Institute of Insurance Economics

University of St.Gallen

Pricing in Microinsurance Markets

Christian Biener

Working Papers on Risk Management and Insurance No. 106

Edited By Hato Schmeiser

Chair for Risk Management and Insurance

November 2011

Pricing in Microinsurance Markets

Christian Biener*

Abstract

Microinsurance markets have exhibited strong growth rates in recent years. Great parts of the industry are, however, challenged by fundamental issues of providing insurance products, one of the most significant of which is pricing risk. In this paper, we provide a non-technical analysis of insurance pricing problems and a review of the set of opportunities that can address some of the specific pricing constraints in microinsurance markets. A key contribution of this paper is the investigation of conventional techniques as potential solutions for improving the pricing of insurance risk in microinsurance markets.

Keywords: Developing countries, microinsurance, data availability, actuarial pricing, credibility methods

1 Introduction

This paper provides a non-technical analysis of insurance pricing problems and reviews the set of opportunities to address some of the specific pricing constraints in microinsurance markets. We thus strive to provide a basic understanding of conventional techniques which are rarely used in microinsurance markets today. Microinsurance is defined as a financial arrangement intended to protect low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved (see

* Christian Biener is with the Institute of Insurance Economics at the University of St. Gallen, Kirchlistrasse 2, 9010 St. Gallen, Switzerland (christian.biener@unisg.ch). The author is grateful to Martin Eling, Nihar Jangle, Sebastian Marek, Mary Yang, Hans-Joachim Zwiesler, and the participants of the ASTIN & AFIR Colloquia 2011 in Madrid, the Contemporary Microfinance: Institutions, Policies, and Performance conference 2011 in Cairo, and the 2012 Microinsurance Conference in Enschede for helpful comments and suggestions.

Churchill, 2007). Despite strong growth rates (see Churchill & McCord, 2012), these markets exhibit considerable limitations in terms of sound insurance practices, one of the most significant of which is pricing risk. To a large degree, this problem is due to constraints on data availability and a lack of utilizing suitable actuarial approaches.

The problem described here is not unique to microinsurance; however, it is especially pronounced and severely distorts the development of these markets. Constraints on data availability require microinsurers to make restrictive assumptions on the risks to be insured. The resulting estimates for expected losses thus require adjusting for potential adverse deviations through loadings (see Wipf & Garand, 2006). Those loadings can be substantial in microinsurance markets, making insurance unaffordable by the target population (see, e.g., Dror & Armstrong, 2006; Linnerooth-Bayer, Warner, Bals, Höppe, Burton, Loster, & Haas, 2009). In certain cases, premiums are subsidized and set on the basis that they will not exceed the target population's willingness to pay (see, e.g., Vaté & Dror, 2002). This practice exposes microinsurers either to substantial risk of insolvency due to underpricing risk (see, e.g., Dror & Armstrong, 2006), or, in case of subsidization, leads to an unsustainable business model since subsidies are typically only temporarily available. Increased precision in premium setting would allow microinsurers to reduce loadings and, consequently, increase their ability to offer more competitive prices (see, e.g., Brown & Churchill, 2000). Current practices put at risk confidence in a developing market if resulting in microinsurers not having sufficient capital to settle insured losses or if premiums exceed the target population's willingness to pay. Thus, to create and promote a sustainable microinsurance industry, it is necessary to design products that offer both a low risk of insolvency and affordability by the target population.

In this paper, we analyze the problems of pricing insurance risk in microinsurance markets and investigate the appropriateness of standard approaches and current practice. We consider both the supply and the demand side of the market. In our discussion, the supply side is represented by the determination of a technical premium; the demand side covers its marketability and interactions between the availability of microinsurance coverage and individual behavior. The integration of both perspectives is an important aspect of this paper, since we often observe a large gap between the technical premium and the customers' willingness to pay (see, e.g., Churchill, 2007; Linnerooth-Bayer et al., 2009). Despite the growing interest in microinsurance, very few studies offer guidance on pricing in these markets given their specific challenges.[1]

Current research confirms significant problems in pricing risk in microinsurance markets (see, e.g., Biener & Eling, 2012; Dlugolecki, 2008), whereas data availability is a prevalent challenge. Meaningful premium estimates, however, cannot be derived without a minimum of reliable data. Whereas internal loss data most appropriate for pricing most risks are often not available, microinsurers have access to informational sources that allow making inferences on risk properties. The use of ad hoc methods such as surveys and the inclusion of expert experience through, e.g., Delphi methods, can increase the accuracy of pricing insurance risk. We discuss the application of transition approaches that aim at adapting risk patterns from regions that have more data to the region of interest.

Credibility models can be valuable in making use of various sources of information, synthesizing risk characteristics into a technical premium, and providing means for updating premiums over time. Bootstrap techniques bypass a severe disadvantage in microinsurance markets: estimating the robustness of pricing estimators from small samples of original loss data, by creating new data. The application of risk management strategies provide further means to adapt to the environment of microinsurance markets and decrease excessive risk-loadings that are prevalent in the presence of data restrictions.

[1] Brown and Churchill (2000), in a review of 32 institutions, present current best practices in microinsurance for life, health, and property insurance, including pricing. Auray and Fonteneau (2002) discuss the issue of pricing health risk and especially offer guidance on acquiring health data. Wipf and Garand (2006) provide a basic introduction to requirements of pricing insurance risk. Garand et al. (2012) present a sound process for pricing microinsurance.

