government health centres, and treated patients in villages for-a-fee. In Odisha, 32.6 per cent of household survey respondents usually approached such "public sector NDAPs" first, mostly in the same or nearby village (27.6%) (Figure 4.2).

Around a quarter or less of respondents in both States approached qualified doctors in the first instance. In AP, these were doctors in private practice in nearby towns (22.1% - Figure 4.1), whereas public practitioners were mentioned by only 3.2 per cent. In Odisha a smaller proportion of respondents (12.9%) approached qualified doctors first, and the majority of those (10.7%) went to public sector doctors (Figure 4.2).

A substantial proportion of respondents in Odisha (36.2%) also approached other non-allopathic practitioners first: traditional healers. Fewer households approached other types of practitioners: only 0.2 per cent respondents in AP and 4.2 per cent in Odisha approached AYUSH practitioners, and 5 per cent in AP and 6.4 per cent in Odisha approached government health workers like ANMs, ASHAs (Accredited Social Health Activist) and AWWs (Aanganwadi Worker).

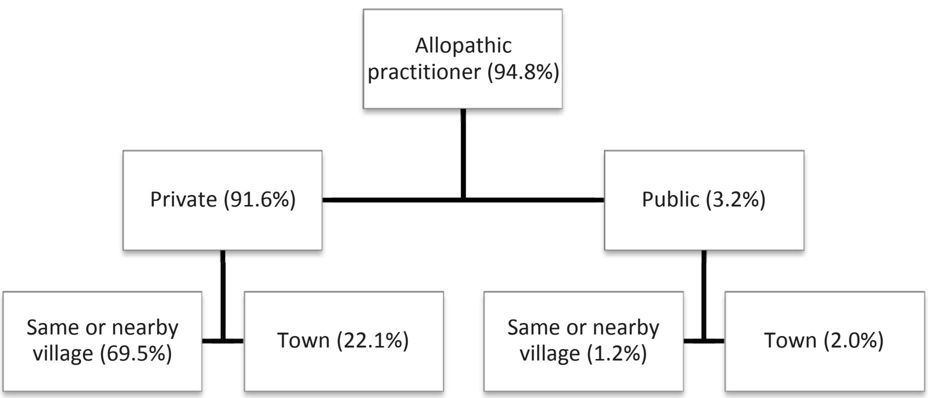

Figure 4.1 First care seeking contact in Andhra Pradesh

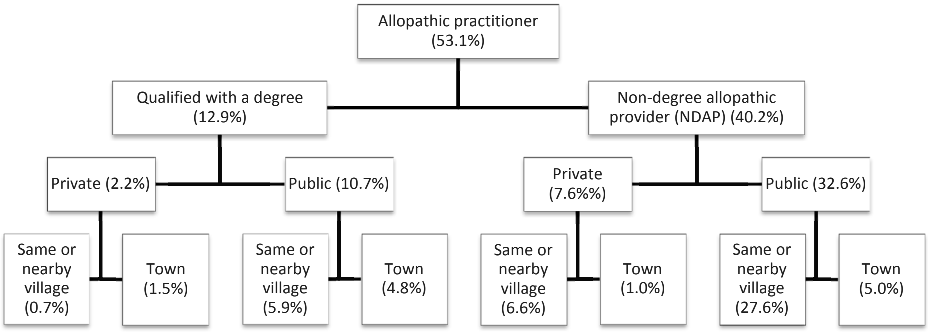

Figure 4.2 First care seeking contact in Orissa (allopathic practitioner details)

4.3.3 Association between income and choice of provider

In view of the diversity of first contact providers, association between income of the population (MPCE quintiles) and choice of first contact provider was examined, a significant association was seen in Odisha but not in AP (Table 4.2). In Odisha, a significant decrease was observed in the frequency of accessing traditional healers with income, which was mainly due to a lower frequency in the fifth income quintile. A positive association was found between income quintiles and frequency of seeking care with qualified doctors. The lowest quintile reported 7.4 per cent and the highest 20.6 per cent. There was a small but significant increase in the frequency of choosing NDAPs with increasing income.

4.3.4 Reasons for choice of first contact provider

Respondents named proximity as the most important reason for their choice of first contact provider. It was the main reason for a majority of respondents that approached NDAPs and traditional healers (77.5% in AP and 58.9% in Odisha for NDAPs; 67.9% for traditional healers in Odisha; Table 4.3). Fewer respondents named their reason as provider being 'best' (18.1% in AP and 32.7% in Odisha for NDAPs; 20.3% for traditional healers in Odisha). However, among those who approached a qualified doctor first, a majority said it was because that provider was 'best' (56.0% AP; 58.2% Odisha) followed by 'closest' (38.9% AP; 35.8% Odisha).

4.3.5 Provider profiles and people's perceptions

Traditional healers: Traditional healers provided a substantial proportion of health care at first contact in Odisha but not in AP. In Odisha, over one-third of the household survey respondents usually sought first consultation with traditional healers (Figure 4.2) as they were their closest providers (Table 4.3).

These practices could not be generalized across all study communities, since care seeking from traditional healers was expressed more by groups that were more remotely

Table 4.2 Type of provider first approached by different MPCE quintiles in Andhra Pradesh (AP) and Orissa

		NDAP[a]	Traditional healer	Qualified doctor	AYUSH practitioner[b]	ANM[c]/ ASHA[d]/ AWW[e]	Any others
AP	Quintile 1	67.3%	N/A[g]	26.5%	0.3%	4.5%	1.4%
	Quintile 2	69.5%	N/A[g]	25.1%	0.0%	4.2%	1.1%
	Quintile 3	69.3%	N/A[g]	22.5%	0.0%	5.9%	2.3%
	Quintile 4	71.3%	N/A[g]	21.7%	0.3%	6.2%	0.6%
	Quintile 5	72.6%	N/A[g]	21.8%	0.3%	4.5%	0.8%
	Significance	ns[f]		ns[f]	ns[f]	ns[f]	ns[f]
Orissa	Quintile 1	35.0%	39.9%	7.4%	3.1%	14.6%	N/A[g]
	Quintile 2	37.1%	44.8%	9.4%	2.3%	6.4%	N/A[g]
	Quintile 3	42.3%	37.4%	12.4%	3.1%	4.8%	N/A[g]
	Quintile 4	40.2%	34.1%	14.9%	6.3%	4.5%	N/A[g]
	Quintile 5	45.7%	25.2%	20.6%	5.8%	2.8%	N/A[g]
	Significance	†††	†††	†††	†††	†††	

[a] NDAP = Non-degree allopathic practitioner.
[b] practitioner of Ayurveda, Unani, Siddha and Homeopathy systems.
[c] ANM = Auxiliary nurse midwife.
[d] ASHA = Accredited social health activist.
[e] AWW = Aanganwadi worker.
[f] ns = non-significant difference between the different income quintiles
[g] N/A = not applicable
††† Significance of difference between the different income quintiles p<0.01 (Chi-square)

located and had fewer allopathic options in or around their villages, or among groups with greater economic impoverishment. These findings were in agreement with the household survey results that showed an inverse relationship between income and care seeking from traditional healers. However, tribal populations (STs) chose traditional healers less frequently than SCs and OBCs (28.3 vs. 43.3% and 40.2% respectively, P<0.001). There was no significant association between frequency of choice of traditional healer and literacy.

Non-degree allopathic providers (NDAPs): NDAPs were sought by almost 70 per cent household survey respondents in AP and 40 per cent in Odisha. NDAPs in AP were private practitioners but in Odisha people also sought care from public sector NDAPs. Some employees in government health centres, especially the primary health centres (PHCs) including pharmacists, nurses, and even health attendants, acted as NDAPs in Odisha in three situations: firstly, when the health facility had no doctor and was managed entirely by non-doctor staff. Doctor shortages in Malkangiri (with large tracts of inaccessible areas) were particularly acute. Secondly, when a doctor was assigned, but absent from duty for any reason, some of the doctor's tasks were routinely performed by other health workers. Thirdly, when the doctor was present but patient load at the

Table 4.3 Reasons why household survey respondents chose first contact health provider

	AP			Orissa		
	Closest	Best	Cheapest	Closest	Best	Cheapest
NDAPs[a]	77.5%	18.1%	1.4%	58.9%	32.7%	2.3%
Traditional healer	N/A	N/A	N/A	67.9%	20.3%	5.1%
Qualified doctor	38.9%	56.0%	1.6%	35.8%	58.2%	1.7%
Overall	66.5%	27.6%	2.2%	57.8%	30.6%	5.8%

[a] NDAP = Non-degree allopathic practitioner.

facility was high, other health workers (e.g. pharmacists, nurses, female/male health workers, health attendants) performed some of the doctor's tasks.

From the FGDs with men and women, and KIIs with 9 NDAPs, some common characteristics as well as differences were identified between private NDAPs in the two States. All were male. Their average age was 36 yr. in AP (range of 24 to 50 yr.) and 43 yr. in Odisha (range of 28 to 60 yr.). All had well-established independent practices with an average professional experience of 13.3 yr. in AP and 20.5 yr. in Odisha. The majority had completed 10 or more years of schooling. Most NDAPs acquired skills through informal apprenticeships, usually with other doctors both private and public. NDAPs in AP delivered mainly mobile services. All 9 possessed mobile phones and responded to emergency calls plus provided services within a radius of 0-5 km (1-5 villages) of where they lived; two who owned a scooter/motorcycle extended their catchment area to 20-25 km. Five NDAPs also had rudimentary clinics. Most, however, spent between 6 and 12 h daily circulating in villages and providing doorstep services. In Odisha, only half the NDAPs provided mobile healthcare in a larger radius of 5-20 km from their village; those who had a motorcycle travelled longer distances. The other half combined static and mobile services, during 1-4 h daily for rounds or to respond to calls, within a smaller radius of 2-5 km.

Most NDAPs in AP saw 20 or more patients daily (range from 10 to 70 patients); mobile providers had most patients. In Odisha, NDAPs saw a smaller average of 12 patients daily (range from 2 to 40 patients) and older practitioners had higher patient-loads. The providers were asked to estimate their catchment population (households they usually served). In AP, it ranged from 50 to 300 households, with an average of 100 households. In Odisha, it ranged from 40 to 1200 households with an average of 300 households.

NDAPs in both States treated the most commonly reported morbidities. We compared five most frequently treated conditions named by NDAPs with replies to the household survey question: "Did a person in the household have an illness episode last month? What kind of illness was it?" The information from both sources tallied closely (Table 4.4). 'Fever' topped the list, followed by body pains and GI symptoms in AP, and malaria in Odisha.

Table 4.4 Most common symptoms/illnesses reported by household survey respondents and private NDAPs in AP and Orissa

	AP		Orissa	
Symptoms	No. of providers reported these among top symptoms (KIIs[a])	Reported as illnesses in last month (HHS[b]) (%)	No. of providers reported these among top symptoms (KIIs[a])	Reported as illnesses in last month (HHS[b]) (%)
Fevers (including typhoid)	8/9	44.0%	11/19	50.6%
Malaria, dengue, kala-azar, chikungunya	N/A	1.2%	8/15	14.0%
Body pain / joint pain	9/9	15.8%	9/15	5.4%
Gastrointestinal symptoms (GI)	9/9	8.5%	14/15	8.3%

[a] KII= Key informant interviews.
[b] HHS = Household Survey.