This paper's main contribution is its investigation of potential approaches for a more accurate pricing of insurance risk in microinsurance markets. The focus of the paper is on the estimation of technical premiums, i.e., the minimum premium an insurer needs to charge for a specific insurance policy to be viable. We also include the interaction of premiums with demand and behavior to discuss possible explanations of the discrepancy between technical and market premiums in microinsurance markets and provide potential solutions.

The industry investigated in this paper—microinsurance—is still in its infancy, but has huge future potential. We analyze the specifics of pricing risk in microinsurance markets and inquire into the appropriateness of standard approaches and current practices. We draw upon the actuarial and economic literature to create a toolbox of approaches that has solved similar problems in other markets. To our knowledge, this paper is the first actuarial and economic discussion of consistent schemes for pricing risk in microinsurance markets. Our results are thus significant for insurers and reinsurers active in these markets as well as for those planning to enter. The results are also of interest to policymakers, regulators, and development organizations that work toward enhancing the development of microinsurance markets. Readers who are not familiar with insurance pricing techniques benefit from this survey to deal with problems specific in microinsurance markets. Readers who are familiar with this field may find interesting new applications of existing approaches in microinsurance. We thus highlight the lessons to be learned from the experiences of different insurance markets to offer solutions to some of the problems in microinsurance markets. In this regard, we explain the fundamental features and refer to the respective literature for a more detailed account.

The remainder of this article is structured as follows. Section 2 reviews the principles of actuarial pricing. In Section 3, we describe the challenges in pricing risk in microinsurance markets. A discussion of the set of opportunities to estimate technical premiums is presented in Section 4. In Section 5, we extend the discussion to the interaction of premiums, demand, and behavior in microinsurance markets. Section 6 concludes.

2 Fundamental principles of actuarial pricing

Insurance is a mechanism to exchange contingent future payments against fixed payments, or premiums (see Wang, 1995). The actuarial rationale for the determination of technical premiums or prices for insurance risk is that these need to be sufficient to cover future losses on average. The equivalence principle is derived from this rationale as the origin for pricing insurance risk and defines the pure technical insurance premium as such that the present value of expected premiums is equal to the present value of expected losses and expected cost for providing insurance coverage.

For the fundamental approach of pricing insurance risk, assume that X is the total random loss from an insured risk pool in a specified time period. The random variable X has mean μ and standard deviation σ. Since the corresponding premium is set ex ante, it is necessary to estimate the parameters μ and σ in advance (see Bühlmann, 1985). Thus, the expectation on losses μ is included in the calculation of the pure technical insurance premium π.

Since future losses are random and the premium π is set ex ante, the pure technical insurance premium may not be sufficient to cover all losses and cost in the future with a certain probability. However, insurers can control the probability of insolvency α by adding a relative or a fixed risk-loading that depends on the distribution of losses X. The required technical premium π for insurance risk that controls for risk of insolvency α is hence defined by $\pi = (1 + \theta)\mu$ for a relative risk-loading θ, and by $\pi = \mu + \tau$ for a fixed risk-loading τ.

The risk-loadings can be derived by a variety of principles, all of which are intended to limit the risk of insolvency to a sufficiently small value (see, e.g., Embrechts, 2000 for a discussion of premium principles). If a large enough number of insured n is assumed, the central limit theorem yields $\theta = (z_{1-\alpha}\sigma)/(\mu\sqrt{n})$ for the relative risk-loading and $\tau = (z_{1-\alpha}\sigma)/(\sqrt{n})$ for the fixed risk-loading where $z_{1-\alpha}$ denotes the $(1-\alpha)$-quantile of the standard normal distribution (see Kliger & Levikson, 1998). In both cases, as the number of insured n increases, the average loss per insured approaches the real mean loss, i.e., the risk-loading becomes arbitrarily close to zero as n approaches infinity (see Cummins, 1991). In the case of independence of losses in the risk pool, both approaches are equivalent and allow the insurer to control the probability of insolvency α either by raising the risk-loading or by increasing the number of insured n.

A central implication of this result is that the risk-loading – and subsequently the premium – may *ceteris paribus* be decreased at a constant level of insolvency risk α when the number of insured n is increased. This is an important result since microinsurance institutions typically are relatively small – in many cases too small to achieve sufficient risk pooling to decrease risk-loadings.

Aside from the total future losses, the insurer has additional cost originating in the organization (e.g., distribution, management, settlement) and from financing of the organization, specifically the cost of capital.[2] These cost need to be covered by premium income and are typically reflected in a cost-loading c. Often, in the insurance literature, the cost-loading is assumed to be proportional to the expected loss of an insurance policy (see, e.g., Raviv, 1979). Thus, the required technical premium π for insurance risk controlling for risk of insolvency and including cost is $\pi = (1 + \theta + c)\mu$ or $\pi = (1 + c)\mu + \tau$ respectively.

Pricing health, non-life, and life insurance originates in the equivalence principle. However, different properties of the risks insured in the respective lines of business require divergent approaches to the application of the equivalence principle. This is mainly attributable to the different durations of risk coverage and properties of risk severities. Whereas health, non-life,

[2] A loading for cost of capital in microinsurance is often criticized on the basis of reservations against profit-maximizing institutions. However, equity capital is not costless and is needed to achieve a sufficient degree of solvency (see Biener & Eling, 2011). Policyholders benefit from higher security levels of insurers, and this provides a rationale for the addition of a cost-loading to the pure technical insurance premium.

and some life insurance coverage is usually short-term and renewed or terminated at the end of the term (commonly one year), most life insurance policies are long-term contracts. In short-term insurance, risk frequency and severity are usually stochastic; in most life insurance only the time of risk occurrence cannot be known with certainty.

3 Challenges in microinsurance pricing

There exist significant problems in the practice of pricing risk in microinsurance markets (see, e.g., Dlugolecki, 2008). The most fundamental of these problems is data availability, for four reasons. First, microinsurance markets have a short track record because the industry is relatively young. Thus, historical data on risk is limited. Second, many microinsurers are small, such that internal experience data generated from insurance pools is insufficient for statistical analysis and premium calculation. Third, internal and external reporting standards as well as the documentation of the loss history of insured are often poor in microinsurance markets, limiting the capacity to analyze risk. Finally, poor infrastructure in many developing countries precludes the use of important macro-level data such as inflation, demographics, meteorological data, and health cost. Data restrictions, thus, severely limit estimating robust distributions of losses and other cost.

Standard actuarial approaches to pricing insurance risk as presented in Section 2 require large sets of data and statistical information. Those range from assumptions on interest rates to mortality rates or frequency and severity distributions of losses. In the absence of extensive and reliable data, standard actuarial approaches need to be applied with caution. Insurers in regular insurance markets rely on exhaustive data and precise actuarial estimates for the distribution of losses. Increased precision is a lever for financial sustainability and enables insurers to decrease the risk-loading in its premium calculations and thus increases an insurer’s ability to offer more competitive prices (see Brown & Churchill, 2000). This is especially important when tailoring insurance coverage to the low-income population of microinsurance markets.

Unlike developed insurance markets, the microinsurance market's institutions face a dilemma. Microinsurance is designed to offer insurance coverage to the low-income population with limited willingness to pay and high price sensitivity (see, e.g., Biener & Eling, 2012; Cole, Giné, Tobacman, Topalova, Townsend, & Vickrey, 2010). Due to data constraints, microinsurers are required to add high risk-loadings for uncertainty in the estimation of expected losses. Consequently, the loading for uncertainty on the pure technical premium is higher in microinsurance markets compared to regular insurance markets, making insurance more expensive and thus less attractive to the low-income population. From this it follows that, when selling insurance at the estimated technical premium, microinsurers run the risk of overpricing risk and thus making the coverage unattractive. When adapting the technical premium to the low-income population's willingness to pay, microinsurers may increase the risk of insolvency because premiums are not sufficient to cover expected costs.[3] Subsidies to fill the gap between willingness to pay and the technical premium are only of limited use since most of these are only temporarily available and might generate moral hazard problems (e.g., inefficient management). If willingness to pay is presumably a constant and not modifiable, the dilemma needs to be resolved either by calculating premiums more precisely, and thus reducing the risk-loading, or by using risk management strategies that limit risk exposure and increase insurance capacity. This paper analyzes both approaches. We present methodologies that can make best use of information by efficiently processing and gathering information and approaches to apply risk management strategies. We include the demand side in our analysis and discuss approaches that may explain the discrepancy between technical and market premiums in microinsurance markets.

[3] Meze-Hausken, Patt, and Fritz (2009) also discuss the tradeoff between affordability and sufficiency of premiums as major challenges for providing microinsurance.

4 Set of opportunities

In the absence of internal loss data specific to the target population, which is the preferred source of information for actuaries, microinsurers need to form expectations and assumptions about the risk to be insured. In the first part of this section, we summarize some potential sources of information that can be accessed for pricing purposes. The second part of this section presents methodologies to process the available data efficiently and use multiple data sources simultaneously. The application of risk management strategies provide additional means to adapt to the environment of microinsurance markets and decrease excessive risk-loadings that will remain prevalent in the presence of informational restrictions. Therefore, the third part of this section discusses suitable risk management strategies.

4.1 Data acquisition

(a) Survey techniques

In cases where no data is available a risk becomes technically uninsurable because no premium can be estimated, not because the risk itself would be considered as uninsurable (see Vaté & Dror, 2002). Microinsurers, however, can apply techniques to access data for the quantitative estimation of risk from experts, households and other institutions such as health care providers.

A wide array of expert opinions, for instance on loss probabilities, can be synthesized into consensus estimates using techniques such as Delphi and nominal group methods (see, e.g., Mehr & Neumann, 1970), or nonconsensual Bayesian and maximum likelihood estimates to derive distribution parameters of the specific risks (see, e.g., Auray & Fonteneau, 2002). An expert is defined here as an individual with specific information about an uncertain quantity of interest (see, e.g., Morris, 1977).

The Delphi method applies independent interviews of an array of experts to obtain estimates of required quantities, such as loss probabilities. This method is based on the rationale that experts possess an intense understanding of the quantity of interest and that given estimates may be re-evaluated conditional on revealed assessments of other experts (e.g., a summary of the other experts' estimates). In the process of re-evaluating estimates in an iterative loop, experts adapt their estimates based on their own understanding and the revealed judgments of other experts (see, e.g., Rowe & Wright, 1999). The resulting estimate (e.g., the mean or median of all experts) thus provides a means to obtain information on unknown risk parameters.

In contrast to Delphi methods, the nominal group technique aims at arriving at a consensual estimate by openly stating, discussing, and synthesizing risk estimates through a vote or a preference-aggregation process. However, the nominal group technique is susceptible to psychological bias from effects such as exertion of influence by dominating group members and the bandwagon effect of majority opinion that can be avoided with the Delphi technique (see Mehr & Neumann, 1970). Regardless of the method used, both Delphi and nominal group technique produce a synthesized expert estimator of the quantity of interest; hence, these methods are especially beneficial in the absence of reliable information (see Auray & Fontenau, 2002).