NDAPs in both States used allopathic medicines to provide symptomatic relief. Typically, they dispensed medicines for 2-3 days (rarely up to a week), and if there was no improvement, they referred patients. NDAPs also referred in emergencies, sometimes providing first aid or accompanying patients to a qualified physician or hospital. In Odisha, NDAPs sometimes performed simple diagnostic tests (e.g. blood test for malaria).

Some NDAPs also prescribed drugs additional to those they dispensed. We listed 37 brand names of drugs named by NDAPs in AP and 49 in Odisha (Table 4.5). The various drug types mentioned were classified by mode of action (following CIMS India Reference System) (CIMS India). CIMS information revealed that 44 manufacturers produced the 37 AP brands and 48 produced the 49 Odisha brands. This suggests that NDAPs were familiar with multiple branded drugs with different names (different manufacturers) and that these brands were available over the counter in the retail market, from where NDAPs said they restocked their supplies weekly or fortnightly. NDAPs used mostly four classes of drugs: analgesics/antipyretics/antimalarial, vitamin and iron supplements, antibacterial and non-steroidal anti-inflammatory drugs (NSAIDs) (Table 4.5). In Odisha, three providers also dispensed ayurvedic remedies. AP providers mentioned no indigenous medicines. Some NDAPs also gave nutritional advice on consumption of foods rich in vitamins and minerals such as leafy vegetables, eggs, milk and fruits.

NDAPs were asked to name five common conditions for which they referred patients, and where they referred to. Most NDAPs referred for gynaecological problems (e.g. pregnancy and institutional delivery), pains, chronic non-communicable conditions (e.g. heart problems, hypertension, diabetes, kidney related problems), acute fevers

Table 4.5 Drugs named by private NDAPs in AP and Orissa

	AP		Orissa	
Drug class[a]	No. of names mentioned by providers	No. of NDAPs[b] mentioned this drug class (KIIs[c])	No. of names mentioned by providers	No. of NDAPs[b] mentioned this drug class (KIIs[c])
Analgesics & antipyretics (including antimalarials)	3 brand names 2 generics	9/9	6 brand names 3 generic	14/15
Vitamins & haematopoietic	2 brand names	8/9	13 brand names 5 generics	13/15
Antibacterial (oral)	6 brand names 8 generics	8/9	11 brand names 5 generic	11/15
Non-steroidal anti-inflammatory drugs	9 brand names 1 generic	9/9	3 brand names 1 generic	7/15

[a] Source: Central Index of Medical Specialities (CIMS), India (CIMS India).
[b] NDAPs = Non-degree allopathic practitioners.
[c] KII= Key informant interviews.

and gastrointestinal conditions, and in Odisha also for accidents and injuries including snakebites.

NDAPs usually referred to private doctors in AP, and to public facilities in Odisha. In Odisha, the public sector doctors (especially in peripheral facilities) confirmed that NDAPs referred cases for pregnancy, delivery and for serious conditions (e.g. malaria and pneumonia).

Yet we could not find any incentive for NDAPs to refer cases, either through training to improve recognition of referral conditions, or through financial incentives similar to those that government workers like ASHAs receive for each delivery they refer. In AP, NDAPs who referred to private doctors, received occasional gifts (like table calendars) but no financial incentives.

Qualified doctors: Around a quarter of household survey respondents in AP and roughly half that proportion in Odisha approached qualified allopathic doctors at first contact (Figure 4.1 & 4.2). The major difference was that doctors approached in AP were primarily town based private practitioners while in Odisha they were public servants employed at government PHCs and CHCs.

FGDs and KIIs confirmed these two different State scenarios. In AP, FGD participants, both men and women, named a number of private doctors and facilities that they approached in nearby towns, whereas in Odisha, when participants talked about care seeking from a qualified doctor, they usually referred to a government facility identifiable by its location and referred to as a "hospital" irrespective of whether it was a PHC or a CHC or a tertiary hospital.

However, whether public or private, people usually approached these qualified doctors as the second step in their care seeking pathway, if the first level intervention in the village did not succeed, or in multiple care-seeking at the same level (e.g. going from one specialist to another in AP). FGDs suggested that seeking first contact care from qualified doctors was related to (i) economic status of the household as only better off households could afford the total higher costs (of transport, wage loss, fees, medicines, and tests) of approaching a qualified doctor, (ii) perceived severity of the health condition: if the condition was seen as beyond the scope of the village doctor (e.g. a snake bite or a heart problem), then people would bypass the village level and go straight to a doctor, and (iii) proximity to the provider/facility: those communities that lived within easy walking distance of a health facility in Odisha were likely to go straight to that facility first.

In AP, people had access to many private doctors even at block level towns and semi urban areas, but not so at the village level. In Odisha, especially in the poorer districts of Kalahandi and Malkangiri, government PHCs and CHCs were the main source of care by qualified physicians (who were government employees), and these were located even in villages beyond the block towns. Although Odisha respondents accessed public facilities more than in AP, many of these facilities were understaffed, especially in Malkangiri and Kalahandi districts. Malkangiri's Chief Medical Officer informed that only 33 out of 100 sanctioned medical doctors were available in the district public health system.

The private sector provided rural AP communities with a multiplicity of options for care seeking from qualified physicians, and both men and women, even from poorer households appeared to prefer private to public because of better perceived care and treatment. For women, it was familiarity and faith in the doctor and the doctor's kindness that was important. More than one women's group close to a certain town (Narsampet) named the same doctors repeatedly as being among the nicer ones whom they approached both for general illnesses and for women's problems as well.

In AP, men, much more than women, had a tendency to analyse the mode of operation of private qualified doctors. They complained about the high costs, doctors' business orientation and malpractices but they still preferred to go to private doctors.

In AP, use of public primary facilities was limited to immunizations at the PHCs. Although intended for the poor and cheaper than private, public facilities were nonetheless not perceived as poor-friendly by poor consumers. In Odisha, public facilities were people's major and, in many places, only source of access to a qualified physician. Though doctor consultations were usually free of charge in PHCs and CHCs and even the sub-divisional hospitals, people said that doctors usually prescribed medicines and tests from outside private sources. In FGDs, people repeatedly complained about two problems: (i) the money they had to spend on transport to reach public facilities - an amount that could exceed the cost of medicines; and (ii) the money they had to spend out-of-pocket for medicines and tests, and at one district hospital (which allowed private practice by public doctors) also for the doctors' consultation fee.

4.4 DISCUSSION

Through multifarious strategies and enhanced funding, the Government of India provides accessible, affordable and quality healthcare to rural persons. The National Rural Health Mission (NRHM) launched in 2005 for implementation up to 2012 is the most recent large-scale programme to strengthen the existing 3-tier public health delivery system (GOI 2005b). Our study demonstrated that the huge need for primary level curative healthcare was different from what the 3-tier system has been able to provide, and that this need was satisfied mainly outside the public system. For one, the data showed that the overwhelming reason given for the choice of first contact curative provider was proximity. From the FGDs it was known that the proximate providers were also available at all hours of the day and night, and responded to telephone calls.

The doctors at public, and even more at private health facilities, often required that patients undergo diagnostic tests and buy prescribed medicines, the combined cost of which was high, plus there were indirect costs of transportation and wage-loss. NDAPs were much closer to care-seekers in villages, made house calls when requested, charged lower fees and provided the all-in-one "quick-fix" service. Thus, more than 75 per cent of the population preferred to go to NDAPs and (in Odisha) also to traditional healers for first contact curative care. This evidence demonstrates that people seek a different type of primary curative care, which is not doctor-centric and is delivered not in a faraway doctor's clinic, and for which clients are willing to pay.

The people did not choose their first contact provider by whether he was a "small doctor" or a "big doctor". Frequently, factors like distance and cost determined people's care-seeking preferences more than providers' skills or accreditation. This alternative treatment trail was mostly at odds with government policy, and people consulted professional doctors only when they, or their first contact NDAP, perceived a specific reason to do so.

Consistent with previous evidence (Dalal & Dawad 2009, Satpathy 2005), staff shortages and low utilization of the public sector were found. However, our findings do not uphold the assumption that the need among rural communities for proximate all-in-one primary curative healthcare would disappear even if all the PHCs and CHCs were to become fully staffed and well equipped. Thus, if the public system should deliver such care, health planners would need to revise the objectives and deliverables of the various tiers in the public system.

Our evidence on practice of NDAPs not only confirms previous reports about their widespread presence in rural areas (De Costa & Diwan 2007, Berman 1998), but also gives new details about the existence, in addition to private practitioners, of "public sector NDAPs".

Some scholars have explained the recourse to traditional healers (accessed by 36% of care seekers in Odisha) by reference to illiteracy and tribal cultures (Vijayakumar et al. 2009); in our examination, this explanation was not confirmed, as there was no significant difference in the rate of consulting traditional healers across literate or illiterate household heads and, interestingly, tribal households approached traditional healers less than non-tribal households. However, our data suggested that there was a negative association between income and frequency of traditional healer care seeking that was most apparent in the richest quintile in Odisha.

It was found that private qualified doctors practiced in AP even at block level, but almost none could be found in Odisha, especially in Kalahandi and Malkangiri (the poorer and more remote districts of Odisha). In these districts, the PHCs and CHCs, were understaffed. The reason why fewer private doctors practiced in Odisha was people's lower ability to pay, demonstrated by lower median MPCE (pattern confirmed by National Sample Survey 2005-06: INR 460.32 for Odisha and INR 704.17 in AP). Our findings provided additional evidence to support this conclusion, as the frequency of accessing qualified doctors increased significantly with income in Odisha.

Based on analysis of illnesses reported by people (juxtaposed against those reported by providers), it appears that NDAPs manage the most frequent illnesses, and thus fill a limited but essential gap in access to first contact curative healthcare in rural India. Similar to findings of others (Rohde & Vishwanathan 1994), NDAPs in our study were mostly male, with long-established practices of allopathy close to where they live, typically dispensing small doses of medicines when consulting patients, and charging a flat fee for both consultation and medicines. A new feature of NDAP services i.e. "on-call" services to respond to clients' needs for doorstep curative care as-and-when needed, anytime was also seen.

We found no signs of conflict of interests or "turf wars" between qualified doctors and NDAPs; on the contrary, we observed even some complementarity between the two categories of providers.

NDAPs referred complex cases to qualified doctors, often by accompanying the patients. This situation explains why, notwithstanding legal restrictions set out by the Indian Medical Council Act (IMC 1956) on the practice of medicine, some experts in the Indian public health community suggest that the role of NDAPs should be reviewed (Yadav et al. 2009). Even certain government commissions made similar recommendations. e.g. the National Commission for Macroeconomics and Health (GOI 2005d), a Health Ministry Task Group on training and accreditation of rural practitioners (GOI

2007a), and the NRHM. Additionally, a Task Force on Medical Education recommended a 3-year programme to train community health practitioners (GOI 2007b), and the most recent official attempt is to design the curriculum for a Bachelor of Rural Health Care programme (Dhar 2010). These programmes probably reflect the concern that the government should provide better than sub-optimal, first contact, primary curative care to rural populations.