Consensus estimates implicitly assume equal credibility of all expert opinions as well as a convergence to a consensus estimate that may not always be achieved. Consensus methods are problematic, since they give no rationale as to why the resulting estimate should sufficiently reflect reality (see, e.g., Morris, 1977). When microinsurers have initial information on the insurable risk, nonconsensual methodologies give more weight to the most credible expert estimate and derive point estimates of the quantity of interest. When particular distributions of specific risks can be assumed, the range of expert opinions can be used to fit the distribution parameters. Suitable approaches in this respect are the maximum likelihood estimator and Bayesian methods (see, e.g., Auray & Fontenau, 2002; Morris, 1977; Winkler, 1981).

Besides the provision of risk estimates when no other reliable data is available, estimates obtained by Delphi, nominal group techniques, and nonconsensual methodologies can be used to obtain prior distributions of parameters in credibility models discussed later in this section. However, the choice of credible experts and the ambiguity of questions are inherent problems of consensual and nonconsensual estimates based on expert assessments (see, e.g., Mehr & Neumann, 1970).

Household and provider surveys are popular ways of deriving estimates of risk and cost from primary sources. These techniques are already applied in microinsurance markets to a certain degree and are successful in supporting microinsurance start-ups (see, e.g., Auray & Fonteneau, 2002; Dror, van Putten-Rademaker, & Koren, 2008; Dror, Radermacher, Khadilkar, Schout, Hay, Singh, & Koren, 2009). They provide valuable information on pricing parameters but those approaches are prohibitively expensive and thus only feasible for a limited sample. To obtain reliable estimates for pricing insurance risk, however, a sufficiently large sample would be necessary. Another limitation pertains to information asymmetries between microinsurers and insured. Surveys can provide estimates of the average frequency and severity of specific events (e.g., property damage, diseases); however, they may not be able to assess risk factors necessary to differentiate categories of risk, thus creating adverse selection (see Akerlof, 1970).

(b) Relational data

Beside internal loss data on a specific target population and risk, several external informational sources allow microinsurers making indirect inferences on risk properties. These sources comprise macro- and meso-level institutional data but also include data from the industry level, neighboring regions, competitors, and reinsurers. Those data do not necessarily represent the actual target population but allow for the identification of risk patterns related to the target population. As with internal data, the external data must meet certain qualitative standards.[4]

Macro-level data is of utmost importance for most kinds of short- and long-term insurance. In most countries, demographic and socio-demographic data such as mortality rates and morbidity data have become increasingly available through registration systems and more complete inquiry of health data at the country-level (see, e.g., Haggerty & Reid, 2002; Lopez, Ahmad, Guillot, Ferguson, Salomon, Murray, & Hill, 2002). To increase the availability of insurance data, regulatory authorities in many countries require insurance companies to file statistical data (see, e.g., Werner & Modlin, 2010). Those are aggregated and made available either to the public or to participating institutions. Data not directly related to insurance can often be supplementary for the pricing of insurance products. At the country-level, the consumer price index at the component-level (e.g., medical costs) may provide insights into costs related to specific risks such as health insurance and their development over time (medical inflation).

In addition, meso-level institutions such as the United Nations (UN), the World Bank, or the INDEPTH Network contribute to increased availability of data on mortality and morbidity in developing countries that is publicly available and can be used by microinsurers.[5] In many developing countries, other organizations are striving for a better understanding of mortality and morbidity risk that can be accessed for pricing. We will elaborate on this below.

The progression of information technology has dramatically increased the resources to evaluate non-life risk such as agricultural or property through significant amounts of weather data and other geological information (see, e.g., Christopherson & Werland, 1996). The use of

---

[4] The Actuarial Standards of Practice define requirements on data quality (see Actuarial Standards Board, 2011).

[5] The UN through the World Health Organization (WHO) provides mortality tables for many developing countries (see, e.g., WHO, 2010). The INDEPTH Network (see http://www.indepth-network.org) collects and offers health and demographic data for developing countries. The World Bank program on Health, Nutrition & Population provides large statistics on populations and health in a database (see http://databank.worldbank.org).

geographic information through geographic information systems can also be applied to health insurance by identifying geographical patterns of diseases and mortality. The geographic location of risk is an important rating variable in many insurance markets (see, e.g., Taylor, 2001). Physical and social conditions in geographically close regions affect risk. Certain physical perils such as extreme weather are found throughout a region but others such as health risk tend to be geographically constrained. Thus, risk-levels will vary from one region to another to a certain degree, but specific patterns or risk factors will be similar (see, e.g., Christopherson & Werland, 1996). The use of data from geographically close regions may thus help to evaluate risk in neighboring markets.

An alternative to accessing a microinsurer's own data or relying on other relational data as the basis for pricing is to get involved in cooperative data pools, through industry data-sharing arrangements. Such cooperative schemes provide access to significantly greater volumes of data, and can be used to complement the existing data. Data sharing arrangements are found in many developed insurance markets (see, e.g., Werner & Modlin, 2010). Data in such schemes can be analyzed at the aggregate level and results made available to the participating microinsurers. Alternatively, data can be exchanged directly for each insurer performing its own analyses. Regulatory authorities and development organizations can promote such schemes to satisfy the need for aggregated data in microinsurance markets. However, as microinsurance markets develop and competition becomes fiercer, regulators also need to take care that data exchange does not lead to pricing agreements between microinsurers to the disadvantage of the insured.

Since reinsurance companies are becoming more active in microinsurance markets, primary microinsurers have the option to use their experience and data sources to support the calculation of insurance premiums. Reinsurers aggregate large amounts of risk data from many regions worldwide and usually have access to more internal loss data. In addition to data sources, reinsurers could contribute to the pricing of insurance risk in microinsurance markets by training staff, providing standardized research tools, and supporting consultancy services (see Bennett & Gotsadze, 2002).

4.2 Data analysis

(a) Transition approaches

The use of information technology has significantly increased the information available for risk analysis at several levels of aggregation. In many countries, long time-series of data covering extensive types of insurable risks exist. The increased availability of good data has strongly influenced the development of sustainable insurance markets. Especially in developed insurance markets, insurers can rely on highly sophisticated data for the evaluation of population-based risks such as mortality and morbidity. In most microinsurance markets, however, the vast amount of population data necessary to derive sensible estimates for age- and gender-specific mortality and morbidity risk is not available due to a lack of a functioning registration system or insufficient quality of data (see Murray, Ahmad, Lopez, & Salomon, 2000). Mortality tables and probabilities for morbidity are the most important sources of information for pricing long-term and health insurance, signifying the relevance of mortality and morbidity risk for insurance.

Instead of directly estimating mortality and morbidity patterns from original population data, indirect approaches exist to model mortality and morbidity estimates based on determinants identified on the basis of data from other countries. The rationale for this approach is based on observed similarities in the age-structures of mortality and morbidity in different populations, such that particular environmental determinants such as economic development (see Lorentzen, McMillan, & Wacziarg, 2008) that influence mortality and morbidity rates can be defined.

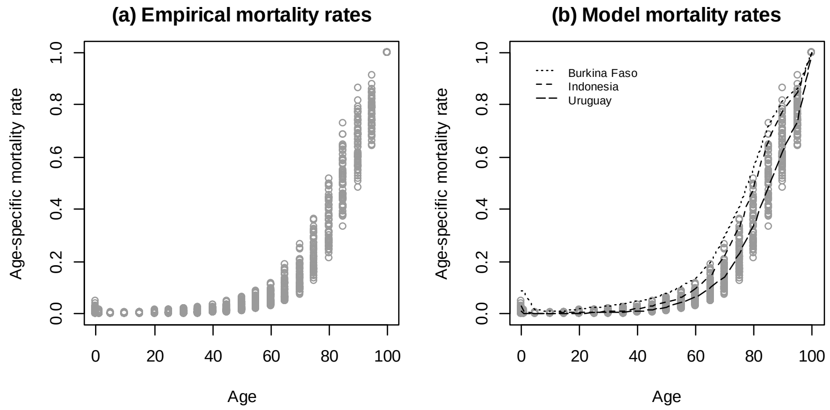
As discussed above, the UN was among the first to create mortality tables for developing countries in order to analyze dynamics of populations and epidemiology (see also approaches by Brass, 1971; Coale & Demeny, 1966). These techniques range from the adoption of mortality structures of neighboring populations with similar characteristics, to the application of sophisticated models (see Murray, Ferguson, Lopez, Guillot, Salomon, & Ahmad, 2003). The purpose of establishing model mortality tables is to obtain a set of parameters that capture the level and age-structure of mortality to derive mortality estimates by age and gender. The early UN model mortality tables are based on a set of 158 gender-specific life tables from countries with vital registration systems and census data. To determine a complete model for age-specific mortality rates, it is assumed that mortality at one age is related to mortality at another age via a quadratic function. Statistical techniques are applied to estimate the parameters for the quadratic function from the set of 158 mortality tables. Knowledge of only one mortality rate is thus sufficient to determine a model mortality table. Several mortality models extend and generalize existing approaches by identifying divergent families of age-specific mortality patterns (see Coale & Demeny, 1966) and adding further parameters (see Ledermann, 1969). Brass (1971) introduced a new category of mortality models based on a standard mortality table and two factors. The standard mortality table is estimated from original population data reflecting age- and sex-specific patterns of mortality in a large array of countries. Two parameters are used to cover variations from the standard mortality table and adapt mortality tables to other countries (Murray et al., 2003). Brass' (1971) model is generalized in Murray et al. (2003).

Despite their different objectives, such approaches can lead to the creation of mortality tables for pricing microinsurance. In most microinsurance markets, infant and child mortality rates are well documented and can be used to fit mortality models for those countries (see Murray et al., 2003). Mortality tables of the UN provided by the World Health Organization (WHO) include most relevant information for evaluating mortality risk with long-term insurance.[6]

[6] The WHO mortality tables provide age-specific death rates among ages x to x+n (${}_nM_x$), probability of dying between exact ages x and x+n (${}_nq_x$), number of people alive at exact age x (l_x), total number of person-years

Figure 1

WHO model mortality rate estimation



Note: The age-specific mortality rates are publicly available from the World Health Organization of the United Nations (WHO, 2009). Figures (a) and (b) plot age against historically observed combined male and female mortality rates for all 63 countries included in the WHO model. Figure (b) additionally includes the modeled age-specific mortality rates for three selected countries, i.e., Burkina Faso, Indonesia, and Uruguay.

Figure 1 illustrates the model mortality rate estimation for countries with insufficient data, in this case for Burkina Faso, Indonesia, and Uruguay. The age-specific mortality rates from a set of countries with highly sophisticated data in Figure 1 (a) are applied to fit the age-specific mortality rates for the three countries with insufficient data in Figure 1 (b).