NDAPs in our study treated with allopathic medicines and were familiar with not just one or two brand names of allopathic drugs, but with several, which they could access without any difficulties. This suggests that representatives and retailers of the pharmaceutical industry succeed in bringing drug related information (and drugs as well) to NDAPs in the same way as they reach qualified prescribers. As this study was not an empirical evaluation of the clinical quality of care of NDAPs, it is not possible to comment on the adequacy of use of the drugs they mentioned. However, the ease of access to drugs by persons lacking formal certification (like the NDAPs) and the absence of effective regulatory oversight of drug distribution in India raise some concern about practices of dispensing of medicines reported through this study.

The main study limitation was that due to resource constraints we could interview fewer first-contact providers than all those who were available. However, some of the providers most frequently approached as identified and located from people's descriptions in the FGDs were interviewed. Thus, these interviews provide a profile of providers that people accessed frequently in the study communities.

4.5 CONCLUSIONS

In conclusion, our study showed that the rural population in India indicates a need for "consult- cum-dispense" healthcare services for most common illnesses to be delivered most hours of the day and at doorstep (or at least served in or near their village). This treatment-trail for primary curative care has evolved unguided and unnoted by the formal system. The architecture of this treatment trail is crafted by the demand side, and has been solidified by the propagation of NDAPs practicing at village level. If the public sector should meet this health need, clearly the bottleneck would be not merely the insufficient number of doctors actually serving in PHCs and CHCs in rural areas. The policy conclusion is that services have to address the need expressed by people for more mobile, proximate - virtually doorstep – primary curative care that should combine consultation and dispensing of medicines, and would function many more hours. NDAPs fill a demand for primary curative care, with a new treatment-mix which the public system is not able to satisfy in rural India under existing operating conditions. The de-facto diffidence about (i) the need of rural populations for very different services than those planned under the existing 3-tier public system, and (ii) the important role of NDAPs in responding to the demand for these primary curative healthcare services, irrespective of policies or law, seems rather incongruous.

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Chapter 5

Estimating Willingness-to-Pay for health insurance among rural poor in India by reference to Engel's law

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ABSTRACT

Community-Based Health Insurance (CBHI) (a.k.a. micro health insurance) is a contributory health insurance among rural poor in developing countries. As CBHI schemes typically function with no subsidy income, the schemes' expenditures cannot exceed their premium income. A good estimate of Willingness-To-Pay (WTP) among the target population affiliating on a voluntary basis is therefore essential for package design. Previous estimates of WTP reported materially and significantly different WTP levels across locations (even within one state), making it necessity to base estimates on household surveys. This is time-consuming and expensive. This study seeks to identify a coherent anchor for local estimation of WTP without having to rely on household surveys in each CBHI implementation. Using data collected in 2008-2010 among rural poor households in six locations in India (total 7874 households), we found that in all locations WTP expressed as percentage of income decreases with household income. This reminds of Engel's law on food expenditures. We checked several possible anchors: overall income, discretionary income and food expenditures. We compared WTP expressed as percentage of these anchors, by calculating the Coefficient of Variation (for inter-community variation) and Concentration indices (for intra-community variation). The Coefficient of variation was 0.36, 0.43 and 0.50 for WTP as percent of food expenditures, overall income and discretionary income, respectively. In all locations the concentration index for WTP as percentage of food expenditures was the lowest. Thus, food expenditures had the most consistent relationship with WTP within each location and across the six locations. These findings indicate that like food, health insurance is considered a necessity good even by people with very low income and no prior experience with health insurance. We conclude that the level of WTP could be estimated based on each community's food expenditures, and that this information can be obtained everywhere without having to conduct household surveys.

5.1 BACKGROUND

Policy makers across the world have recognized that adequate access to health services is important for the entire population and that this cannot be achieved without a well-functioning health financing system. Member States of the World Health Organization committed in 2005 to develop their health financing systems so that all people have access to services and do not suffer financial hardship paying for them (World Health Assembly resolution 58.33). Health financing policies across the world promote risk pooling mechanisms in order to move away from direct payments (out-of-pocket spending at the point of delivery) and achieve universal health coverage(James & Savedoff 2010, WHO 2010).

Most developing countries cannot mandate affiliation to health insurance because the vast majority of the population is living and working in the "informal sector" (Bacchetta et al. 2009, Pratap & Quintin 2006). This is also why these countries cannot fully subsidize health insurance forever for all people in the informal sector. Thus, voluntary affiliation to a contributory scheme like Community-Based Health Insurance (CBHI) or micro health insurance is the most likely route to achieve broad-based health insurance coverage in settings where governments can neither mandate nor subsidize the full cost. India is a case in point, as a large share of its population lives in rural areas, works in the informal sector and does not pay taxes. Notwithstanding a policy of delivering healthcare through the public sector, these facilities commonly suffer from shortages in qualified staff and supplies, especially in rural and peripheral areas (Reddy et al. 2011a, Peters et al. 2002, Berman 1998). Therefore, the rural poor mostly seek care with private practitioners (NSSO 2006) and have to bear the costs of care out-of-pocket at the point of delivery. It has been shown that often, rural poor pay for this care by resorting to borrowing or selling assets (Binnendijk et al. 2012c). Additionally, rural poor cannot easily find health insurance in rural areas; the more likely option to become insured in rural areas is through CBHI providing affordable (but partial) health insurance coverage (Bhat & Jain 2006, Devadasan 2006, Ahuja 2005, NCMH 2005). CBHI schemes are organized mostly by NGOs serving poorer segments of society on a not-for-profit voluntary basis. One of the strengths of CBHI is keeping transaction costs low and tailoring the benefits to suit local needs (Bhat & Jain 2006, Ahuja 2005). Typically, CBHI schemes do not benefit from premium subsidy. Therefore, the expenditure on benefits is limited to premium income of single schemes. It is self-explanatory that people will buy health insurance voluntarily only if the package suits their needs, if the premium is affordable, and if they expect the contract to be executed as promised. Estimating what people are willing to pay for health insurance (WTP) before the insurance can be launched is thus essential because it defines the financial boundaries within which a to design the package.

Contingent valuation is the method used most often to get information regarding WTP; people are asked to declare their WTP for something that is not yet available in the market (Dror & Koren 2012). It should be noted that the query about WTP is not an offer to sell a product; it is a hypothetical question about a product that does not yet exist, i.e. it precedes the offer of insurance. This query has often been part of a household survey. However the time and cost needed to conduct household surveys render this method of data acquisition impractical for generalized implementation of CBHI. Furthermore, it has been found, both in India and Nigeria, that WTP for health insurance differs significantly and materially across locations even within the same country or district (Onwujekwe et al. 2010a, Dror et al. 2007b), suggesting that it is necessary to estimate WTP for every location separately. The purpose of this study is to identify a coherent anchor for such local estimation of WTP without having to carry out a household survey.

Several studies have looked at factors influencing the level of WTP for health insurance in developing countries, such as economic and socio-demographic status of respondents, availability of healthcare facilities, financial exposure to healthcare costs. However, variables that significantly explain WTP in one study were not significant in other studies (Dror & Koren 2012). Household income (or income-proxy) turned out to be a positive predictor of WTP in many studies (Onwujekwe et al. 2010a, Gustafsson-Wright et al. 2009, Lofgren et al. 2008, Dror et al. 2007b, Barnighausen et al. 2007, Ying et al. 2007, Dong et al. 2005, Asfaw & von Braun 2004, Binam et al. 2004, Dong et al. 2003c, Dong et al. 2003a, Masud et al. 2003, Mathiyazhagan 1998, Asenso-Okyere et al. 1997). This finding is not surprising and tallies with the prevalent practice in developed countries to price social health insurance premiums as a fixed percentage of household income (Saltman et al. 2004). On the other hand, it has also been shown that while nominal WTP increases with income, when expressed as a percentage of income, WTP decreases as income increases. This relationship between WTP and income reminds of Engel's Law, the important observation in economics stating that the proportion of income spent on food decreases as income increases, even if actual expenditure on food rises (Perthel 1975, Engel 1957). This finding relating to WTP for health insurance suggests that similar to food, health insurance should be considered a 'necessity good' rather than a 'luxury good', i.e. goods that people cannot live without and the demand for which is not easily reduced even when times are tough. We therefore queried whether the cost of a necessary commodity like food could serve as a better anchor for estimation of WTP, rather than disposable income or total household income. We tested our hypotheses by comparing data from six rural locations in India to identify the anchor that, in every location separately (intra-community) as well as across the locations (intercommunity), showed the most consistent relation with WTP.

5.2 DATA AND METHODS

5.2.1 Setting and sampling

We used data from household surveys we conducted in rural areas of six Indian locations. Two were undertaken in 2008 in Warangal and Karimnagar districts in Andhra Pradesh; three in 2009 in Kalahandi, Khorda and Malkangiri districts in Odisha; and the last in 2010 in Gaya district in Bihar. These surveys formed part of a baseline study prior to launching a development project among members of local Non-Government Organizations (NGOs), and the locations were selected in agreement with the implementing local NGOs: CDF in Andhra Pradesh; Madhyam Foundation in Odisha (comprising 11 grassroots NGOs: Parivartan, PUSPAC, SOMKS, SDS, ODC (Malkangiri); Mahashakti Foundation, DAPTA, Lok Yojana, Sanginee (Kalahandi); MVPS, DSS (Khorda)) and BASIX in Bihar.

We followed a two-stage sampling procedure in each location. In stage one, villages were selected; In Warangal and Karimnagar the survey was conducted in 8 and 12 villages respectively listed by the local NGOs; in Kalahandi, Khorda and Malkangiri respectively 27, 22 and 31 villages were randomly sampled from lists provided by the local NGOs; and in Gaya, 50 villages were selected randomly from the Census 2001 registry of villages. In stage two, in each selected village, households were sampled randomly by applying the “four winds” (or “line sampling”) technique (Som 1996). The overall response rate of the survey was 100% because most people were keen to participate and there was always a willing adult in the household who could respond.

The households (except in Gaya) were sampled in two cohorts of equal size: member and non-member households. Households were defined as “Members” if at least one person participated in a Self-Help-Group linked to partner-NGOs; unaffiliated households were “Non-members”. In Gaya only non-member households were sampled. As we found no significant difference in WTP levels between the “member” and “non-member” sub-cohorts in the same locations, we aggregated the two sub-cohorts for the purpose of the analysis reported here. Sample size was 625 households in Warangal (2429 individuals), 1089 in Karimnagar (4328 individuals), 1805 in Kalahandi (8173 individuals), 1758 in Khorda (9049 individuals), 1597 in Malkangiri (7326 individuals), and 1000 in Gaya (6607 individuals). 100% of the sampled households were rural.

The survey questionnaire was translated from English into the local languages (Telugu, Oriya and Hindi respectively for AP, Odisha and Bihar), back translated for verification, and pre-tested among 80 households per language. Surveyors fluent in local dialects conducted the interviews. We obtained verbal informed consent of the respondents prior to interviews, and kept confidential participants’ names in data recording and analysis. Our research tools were reviewed for ethical compliance by an ad-hoc advisory committee, as at the time of the rollout of the survey there was no local ethics committee in place in Odisha, India. We however held a two-day workshop in preparation of the study in which we discussed the ethical aspects of the study with scholars and senior scholars from India and other countries.