However, the methodology has several limitations. The modeled mortality rates for developing countries with no sufficient population data are derived from a set of high-quality mortality tables, predominantly from developed economies. Predicted age-mortality structures may thus not accurately represent the specifics of developing countries. Especially high and highly dynamic AIDS/HIV rates can lead to an underestimation of mortality patterns. A bias resulting from dynamic AIDS/HIV rates can, however, not be readily tested for the whole population owing to the lack of data (see Murray et al., 2003).

In the recent past, the availability of empirical population data in developing countries has, however, increased, providing an opportunity to improve the modeling of mortality rates (see Lopez et al. 2002; Murray et al., 2003). Microinsurers thus need to be careful when applying such approaches especially for long-term insurance and thoroughly track the performance of

lived between exact ages x to x+n ($_nL_x$), number of life table deaths in the age interval x to x+n ($_nd_x$), total number of person-years lived after age x (T_x), and life expectancy for a person age x (e_x) (see WHO, 2010).

modeled mortality patterns versus experience from their insurance pool. For short-term insurance such as credit-life insurance, the approach provides the microinsurer with suitable initial estimates that can be adjusted in following years.

Evaluating morbidity risk is relevant for both long-term insurance such as disability insurance and short-term insurance such as health insurance as it is implemented in most international insurance markets. A common problem in most developing countries where institutions strive to establish morbidity-related microinsurance, however, is the unavailability of data. Microinsurance can benefit from the application of epidemiological analysis, such as the study of determinants of diseases and their distribution in populations, by identifying common illnesses as well as their respective rates of occurrence (see Haggerty & Reid, 2002). Epidemiological data are mostly available at higher levels of aggregation such as country-level data, either through national or international organizations. The problem, however, is to obtain sufficient data at the operating level of microinsurance institutions. To gain insight into the predominant illness patterns in microinsurance markets it is functional to apply the concept of epidemiological transition that classifies populations into stages of development with specific prevalent illnesses (see Haggerty & Reid, 2002). The concept goes back to Omran (1971) and identifies three stages: the age of pestilence and famine, the age of receding pandemics, and the age of degenerative and man-made diseases, each of which exhibits specific morbidity and mortality patterns.

In this respect, the large body of literature in medical science aiming at the detection of risk factors for specific diseases is of utmost relevance. Especially the prevalence of contagious diseases such as malaria, tuberculosis, or AIDS/HIV is problematic for morbidity-related microinsurance (see, e.g., Biener & Eling, 2012). For a more detailed understanding of morbidity-related risk factors, more interdisciplinary work on the framing of morbidity patterns in developing countries is needed. Meta-analyses such as the work by Bates, Fenton, Gruber, Lalloo, Lara, Squire, Theobald, Thomson, and Tolhurst (2004a,b), who review a broad literature on determinants of contagious diseases in developing countries, are suitable approaches to achieve progress.

(b) Credibility models

In the process of estimating premiums, microinsurers need to utilize all available data on the risks to be insured. Credibility models provide a setting to condense several sources of data in an actuarial model for pricing insurance risk and to update premiums when more data becomes available in the course of time (i.e., experience rating).

Microinsurers' actuaries and experts may have an intuition or belief on the frequency and severity of specific risks based on experience from a variety of sources (e.g., experts and household surveys; see Section 4.1). Specific data on risk that is not directly related to the target population but stems from comparable populations (e.g., neighboring region) or is based on a broader level of aggregation (e.g., country-level data) is available in some cases. Credibility models can be powerful tools for making use of various sources of information and aid in synthesizing risk characteristics into a technical premium (see, e.g., Morris, 1977; Winkler, 1981). Repeated interactions, i.e., loss experience over the contract period, provide further means of deriving more accurate and appropriate premiums over time (see, e.g., Cooper & Hayes, 1987). In this respect, credibility models can be used to update premiums when new loss experience data is gathered over time (see, e.g., Hosios & Peters, 1989; Watt & Vazquez, 1997). Insurance companies in developed insurance markets frequently apply experience rating to penalize higher and to reward lower loss experience in bonus-malus systems according to the individual loss experience (e.g., automobile third-party liability insurance). Since most microinsurance policies are short-term and renewed on a regular, usually annual basis, premiums might be adjusted in relation to the loss experience over the expired contract period. Thus, all knowledge can be included in the pricing model using credibility theory.

Credibility models are applications of the Bayes' theorem and include existing knowledge on the distribution of a risk in a prior distribution. Prior distributions can be based on various sources such as expert experience or on existing loss experience with other markets and risks.[7] When additional knowledge on the risk is obtained by observations, it is worthwhile to reconsider the assumptions made in the prior loss distribution and re-evaluate the risk in terms of the distribution of experienced losses conditional on the prior distribution. The resulting posterior distribution will reflect the enhanced level of information to model an updated risk distribution. The derivation of posterior distributions in closed form can be difficult or even impossible. Thus, estimators of the posterior distribution are required in most cases. In this case, numerical as well as linear credibility methods can be used to estimate model parameters.

Credibility models were first applied to problems in insurance pricing by Bühlmann (1967) and Bühlmann and Straub (1970). Those papers provide the foundation for a set of linear credibility methods and the Bayes' credibility premium formula (see Makov, Smith, & Liu, 1996). In the classical linear approximation of the Bayesian pure technical premium, Bühlmann (1967) relates the estimator for expected losses to the prior mean loss, based on the prior data, and the mean loss from the supplementary data in a linear model. The credibility adjusted pure technical premium is then defined as a linear combination of these two variables. To each of the data sets' mean values, credibility weights ranging between 0 and 1 are attributed that sum up to 1. The basic idea is to give more weight to the set of data which is larger and more homogeneous. Thus, the weights are estimated as a function of the size of the risk collective and their respective variance.