5.2.2 Data

With the use of the household survey questionnaire we queried about expenditures on many items of household consumption in order to obtain a proxy for household income (Grosh & Glewwe 2000). We followed the method as adopted by the Indian National Sample Survey Organization (NSSO 2008). These items of consumer expenditures included expenditures on food, tobacco, alcohol, fuel, gas, electricity, transportation, household disposables, toilet articles, entertainment, telephone, internet, (house) rent, consumer taxes, water fees and domestic servants for last 30 days and expenditures on bedding, clothing, footwear, education, household durables, agricultural equipment/ inputs, life-stock, business inputs, repair/maintenance, holidays, functions and insurance premiums for last 12 months. All these expenditure items, normalized per person per month, serve as our proxy for socio-economic status and are labelled 'income-proxy'. Our income-proxy does not include health expenditure, unlike the National Sample Survey Organization (Flores et al. 2008, Wagstaff 2008).

We also estimated "discretionary income", i.e. the income available to households after paying for food (Imber & Toffler 2008). Stated differently, discretionary income is income-proxy minus food expenditures per person per month. Discretionary income is sometimes defined as disposable income, i.e. total income minus necessities. For people living in the Western world expenditures on water, fuel and electricity are considered necessities besides food. For the rural poor populations we dealt with in this paper, paying for necessities meant something quite different. For example, the water consumed is sourced from wells or streams and does not command payment. Most of the necessary fuel (to cook or heat for instance) is gathered from sources that do not require payment, e.g. cow dung cakes, crop residue or wood collected in the field; most of the other fuel is not a necessity good as most people don't have motorized transportation. And finally, electricity does not exist everywhere and is not always paid for. Therefore food is the only generally applicable necessity good which is retained in this analysis.

In the survey questionnaire we also queried about caste, education and occupation of the household head, household size and other indicators of demographics and socio-economic status of the household. The government of India has "scheduled" certain backward Indian classes or groups in order to promote their welfare: Scheduled Tribes (GOI 1950b), Scheduled Castes (GOI 1950a), and "Other Backward Castes". Scheduled Tribes (tribals or adivasis) are mostly not Hindu and thus out of the caste system and are considered the most disadvantaged economically. Scheduled Castes (Dalits and those sometimes labelled "untouchable") are considered at the bottom of caste hierarchy. The list of Other Backward Castes is quite dynamic and changes from time to time in many states. All other castes are described here as General Caste.

Finally, we queried about WTP for health insurance using the Descending Bidding Game method in order to obtain the maximum values. First the interviewer explained what health insurance is, how it works and the coverage of the package: "To buy a health insurance you have to pay a premium per month for your whole household. This health insurance will then pay you back some of the money you spend on healthcare costs for your household members. Suppose we offer you a health insurance that will cover part of the cost of hospital, medicines, tests, consultations and maternity? How much would you agree to pay for that? If you are willing to pay more, you will get more benefits and if you are willing to pay less, you will get fewer benefits. But the condition is that all household members must join." Then the interviewer started with the relatively high opening bid of INR 30 per person per month (around PPP$ 1.8), again emphasizing that all household members have to join and their premium must be paid every month. Every time the bid was not accepted, it was lowered by INR 1 until it was accepted or reached INR 0. The accepted bid was recorded as the WTP level.

5.2.3 Analysis

We conducted all analyses at household level (reflecting the condition that in this experiment health insurance was available only when the whole household joined). For the analysis we used only households for which WTP and all expenditure items were available (in Warangal 1.4% of households had at least one expenditure item missing, in Karimnagar 1.0%, Kalahandi 3.5%, Khorda 6.4%, Malkangiri 2.6% and Gaya 0.2%). We also only included households whose WTP level was higher than zero; in context, households that were unwilling to join health insurance at any price could only express that through WTP equal to zero; as they are out of scope for voluntary affiliation of health insurance they were not included. The resulting sample is: Warangal 609 households (2.6% excluded), Karimnagar 1051 households (3.5% excluded), Kalahandi 1698 households (5.9% excluded), Khorda 1592 households (9.4% excluded), Malkangiri 1524 households (4.6% excluded), and Gaya 862 households (13.8% excluded).

We calculated WTP in several ways: as percentage of income proxy; as percentage of food expenditure; and also as percentage of discretionary income. The effect of income on these different expressions of WTP was checked separately for each location by using a concentration index, which measures how equitably an indicator is distributed across households with different income. The closer the concentration index is to zero, the more equitable the indicator is (O'Donnell et al. 2008).

We used STATA version 11 for all analyses. All amounts, reported in Indian Rupee (INR) during the surveys were converted into international dollars (purchasing power parity, PPP$) using the exchange rate of PPP$ 1 = INR 16.130 for the survey conducted in 2008, INR 16.692 for the 2009 survey and 18.073 for the 2010 survey (IMF 2012).

5.3 RESULTS

5.3.1 Socio-economic profile

The socio-economic profile of the studied populations is summarized in Table 5.1. With income-proxies between PPP$ 1.0 and PPP$ 2.7 per person per day, all locations can be considered poor but the differences in poverty are quite considerable across the different locations. Food expenditure was on average about half of the total income-proxy (ranging from 36% to 57%). This percentage was lower in the higher income cohorts, as one could expect by reference to Engel's law.

In all locations, the majority of household heads have no or very little education (below class 5), but there is a marked difference across the locations in the percentage of household heads with higher education. The occupation of the majority of household heads differs across locations from self-employed in agriculture to daily wage labourers and self-employed in business/trade. The distribution of the castes is very different across locations with some locations having a very small minority Scheduled Tribe (1-3%) while in Malkangiri nearly 65% of households were Scheduled Tribe.

5.3.2 WTP for health insurance

Respondents of the household survey were asked how much they were willing to pay for health insurance per person per month, under the condition that the entire household had to be included in the insurance and the premium had to be paid for every person in the household. The average WTP values as reported in the different locations are displayed in Figure 5.1.

From the data in Figure 5.1 it can be seen that average WTP for health insurance varies greatly (nearly three-fold) across the locations; this finding tallies with previous reports (Onwujekwe et al. 2010a, Dror et al. 2007b).

Figure 5.2 shows the average WTP values by quintiles of income proxy in each location. It is clear that nominal WTP increases when the income of the household increases and thus that there is also great variation of WTP for health insurance across income groups within the locations.

In all the locations studied, WTP values increased with income; this finding tallies with earlier reports. We wandered whether a fixed percentage of income could serve as an anchor to predict WTP of households for health insurance? We therefore expressed WTP as a percentage of income-proxy and checked whether this resulted in a constant percentage across locations and within locations (Figure 5.3).

As can be seen, there is a strong intra- and inter-location variation in WTP as percentage of income-proxy. Even though relative WTP decreases in all locations as income increases, the decrease is not identical across locations (or relative to income quintiles).

Table 5.1 Socio-economic profile of the studied locations

	Warangal	Karimnagar	Kalahandi	Khorda	Malkangiri	Gaya
			Mean (±SE[a])			
Income-proxy pppm (PPP$)[b]	79.77 (±2.62)	79.17 (±2.13)	29.46 (±0.48)	35.65 (±0.52)	29.97 (±0.47)	50.24 (±1.15)
Food expenditures pppm (PPP$)	31.34 (±0.81)	28.59(±0.85)	14.68(±0.20)	20.49 (±0.30)	15.92 (±0.23)	23.09 (±0.47)
Household size	3.89 (±0.06)	4.01 (±0.05)	4.52 (±0.04)	5.15 (±0.05)	4.58 (±0.05)	6.62 (±0.10)
			% of total			
Caste[c]						
Scheduled Tribe	1.0%	2.8%	22.0%	6.7%	64.6%	2.2%
Scheduled Caste	16.7%	20.5%	15.3%	28.5%	21.6%	35.3%
Other Backward Caste	73.1%	54.2%	52.7%	33.2%	7.7%	43.0%
General Caste	9.2%	22.6%	10.0%	31.6%	6.2%	19.5%
Education of household head						
No education	42.3%	47.6%	53.9%	32.5%	69.1%	43.4%
Class 1-5	13.3%	12.3%	21.2%	29.5%	16.0%	12.2%
Class 6-10	29.0%	25.4%	22.4%	34.1%	13.7%	33.2%
Class 11 and higher	15.3%	14.8%	2.5%	3.8%	1.2%	11.3%
Occupation of household head						
Self-employed agriculture	17.9%	33.0%	43.5%	26.8%	48.3%	28.8%
Self-employed business/ trade	18.4%	14.1%	9.0%	32.7%	5.8%	7.0%
Regular Salaried employee	11.0%	5.5%	3.3%	4.8%	3.9%	4.5%
Daily wage labourer	46.8%	39.0%	38.1%	19.3%	35.8%	47.9%
Not working	5.9%	8.4%	6.2%	16.4%	6.1%	11.8%

[a] SE = Standard Error.
[b] Income is proxied as monthly per capita consumer expenditure through questions on many items of household expenditure and expressed in Purchasing Power Parity International Dollar.
[c] Caste is a proxy for socioeconomic status in India. Scheduled Castes (Dalits and those sometimes labelled "untouchable") are considered at the bottom of caste hierarchy. The list of Other Backward Castes is quite dynamic and changes from time to time in many states. All other castes are described here as General Caste.

5.3.3 Anchor for determination of WTP

Figure 5.2 illustrated that richer households were willing to pay higher premiums for health insurance in nominal term, but the higher amounts represented a smaller percentage of income compared to poorer households in the same location (see Figure 5.3). As mentioned before, the relation between WTP and income reminded of Engel's Law, an observation in economics stating that as income increases the proportion of income spent on food decreases, even if actual expenditure on food rises (Perthel 1975, Engel 1957). Prais and Houthakker (1971) introduced the concept that the shape of Engel's curve can reflect a distinction between luxury and necessity goods like food. We

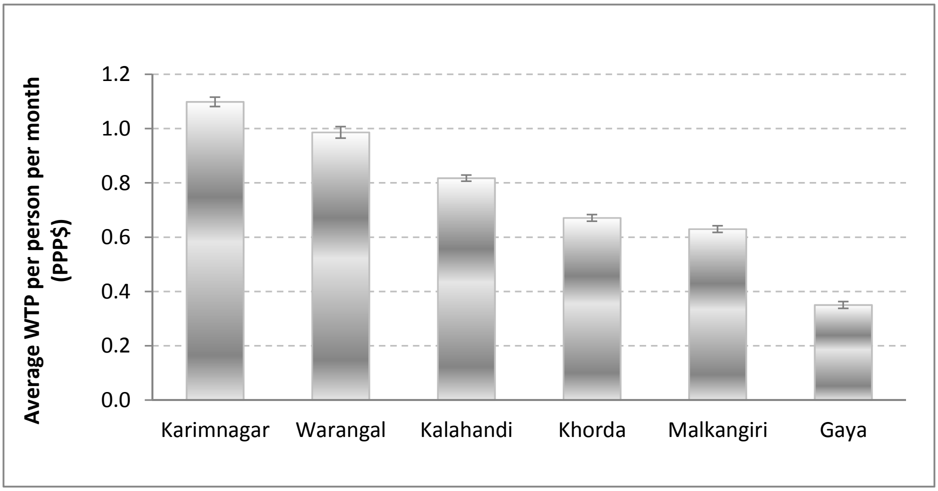

Figure 5.1 Nominal WTP per person per month

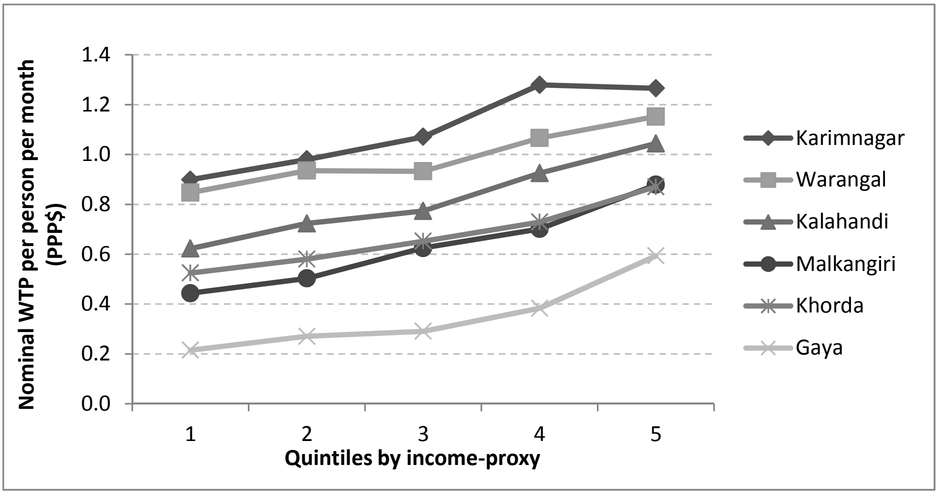

Figure 5.2 WTP by income-proxy

therefore examined the notion that actual spending on one necessity (food) can serve as an anchor for the estimation of WTP for another necessity (health insurance). To this end we checked the consistency of WTP as percentage of reported food expenditures within and across locations.

For a more robust comparison we also examined the opposite notion, that WTP is considered a 'luxury good' a household can only buy when it has enough money to spare. To this end we calculated discretionary income (income-proxy minus food expenditures) and checked the consistency of WTP as percentage of discretionary income within and across locations. Figure 5.4 shows the averages of both indicators for all six locations.

The data in Figure 5.4 indicates that the variation in WTP as percentage of discretionary income across locations (average values) is more pronounced than the variation in WTP expressed as percentage of food expenditures. This consistency across locations was quantified by calculating the coefficient of variation (the ratio of the standard deviation to the mean). The overall average WTP as percentage of food expenditure was 4.6% (with a standard deviation of 1.6%), and the overall average WTP as percentage of discretionary income was 5.0% (with standard deviation of 2.5%).

The coefficient of variation of WTP expressed as percentage of food expenditure was 0.36 and of WTP expressed as percentage of discretionary income was 0.50. For reference, the coefficient of variation of WTP as percentage of income was 0.43. This means that WTP expressed as percentage of food expenditure varied the least across locations.

We also examined the consistency of the indicators within locations, by calculating the concentration indices of the WTP indicators. This measure can show whether an indicator is distributed equitably across households with different income within the

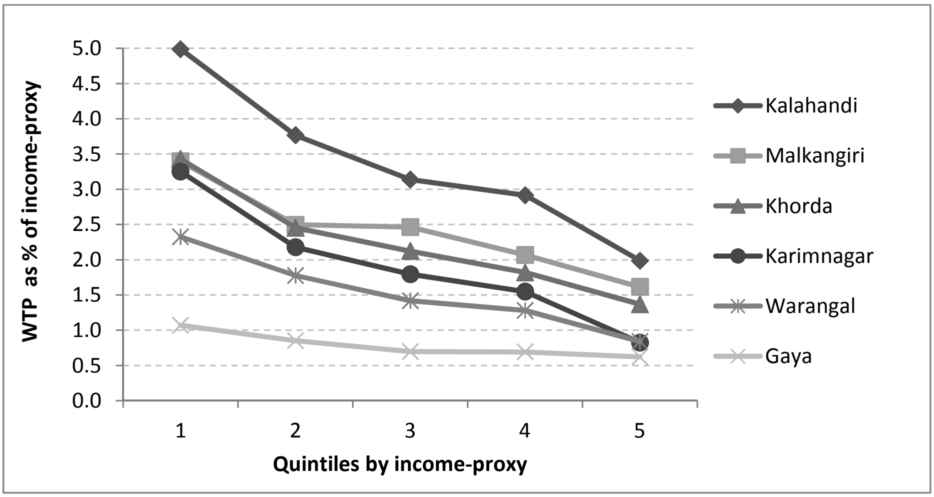

Figure 5.3 WTP as percentage of income-proxy by income-proxy

same location (O'Donnell et al. 2008). The more equitable the determinant of WTP (concentration index closer to zero), the better it can serve as an anchor across income groups in a location (least income-dependent).

WTP expressed as percentage of food expenditure has a lower concentration index than WTP expressed as percentage of discretionary income in all locations (Figure 5.5). This means that the amount a household spends on food is a much better predictor of WTP for health insurance than the amount available to the household for spending after paying for food.

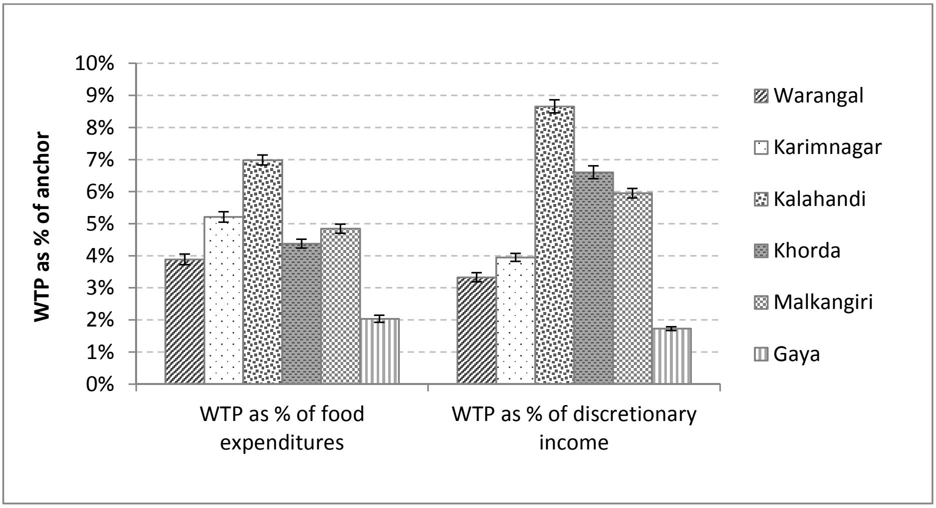

Figure 5.4 WTP as percentage of food expenditures or discretionary income

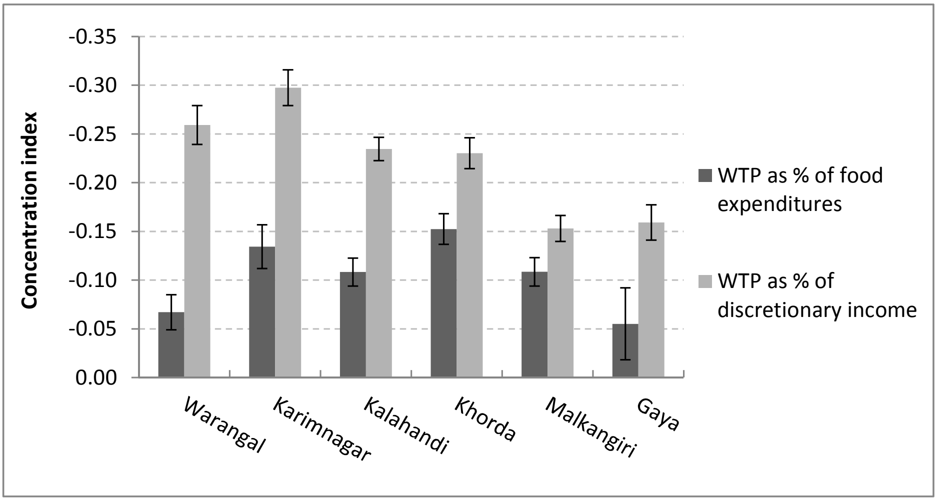

Figure 5.5 Concentration indices of WTP as percentage of food expenditures or discretionary income

5.4 DISCUSSION

The purpose of this study is to find an anchor to obtain initial estimates of WTP for community-based health insurance (CBHI) under conditions of voluntary affiliation. The WTP represents the price that the household was willing to pay per person per month for health insurance that would cover part of the healthcare expenditures, within the WTP level. The prevailing practice has hitherto been to estimate WTP based on specific questions included in household surveys. We aim to identify the parameter that would yield the most consistent estimate of WTP and which could be established without resorting to household surveys, as these are costly and time-consuming.

We compared data from six locations in rural India; we found a positive relation between WTP and income, but this relation was neither consistent across income-groups within locations, nor across the locations. In a previous study it had been shown that there is a positive relation between nominal increase in income and in WTP, but a negative relation when WTP is expressed as share of income (Dror et al. 2007b). This characteristic of the relationships is remindful of Engel's Law which expresses the same kind of relationship between food expenditures and income (Perthel 1975, Engel 1957). In our study, the described relationships between income and WTP repeated itself in all the locations, leading us to consider that (WTP for) health insurance behaves like a typical necessity good, like food.

We therefore checked the relationship between WTP and food expenditures and between WTP and discretionary income (the amount available after paying for food). We measured intercommunity differences by using the coefficient of variation, and intra-community variations with the concentration index. The most important insight gained from these calculations has been that average household spending on food provided a good indication of the WTP for health insurance of the studied populations in all locations as well as across the locations. WTP estimations based on food expenditure were most consistent, more so than overall income and better than discretionary income. That said, this higher consistency in the measure of WTP across and within locations does not mean that the actual values reported across locations are uniform; naturally they are not, as can be seen e.g. that Gaya is a clear outlier; the differences in values are likely to reflect other (cultural, demographic) parameters.

It has been shown that on average WTP for health insurance can be estimated at around 4.5% of food expenditures. This estimation means that a simple and cost-effective method to establish average food expenditures in a target community would also provide a reliable handle for WTP prior to the launch of contributory CBHI. This is a simplification of current practices, with no sacrifice to quality of estimates of WTP. This method would obviate the need to conduct costly and time-consuming WTP studies through household surveys, and would also remove confounding information (e.g.

inconsistent WTP as percentage of overall income or discretionary income, revealed in this study). The only reference data that would be needed would be food expenditure, which e being everyday expenditures e are much better known to all, and can be obtained easily through focus group discussions or from data published routinely and in the public domain.