We may distinguish at least two possible situations in which credibility theory as proposed by Bühlmann (1967) can condense information from different sources to a single distribution in

7 Garthwaite, Kadane, and O'Hagan (2005) provide an overview on various ways to derive prior distributions based on expert knowledge.

microinsurance markets. Microinsurers may gain information on their own insured risk pool over time or they may access information different from their own risk pool at a single point in time and adapt premium rates accordingly.[8] The first situation can be thought of as a relatively new microinsurer using experience loss data from previous years for premium calculation. With each year of operation, the additional information can be used to update premiums according to the experience in the preceding year.[9] Since high operational costs to adjust individual premiums and asymmetric information often are problems in microinsurance markets (see, e.g., Biener & Eling, 2012), it may also be feasible to apply experience rating schemes at the level of group insurance common in microinsurance markets or even at the level of the total insurance risk pool. Sloan (1990) presents an approach to experience rating on the group-level for medical malpractice insurance that may also be feasible with microinsurance.

The second situation may refer to microinsurers having no or only very limited information on the risks to be insured, such as new microinsurers, microinsurers expanding operations to new regions or risks. Here, various sources of information such as data from geographically close regions, especially those from similar socio-economic groups, survey data, and expert knowledge can be of relevance and therefore be included in the prior distribution.

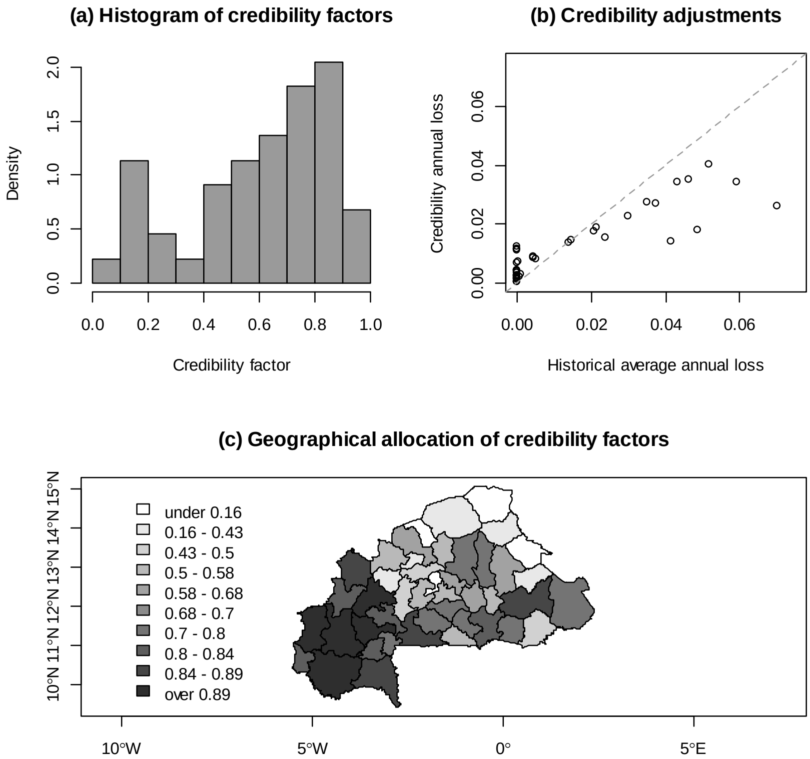
As an example, consider a simple crop insurance policy that compensates a maize farmer in Burkina Faso in case the yield for maize falls below a threshold yield of 0.5 tons per hectare due to drought, flood, or similar perils. Yield data for all of the 45 administrative provinces is available; however, differing substantially in certain cases. Using credibility theory, a microinsurer may combine the loss experience in all other provinces with that of an individual province. Figure 2 shows the resulting credibility estimates of expected annual losses (b), a

8 See Wipf and Garand (2006) for a discussion on implementing adequate data bases.

9 Churchill, Liber, McCord, and Roth (2003) provide a detailed description of applying a simplified implementation of credibility theory to microinsurance operations.

histogram of the credibility factors (a), and the geographical distribution of credibility factors in Burkina Faso (c).

Figure 2
Credibility estimates and historical averages of maize losses in provinces of Burkina Faso



Note: The yield data is publicly available from the Food and Agriculture Organization of the United Nations (FAO, 2012). A yield smaller than 0.5 tons per hectare is defined as loss. Figure (a) shows a histogram of Bühlmann (1967) credibility factors for all provinces. Figure (b) plots historical average annual maize losses (tons per hectare) against the respective Bühlmann (1967) credibility annual losses for all 45 provinces of Burkina Faso. Figure (c) provides a geographical overview of Bühlmann (1967) credibility factors in Burkina Faso.

The resulting credibility estimates of expected annual losses for each province are based on the average loss of the total collective and the respective province. The credibility factors in Figure 2 (c) show the respective influence of the individual loss experience of each province relative to the overall loss experience of all other provinces. Several provinces have high credibility factors indicating a significantly higher credibility of own historical data compared to the overall loss experience; especially the provinces in northern Burkina Faso exhibit a lack of credible historical data. Lower credibility factors translate into higher adjustments of the individual historical average annual loss and thus to larger deviations from the dashed line in Figure 2 (b).