WTP estimated at 4.5% of average food expenditures was obtained based on data collected in six rural locations in India, which of course differ from each other in several socio-economic and demographic features. Before our findings can be generalized for other places, further research would be needed to validate that the estimated WTP is similar elsewhere. The actual anchor could differ from this 4.5% of food expenses in other countries, but we expect that the expression of WTP relative to food expenditure will remain the most consistent compared to other measurements. Further research to test that the relationship to food expenditures applies elsewhere would be able to confer a more general validity to our findings in rural India. Finally, further research could also refine the most effective method to extract information on average food expenditures in a community, for instance through focus group discussions.

The finding that WTP for health insurance behaves like a necessity good rather than a luxury good is quite surprising. Intuitively one could have expected health insurance to be a luxury good, in particular as the rural poor that were the focus of our study had such very low income, and hardly any experience with health insurance or insurance in general. However, these insights actually flow quite logically from a previous finding of the same authors that health-related hardship financing among rural poor populations (i.e. borrowing with high interest or selling assets) was considerable (Binnendijk et al. 2012c). Therefore, it seems logical that people who are exposed to such financial risk would seek to reduce illness related financial shocks, and would consider affordable and relevant solutions as essential. It follows that the scoping of WTP levels among rural poor prior to launching CBHI can proceed successfully even among cohorts that are inexperienced with the financial instrument, when given coherent explanations.

5.5 CONCLUSIONS

The first and most striking insight gained through this study in six locations in India is that WTP for health insurance could be estimated as a percentage of average food expenditure in the target communities. This is related to the second important finding that the relationship between income and food expenditures is similar to the relation between income and WTP for health insurance, indicating that even rural poor, with very little money, education or experiences with (health) insurance consider health insurance as a necessity good (akin to food). The average expenditure on food can serve as a better data series for the estimation of WTP for health insurance than either overall income or discretionary income. Thirdly, the detailed calculations show that the level of WTP for community-based health insurance (CBHI) was approximately 4.5% of food expenditure in the six locations we studied in India. Further research could verify whether the same percentage applies everywhere; but we expect the relationship to food expenditure to offer best-fit elsewhere as well. Finally, the analysis described in this article strongly suggests that it is possible to estimate WTP for health insurance without having to conduct household surveys to obtain essential data first; the only data source needed would be information on average food expenditures in the community. We submit that this can be obtained through cheaper and faster research methods, such as focus group discussions with target communities or, if sufficiently accurately available, existing data sources. This means that it would be much easier, faster and cheaper to implement CBHI among rural poor populations (in India) than hitherto, as one of the critical needs that required doing a baseline is obviated by the new method presented in this article.

ACKNOWLEDGEMENTS

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Chapter 6

Illness Mapping: A time and cost effective method to estimate healthcare data needed to establish community-based health insurance

Based on: Binnendijk, E., Gautham, M., Koren, R., Dror, D.M.
Illness Mapping: A time and cost effective method to estimate healthcare data needed to establish community-based health insurance.
BMC Medical Research Methodology 2012, 12:153.

ABSTRACT

Objective Most healthcare spending in developing countries is private out-of-pocket. One explanation for low penetration of health insurance is that poorer individuals doubt their ability to enforce insurance contracts. Community-based health insurance schemes (CBHI) are a solution, but launching CBHI requires obtaining accurate local data on morbidity, healthcare utilization and other details to inform package design and pricing. We developed the "Illness Mapping" method for data collection (faster and cheaper than household surveys). ***Methods*** Illness mapping is a modification of two non-interactive consensus group methods (Delphi and Nominal Group Technique) to operate as interactive methods. We elicited estimates from "Experts" in the target community on morbidity and healthcare utilization. Interaction between facilitator and experts became essential to bridge literacy constraints and to reach consensus. The study was conducted in Gaya District, Bihar (India) during April-June 2010. The intervention included the illness mapping and a household survey. Illness mapping included 18 women's and 17 men's groups. The household survey was conducted in 50 villages with 1,000 randomly selected households (6,656 individuals). ***Results*** We found good agreement between the two methods on overall prevalence of illness (illness mapping: 25.9% ±3.6; household survey: 31.4%) and on prevalence of acute (illness mapping: 76.9%; household survey: 69.2%) and chronic illnesses (illness mapping: 20.1%; household survey: 16.6%). We also found good agreement on incidence of deliveries (illness mapping: 3.9% ±0.4; household survey: 3.9%), and on hospital deliveries (illness mapping: 61.0%. ± 5.4; household survey: 51.4%). For hospitalizations, we obtained a lower estimate from the illness mapping (1.1%) than from the household survey (2.6%). The illness mapping required less time and less person-power than a household survey, which translate into reduced costs. ***Conclusions*** We have shown that our illness mapping method can be carried out at lower financial and human cost for sourcing essential local data, at acceptably accurate levels. In view of the good fit of results obtained, we assume that the method could work elsewhere as well.

6.1 BACKGROUND

A large part of health care spending in developing countries is private and out-of-pocket (OOP). India is typical: 70% of spending is private, of which 86% is OOP (Karan & Selvaraj 2012, World Bank 2010). Moreover, private insurance rates remain below 5% (Ma & Sood 2008). The dearth of insurance is surprising, given the high frequency and cost of borrowing from moneylenders even for outpatient care and maternity (Binnendijk et al. 2012c) in addition to inpatient care (Binnendijk et al. 2012c, Peters et al. 2002), and the inability of rural poor to pay for non-communicable diseases (Binnendijk et al. 2012b) even as the prevalence of NCDs increases in low-income countries (WHO 2011a, Lopez et al. 2006). One possible explanation for low insurance penetration is that poorer individuals in the informal sector doubt their ability to enforce contracts with insurance companies. A solution to the problem is community-based health insurance schemes (CBHI) (Bhat & Jain 2006, Ahuja 2005, NCMH 2005, Ahuja 2004). These schemes are owned and run locally, at village level (Dror et al. 2009a, NCMH 2005). One of the hurdles to launching CBHI schemes is obtaining relevant information on local morbidity, healthcare utilization and other information that would inform the design and pricing of a relevant and affordable insurance package. A number of experiments with micro health insurance have relied on household surveys to obtain reliable local actuarial estimates and other information required for package design and pricing (Doyle et al. 2011, Dong et al. 2004, AC Nielsen ORG-MARG Pvt Ltd. 2001). Obtaining accurate local data is essential both because the income of CBHI is often limited and because of significant differences across locations in the number and type of illness episodes (Dror et al. 2009b, Dror et al. 2008, Dror 2007). However, household surveys are both expensive and time consuming. Thus a faster and cheaper method would be instrumental in promoting the expansion of micro health insurance.

Our study is located in Gaya district, Bihar state, India. The main source of data on incidence/prevalence of illnesses and hospitalisations is the Indian National Sample Survey Organization (NSSO) (NSSO 2006). The NSSO however provides information only at state level and not at district or block level, which are the more relevant units for CBHI. In addition, the most recent edition of NSSO with information on morbidity and healthcare utilization dates to 2004 (NSSO 2006) with an earlier survey in 1995/96 (NSSO 1998). And, health information sourced from local medical record-keeping does not provide sufficiently accurate location-specific data.

This paper contains a description of a cheaper and faster method to derive quantitative estimates of healthcare events through qualitative approaches (Jones & Hunter 1995). The experiment we conducted is inspired by previous methodologies aiming to achieve similar objectives. For instance, Auray and Fonteneau (2002) suggested possible group methods using consensus-building techniques, notably the Delphi and the Nominal Group Technique (NGT), to derive estimates from expert opinions on prevalence of hospitalizations, incidence of illness etc.

In the Delphi method, individual experts that are not in contact with each other first provide their quantitative estimate to a query; then, each expert is informed about other experts' replies, and invited to adjust the value (but each expert does so alone, without interacting with the others); this process can be repeated several iterations until consensus is reached (Jones & Hunter 1995, Woudenberg 1991). In the NGT, experts that are assembled in the same place at the same time individually write down their views on the topic in question and present one idea to the facilitator which is recorded. There is a group discussion to clarify and evaluate each idea and following this discussion each participant privately ranks each idea. This ranking is tabulated and presented. The group then discusses the overall ranking to reach consensus (Jones & Hunter 1995, Sample 1984, Van de Ven & Delbecq 1974). It is noted that while there is some interaction between NGT group members to discuss or clarify ideas, other major group processes, such as idea generation and final rankings, are conducted silently and individually (Van de Ven & Delbecq 1974). So, while both the Delphi and NGT are methods to reach consensus, both unfold among non-interacting groups (participants do not interact and discuss with each other during the group process) (Van de Ven & Delbecq 1974, Van de Ven & Delbecq 1971). In interacting groups on the other hand, participants are allowed to interact and discuss with each other at each step of the process (generation of information, ideas, views, evaluation and final consensus) (Van de Ven & Delbecq 1971). Interacting groups are usually unstructured (participants have complete freedom to think, review and synthesize together); examples are Brainstorming discussions and Focus Group Discussions (Kitzinger 1995). Non-interacting groups however, are usually structured (participants receive systematic procedural guidance) (Woudenberg 1991, Van de Ven & Delbecq 1974).

Research in the 1960s and 70s compared non-interacting groups with interacting groups (Van de Ven & Delbecq 1974, Bouchard 1972, Van de Ven & Delbecq 1971, Bouchard 1969). Delphi and NGT have been found superior to interacting groups for finding solutions to problems (Van de Ven & Delbecq 1974), but when group interactions were structured to enhance exchanges among the participants during thinking, visualizing and estimating, results were better than with unstructured interactions (Lowry 2002, Hart et al. 1985). Moreover, Van de Ven and Delbecq (1971) found that the most optimal group processes occurred when a structured procedure entailed interactive discussions after the initial exposé of ideas/views. Bouchard (1972) found that group-results were enhanced when the groups consisted of carefully selected individuals who had some prior knowledge of each other and some practice of working or being together (where differences that might inhibit group effectiveness were minimized).

Our study entailed a variation of an interactive group technique, inspired by the non-interactive group techniques. We elicited expert opinion in which our experts were members of the target community that knew each other, whose opinions were obtained in a structured, interactive group situation. The purpose of the inquiry has been to derive estimates of healthcare data needed to establish micro health insurance. We call this method “Illness Mapping”. With the view to verifying robustness of results of the Illness Mapping method, we compared them to household survey data from the same locations and period. Our working assumption was that if the Illness Mapping delivered useful comparator data in this case, this method could be used elsewhere as an alternative to household surveys for faster and cheaper resourcing of the context-relevant essential data.

6.2 DATA AND METHODS

6.2.1 Setting and sampling

The study was conducted in Gaya District of Bihar state, India. Gaya district is subdivided into 24 blocks. We selected 7 contiguous blocks purposively because this is where a local partner Non-governmental Organization (NGO) intended to implement a micro health insurance scheme. The intervention included two exercises: the Illness Mapping and a household survey. Both activities were conducted during April-June 2010.

For the Illness Mapping, we divided the 7 blocks into 3 clusters (northern, middle and southern) and selected 6 villages in each cluster based on distance from the nearest government primary health centre (0–5 kms; 5.1-8 kms; and more than 8 kms). Our total sample included 18 villages, (7 villages in the 0–5 kms category; 6 villages in the 5.1-8 kms category; and 5 villages in the >8 kms category). In consultation with the field partner, we selected a male group and a female group in each village, each with about 10 participants. The groups were gender homogenous to enable participants to speak freely on the given subject. There were 18 women’s groups (263 participants) and 17 men’s groups (147 participants).

The household survey was conducted in 50 villages across Gaya district, selected randomly (using census list of villages) from all 24 blocks in the district, proportional to the number of villages in each block. Within each village, we interviewed 20 households, selected randomly by applying the “four winds technique”, or “line sampling” (selecting households according to a predetermined staggering e.g. every second/third household starting from the centre of the village and progressing in the four cardinal directions) (Som 1996). In total, 1,000 households were interviewed, representing 6,656 individuals.

Verbal informed consent was obtained from respondents of the household survey at the beginning of the interviews, and from participants of the Illness Mapping before the discussions began. 100% of the interviewed sample was rural.

6.2.2 Illness mapping

The Illness Mapping technique is an adaptation of two non-interactive consensus group methods (Delphi process and Nominal Group Technique – NGT) operated in an interactive manner. The adaptation was necessary because it was impossible to apply the Delphi and NGT as is (i.e. sending our experts a questionnaire and/or requesting each to write ideas individually) due to the limited literacy of the population. Rather, interaction between the facilitator and the group members became essential, especially as the option of reaching decisions by vote was discarded, in light of the finding in one of our previous studies in India that rural participants preferred to reach a consensus (Danis et al. 2007).

Like the Delphi and NGT techniques, Illness Mapping relies on the knowledge of experts. Prior to the selection of the experts, our research team met with key informants in the village [health/development workers such as the Accredited Social Health Activist (ASHA), Aanganwadi Worker (AWW) or Auxiliary Nurse Midwife (ANM), representatives of Self Help Groups, etc.] to get an overview of the village, its size, social segmentation, and a general impression of its socio-economic status. Using this knowledge, we selected our experts by applying the following criteria:

1. They should be living in different parts of the village.
2. They should be sociable, outgoing and interacting frequently with their neighbours, so that they would be knowledgeable about people and events in the village. Not surprisingly, participants with higher interpersonal skills have been found to perform better in group discussions (Bouchard 1972).
3. Group members should reflect similar social or income groups.

In the Illness Mapping facilitators (of the same gender as the participants) guided group meetings to enhance recall of the parameters needed for the calculation of the prevalence of illnesses and utilization of health services. Such facilitated recall procedure does not occur either in the Delphi or the NGT, but publications suggested that compared to unstructured interventions, participants recall the relevant parameters better when procedures are structured during the thinking, visualizing and estimating stage of the interaction with the facilitator (Lowry 2002, Hart et al. 1985). Considering that people with motivation or training have been reported to perform better in group interactions (Bouchard 1972), we motivated our participants by explaining that they were selected for this discussion from the entire village, and that the information they provided would help develop the right kind of health insurance benefits for them and the entire village.

With each group, we first obtained a rough estimate of the number of households in different parts of the village, the rough household size (i.e. number of family members that ate from the same pot), and the total population of the village. Then we asked the number of persons who had been sick over the last one month, and the nature of their illness. We then asked every participant to name, one after the other, all the illnesses they could remember. To facilitate recall, the facilitator prompted periodically by asking about specific illnesses by name, both common and not so common ones. We also enquired about incidence of hospitalizations and deliveries (during the last 12 months) including information whether the delivery occurred at home or in an institute.

Consensus was reached through a structured group discussion of the final tallies, similar to the final round of the NGT. We presented to each group the final tallies of the main illness categories and frequencies of illnesses, hospitalizations and deliveries, and asked for feedback on the illness tallies (presented both as a number and as a percentage of the total village population). Usually participants chose to increase the final cumulative percentage. In the few instances where the group was not able to arrive at a single estimate, we noted the different estimates (usually 2–3 different estimates) and averaged them.

Similar to the Delphi method, our facilitator combined all responses and fed those back to the experts, who then ranked all opinions/solutions to obtain a new "agreed value", which was again combined and distributed. Like in the Delphi, the experts can re-evaluate their ranking and possibly change their original opinions/solutions (Jones & Hunter 1995).

As in NGT, our Illness Mapping process occurs in a meeting. And, like NGT interaction is limited in the first part of the process when each expert gives their response to the facilitator (in NGT this is done in writing). A group discussion follows, to clarify and evaluate responses, and reach consensus (in NGT, unlike our Illness Mapping, before discussion to reach consensus each expert ranks responses separately, and the ranking is tabulated and presented) (Jones & Hunter 1995, Sample 1984).

Data obtained in group discussions were recorded on pre-designed data sheets; a second person, other than the facilitator recorded the responses. Names and frequencies of illnesses[7] were recorded; we classified the illnesses reported as acute, chronic, accidents, and undefined. 18 groups from 14 villages provided 8 or more names of illnesses; only these groups were retained for the analysis of illness types. Hospitalizations and deliveries were counted and presented separately.

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7. The following conditions were usually included: (i) acute: fevers, diarrhoeas, body pains, respiratory conditions (not including asthma/COPD), TB and skin problems; (ii) chronic: asthma/COPD, diabetes, hypertension, kidney diseases, and cardiovascular problems.

6.2.3 Household survey

The household survey questionnaire included questions on general demographics (age, gender, education, and economic activity), socio-economic status (queried through questions on many items of household expenditures) and health status of household members. Following the method of the Indian National Sample Survey Organization (NSSO 2008), we consider the monthly per capita consumer expenditure excluding healthcare costs as a proxy for income. Respondents were asked about illness episodes in the household during the month preceding the survey. Using the replies regarding the illness (related to symptoms, length of illness, recurrence, medication etc.), we classified illnesses into four categories: acute, chronic, accidents and undefined. Respondents were asked about hospital admissions in the year preceding the survey and deliveries in the two years preceding the survey including where the delivery took place (home or hospital). The household survey questionnaire was translated into Hindi (the local language), back translated for validation, and pre-tested among 80 households in the area. Surveyors who spoke the local language fluently conducted the survey.

6.2.4 Data presentation and statistical analysis

We used Stata (version 11) for a descriptive analysis of the household survey. We used MS Excel (version 2003) for the Illness Mapping data tabulation and analysis.

The incidence of illness and health care utilization derived from the household survey are represented in percentages by dividing the number of cases by the overall number of members of the sampled households. The estimates derived from the Illness Mapping are presented as the mean and standard error of the mean (SEM) of all the group estimates arrived through consensus (male/female groups separately and all groups). We compared information obtained from male vs. female groups to ascertain that familiarity with local illnesses was comparable, and significance of this difference was assessed by Student's t-test. When comparing the results from the Illness Mapping with the results from the household survey we considered as "good fit" results of the Illness Mapping that were less than two SEM of the household survey data and as "very good fit" the results that were less than one SEM.

6.3 RESULTS

6.3.1 Socio-economic and demographic profile of the sampled population

The information on socioeconomic and demographic status of the sampled population in Gaya (one of the districts of Bihar state) is summarized in Table 6.1. As can be seen, the population is resource-poor (income is about PPP$ 1.53 per person per day), poorly educated (44% with no schooling whatsoever), and the main source of earning is daily wage labour (60%) and self-employed in agriculture (24%). As a comparison, monthly per capita consumer expenditure (not including medical expenditures) was INR 753 in rural Bihar according to NSSO (=PPP$ 1.39 per person per day) (NSSO 2011b).

Table 6.1 Socioeconomic and demographic information obtained

	Mean (± SE[a])
Income-proxy p.p.p.m.[b] (INR)	832.62 (± 7.05)
Household size	7.97 (± 0.04)
	Share of population
Education of population (15 years and older)	
No schooling	43.67%
Class 1-5	12.08%
Class 6-10	34.55%
Class 11 and higher	9.69%
Economic activity of income earners (15 years and older)	
Daily wage labourer	60.43%
Self-employed in agriculture	24.30%
Self-employed in business/trade	7.89%
Regular salaried employee	7.38%

[a] SE = Standard Error.
[b] Monthly per capita consumer expenditure – our proxy for income – is obtained through questions on many items of household expenditure (excluding healthcare expenditures).

6.3.2 Prevalence of illnesses

Local prevalence of illnesses is one of the main parameters for designing and pricing health insurance. We compared the estimate of prevalence of illnesses (the percentage of persons ill in the last month) from the Illness Mapping methodology with the conventional household survey (Table 6.2). The comparison of the mean value of prevalence of illness obtained through the Illness Mapping and that obtained through the household survey were less than two SEM, and provided "good fit". Furthermore, the results obtained from groups composed of males and females were not significantly different from each other (t test).

Table 6.2 Estimates of prevalence of illness from Illness Mapping and household survey

Proportion of ailing persons (last month) obtained from the Illness Mapping			Proportion of ailing persons (last month) obtained from the household survey
Male and female groups combined	Male groups only	Female groups only	
(±SE[a])	(±SE[a])	(±SE[a])	
25.9% (±3.6%)	24.5% (±4.8%)	28.5% (±5.4%)	31.4%
	p = 0.587[b]		

[a] SE = Standard Error.
[b] Test of significance between male and female groups (*t*-test).

6.3.3 Types of illnesses

The proportion of acute and chronic illnesses in the Illness Mapping and the household survey data is shown in Table 6.3. Acute illnesses represented most of the morbidity under both counts (76.9% of all illnesses based on the Illness Mapping compared to 69.2% derived from the household survey). Chronic illnesses were 20.1% and 16.6% respectively. The proportion of accidents in the Illness Mapping (2.0%) was lower than that reported in the household survey (5.0%). There were fewer undefined illnesses in the Illness Mapping than in the household survey (1% vs. 9.1%).

Table 6.3 Estimates of types of illness from Illness Mapping and household survey

	Illness types as share of illnesses:			
	Acute	Chronic	Accidents	Undefined
Data obtained from the Illness Mapping	76.9%	20.1%	2.0%	1.0%
Data obtained from the household survey	69.2%	16.6%	5.0%	9.1%

Note: The above percentages for illness types were calculated for all groups together.
Standard errors for these values are therefore not available.

6.3.4 Hospitalizations

The Illness Mapping estimate of incidence of hospitalization was 1.1% (±0.4) and the household survey estimate was 2.6% (Table 6.4). Data from the household survey gave a much higher estimate than the Illness Mapping. The difference was significant and material even after taking the standard errors into account.

Table 6.4 Estimates of incidence of hospitalization from Illness Mapping and household survey

Percentage of hospitalized persons (last year) obtained from the Illness Mapping			Percentage of hospitalized persons (last year) obtained from the household survey
Male and female groups combined (±SE[a])	Male groups only (±SE[a])	Female groups only (±SE[a])	
1.1% (±0.4%)	1.6% (±0.8%)	0.5% (±0.1%)	2.6%
$p = 0.213$[b]			

[a] SE = Standard Error.
[b] Test of significance between male and female groups (*t*-test).

6.3.5 Deliveries

Data on incidence of deliveries and on percentage of hospital deliveries is presented in Tables 6.5 and 6.6. We found very good agreement between the Illness Mapping data and the household survey data on incidence of deliveries: 3.9% (±0.4) in the Illness Mapping data for all groups combined and 3.9% in the household survey.

The Illness Mapping estimate of hospital or institutional deliveries was 61.0% (±5.4) for all groups combined, while the household survey estimate was 51.4% (Table 6.6). The two data series were within the good fit limit, but results reported by the female groups were in closer agreement (very good fit).

Table 6.5 Estimates of incidence of deliveries from Illness Mapping and household survey

Number of deliveries per 100 persons (last year) obtained from the Illness Mapping			Number of deliveries per 100 persons (last year) obtained from the household survey[b]
Male and female groups combined (±SE[a])	Male groups only (±SE[a])	Female groups only (±SE[a])	
3.9% (±0.4%)	4.4% (±0.7%)	3.4% (±0.6%)	3.9%
p = 0.293[c]			

[a] SE = Standard Error.
[b] Based on the reported number of children less than or equal to 1 year in the household.
[c] Test of significance between male and female groups (*t*-test).

Table 6.6 Estimates of percentage of hospital deliveries from Illness Mapping and household survey

Percentage of hospital deliveries obtained from the Illness Mapping			Percentage of hospital deliveries obtained from the household survey
Male and female groups combined (±SE[a])	Male groups only (±SE[a])	Female groups only (±SE[a])	
61.0% (±5.4%)	67.3% (±7.8%)	55.4% (±7.3%)	51.4%
p = 0.275[b]			

[a] SE = Standard Error.
[b] Test of significance between male and female groups (*t*-test).

6.3.6 Cost and time comparison between household survey and Illness Mapping

Table 6.7 gives a record of the time and human resources required for the household survey of 1,000 households compared to the Illness Mapping for 35 groups. The comparison is limited to the core activities related to the two methods, since the exact related costs could presumably be context dependent (salaries, traveling conditions, accommodations, will be different in different locations). The table shows that Illness Mapping represented a reduction of 59% in work-days, i.e. requires less time and less costs than conducting a household survey.

Table 6.7 Number of working days required for Illness Mapping and household survey

	Illness Mapping	Household survey
Preparation (including translation of tools, training of interviewers and pre-test)	3 days	8 days
Field work (with 1 supervisor and 4 or 5 interviewers)	18 days	30 days
Data entry (1 person)	1 day	20 days
Data cleaning and analysis (1 person)	8 days	14 days

6.4 DISCUSSION

In this study we set out to develop a reliable method that may in future enable us to access the necessary data for the establishment of a micro health insurance in low income rural communities where data would not be available otherwise. The objective before us was to find a way to overcome the two constraints associated with data sourcing through household survey, namely, the cost and time required. The Illness Mapping method we describe here seems to meet this objective. The information given in Table 6.7 illustrates the advantage of the Illness Mapping method in terms of human resources and time required, which obviously translate into differences in costs (e.g. salaries, travel, accommodation etc.).

The design of an insurance product requires estimates of the prevalence/incidence of the events covered by the insurance. Our previous studies showed that: (i) the incidence of illness episodes, and prevalence of hospitalizations and delivery is strongly context-dependent and varies across locations even in the same country (Dror et al. 2009b) making it necessary to obtain local data. (ii) Prospective clients of health insurance in rural India are exposed to hardship financing not only in cases of hospitalizations but also in cases of outpatient treatment and in deliveries (Binnendijk et al. 2012c). In fact, this is even more pronounced in case of chronic illnesses (Binnendijk et al. 2012b). (iii) When expressing their priorities regarding benefits that should be covered by insurance, prospective clients expressed a clear wish to include both inpatient and outpatient benefits (Dror et al. 2007a, Danis et al. 2007). It is thus clear that the information obtained through Illness Mapping regarding the prevalence/incidence of prioritized cost generating events is essential for the design and pricing of context-relevant health insurance.

We followed a strategy of soliciting local information from groups rather than from individuals. We were inspired by group techniques, assuming that the small cosmos of a village community could be captured through harvesting the knowledge that is readily available to its inhabitants free of charge. Having failed to find a readymade suitable method in the published literature, we opted to utilize a combination of established methods and adapt them to our settings. Group approaches such as the Delphi and NGT have been used successfully and with high accuracy for business forecasting as well as for public policy (Hilbert et al. 2009, Basu & Schroeder 1977). We adopted the criteria for resourcing quantitative information from qualitative non-interacting groups such as Delphi and NGT (Jones & Hunter 1995, Van de Ven & Delbecq 1974), and modified those to take account of the advantages of interactive group situations in which the discussions are moderated and facilitated rather than left to chance (as often happens in exploratory brainstorming groups or focus groups (Kitzinger 1995)). Such structured group methods are based on the principle of collective intelligence (Surowiecki 2004), or group intelligence that emerges through managed consensus decision making (Hart et al. 1985).

Our method was based on small group discussions with people who were marginally literate and numerate, but nonetheless experts or valid representatives of their village communities. They were chosen (with the help of our partner NGO staff who had prior access to the village) for their social attributes and their knowledge of households in their own neighbourhood in the village. In each village we carefully identified such participants and facilitated their interaction to obtain estimates for the prevalence of illness for the entire village. Other key contacts in the village such as teachers, village head, and health workers could also be recruited to provide similar information if there were no prior links with the village.

We organized gender homogenous groups in each village to ensure that both men and women would be able to express themselves freely. We thought that women, who are usually caregivers, might be more familiar with illnesses than men. However we found no statistical difference between the estimates given by men's and women's groups. We found it more difficult to assemble men's groups as men were usually away during the day. From this experience we infer that Illness Mapping could be extracted from interactions with either gender of respondents, and that women's groups are likely to be easier to assemble than men.

Our method had to be adjusted to the field reality of low literacy which meant that written consensus and voting was not the best option and so we employed a strategy which involved everyone in a sequential and structured interaction. Our structure emerged from the motivation, explanations, and facilitation techniques that we used to encourage accurate recall and steer discussions towards final consensus.

We examined the potential of our new Illness Mapping method by comparing the results obtained with those derived through a household survey. We compared three parameters which are important for implementation of micro health insurance: (i) prevalence of illness for acute and chronic illnesses, both of which entail cost implications which can be much higher in the case of chronic illnesses (Dror et al. 2008), (ii) incidence of hospitalization, as this cost is included in most health insurance programmes, and (iii) incidence of deliveries, especially hospital deliveries. We found very good agreement between the two methods on incidence of deliveries, and good agreement on prevalence of illnesses (in the last one month) and on prevalence of acute and chronic illnesses, as well as on the share of deliveries in hospital.

We obtained a lower estimate of incidence of hospitalization from the Illness Mapping than from the household survey (1.1% (±0.4) from the first source versus 2.6% from the second source). This discrepancy could be the result of two types of memory effects that can lead to erroneous reporting by respondents: errors of omission and of telescoping (Sudman & Bradburn 1973). While omission means forgetting or omitting to report an episode entirely, telescoping works in the opposite direction, i.e. the respondent remembers and reports an event as having occurred more recently than it actually had. The telescoping effect increases the total number of events reported in a given period. It has also been found that telescoping may be greater in face to face interviews as the presence of an interviewer and the face to face interaction may prod the respondent to give "too much rather than too little information" (Sudman & Bradburn 1973). It is possible that the telescoping effect may have resulted in an overestimation of hospitalizations in our household survey. In contrast, hospitalizations may have been underestimated in the Illness Mapping method as the group members may have only been aware of the longer duration hospitalizations in their communities and those due to major procedures such as surgeries. They may have omitted the shorter and less severe hospitalizations. This view is supported by prior evidence that longer duration stays and surgeries are more positively associated with recall than other hospitalizations (Harlow & Linet 1989). We do not have a definitive basis to determine which of these estimates is more pronounced, and only actual utilization data could indicate which estimate is the more accurate prediction.

Data obtained either from Illness Mapping or from a household survey would usually be treated by insurers with some reserve, as both methods are less reliable than actual claims data over a long period of time. The Illness Mapping did not, a-priori, show any difference on this count relative to the data obtained from the household survey. In insurance business, it is therefore common practice to include a safety loading in premium calculations, to account for errors in assumptions or inaccuracy of estimates.

The main advantage of the Illness Mapping method is that it is cheaper and faster to operate, and could replace a household survey for estimating morbidity and healthcare utilization, especially where local data is needed but not readily available. While we have tested this method in rural settings in India, we have no reason to think that it could not be equally effective in urban settings (e.g. slums), or in other countries. The estimates about morbidity and healthcare utilization are of course essential not only for insurance purposes, but also for health policy choices more generally. Limitations of this method include the need to establish good contacts with the study communities in order to identify the most suitable community experts. Secondly, high quality group facilitation is essential, by facilitators that must speak the local language and understand the local social settings (and probably be local). Finally, as the estimates obtained by both methods are predictive, one powerful way to evaluate the robustness of the estimates obtained would be to examine both Illness Mapping data and household survey data against actual claims data. Such a follow-up examination is needed to validate the accuracy of the Illness Mapping as a generally applicable alternative to household surveys for the data in question.

6.5 CONCLUSIONS

The effort to introduce health insurance among low income persons in areas in the informal economy requires that the benefit packages as well as the premiums payable will be customized to local conditions. Evidence has shown that those local conditions are context-specific and that one-size-fits-all simply will not do. This customization therefore is contingent on obtaining at least some local data on such pieces of information as prevalence of illness, hospitalizations, chronic and acute illnesses, and deliveries. We have explored the Illness Mapping method on the assumption that it can deliver a cheaper and faster resourcing of the essential local data, at acceptably accurate levels. We have shown in this study that the results obtained through the Illness Mapping method were comparable to those obtained through household survey. We have also shown that obtaining these results costs less time and money than conducting a household survey. We therefore conclude that for as long as health insurance solutions must be adapted to context relevant conditions and that these differ from one location to the next significantly, the Illness Mapping method tested in this study and explained in this article may serve the purpose.

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Chapter 7

A model to estimate the impact of thresholds and caps on coverage levels in community-based health insurance schemes in low-income countries

Based on: Binnendijk, E., Koren, R., Dror, D.M.
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ABSTRACT

Objective Community-based health insurance (CBHI) schemes are increasingly implemented in low-income settings. These schemes limit the coverage they offer both by a limited set of types of care, and by applying thresholds and/or caps to costs of benefit types covered. The consequences of these thresholds and/or caps on insurance coverage have hitherto been usually ignored, for lack of data on the distributions of healthcare costs or understanding of their impact on effective coverage levels. This article describes a theoretical model to obtain the distributions even without data collection in the field, and demonstrates the quantitative impact of thresholds and/or caps on claim reimbursements. ***Methods*** We looked at hospitalizations and tests; we compared the simulated distributions to empirical data obtained through 11 household surveys conducted between 2008 and 2010 in rural locations (9 in India and 2 in Nepal). ***Results*** We found that the shape of the distributions was very similar in all locations for both benefits, and could be represented by a model based on a lognormal distribution. The agreement between theoretical and empirical results was satisfactory (mostly within 10% difference). ***Conclusions*** The model makes it possible to simulate the expected performance of the CBHI (represented by the percentage of costs or bills covered). The aim is to match costs with local levels of willingness-to-pay for health insurance. This model makes it possible to determine at the stage of package-design the optimal levels of thresholds and/or caps for each benefit-type included.