Credibility models provide a means to condense information from additional sources and derive meaningful premiums. Morris (1977) and Winkler (1981) show how credibility models can be applied to integrate conflicting assessments of various experts. Ker and Goodwin (2000) apply a credibility approach to the estimation of nonparametric kernel densities with crop insurance, an approach that has the potential to significantly reduce the amount of time-series data needed for estimating credible premiums. Fuzzy logic may be another useful theoretical approach in the context of credibility theory. This type of approach integrates data that are imprecise or vague. Ostaszewski and Karwowski (1992) consider an insurer having experience in particular geographical areas extending the provision of insurance services to another. They apply fuzzy clustering to utilize the existing knowledge for insurance pricing in the new geographical area (see Shapiro, 2004). Taking advantage of less-than-completely-concrete information may be extremely useful in microinsurance markets (a detailed description of fuzzy logic in insurance can be found in Shapiro, 2004).

Besides these sophisticated methodologies, some pragmatic solutions condense several sources of data to a single estimate by assigning credibility to the different sets of data. Christopherson and Werland (1996) show how data from adjacent regional areas can be condensed by assigning credibility to the sets of data based on the amount of data and their geographical distance from the region of interest. This approach is based on the assumption that, the closer the adjacent region is to the region of interest, the more comparable the risk characteristics are and thus the more credible the data. Clarke, Mahul, and Verma (2012) use the linear Bühlmann (1967) credibility model for smoothing threshold yields and premiums among districts having different risk characteristics for the modified National Agricultural Insurance Scheme (mNAIS) in India, providing good results for the applicability of credibility models in a microinsurance context based on ten years of data.

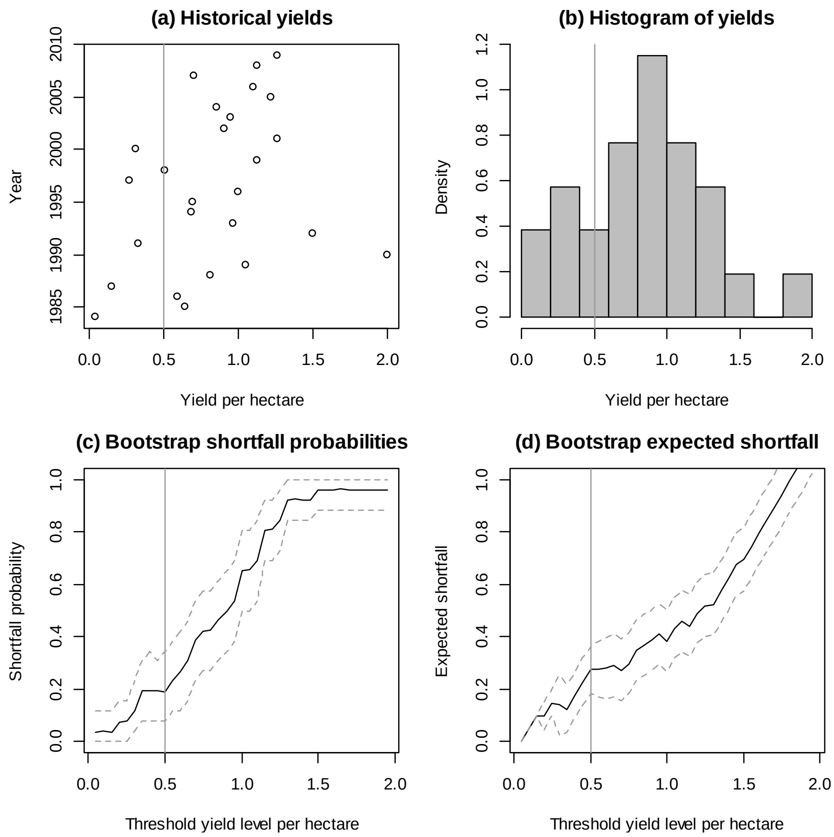
(c) Bootstrap methodologies

Bootstrap techniques can be suitable ways to estimate premiums for insurance risk and significantly leverage the data available (see Wipf & Garand, 2006). When pricing insurance risk, it is essential to know the variability of the expected loss to determine the risk-loading. Small samples of original data often represent the best guess of the actual distribution in microinsurance markets. Bootstrapping makes inferences on the accuracy of particular estimates of distribution parameters through resampling from the original data. The premise of bootstrapping is to use the properties of these samples instead of assuming specific distributional properties. As such, it offers a means to strengthen the basis for relevant pricing parameters when data are scarce.

As an example, again consider the crop insurance policy of Section 4.2.2 that compensates a maize farmer in case the yield for maize falls below a threshold yield of 0.5 tons per hectare due to multiple perils. Unlike in the prior example, here, we only focus on one province – the Kadiogo province. A microinsurer has some limited number of observations on annual maize yields (1984 to 2009). There are no other data available; thus, the available data represent the best guess of the actual yield distribution.

To price the above insurance policy, an estimate for the expected loss is needed. As noted in Section 2, non-life insurance pricing is mostly based on risk frequency and severity because both are stochastic. Based on the maize yield distribution illustrated in Figure 3, the probability of a yield smaller than the predefined threshold of 0.5 tons per hectare (shortfall probability) and the expected loss for these cases (expected shortfall) is estimated based on the bootstrap approach. We use shortfall probability and expected shortfall measures as they are two widely used risk measures (see Inui & Kijima, 2005). Bootstrap approaches rely on the empirical observations to produce new samples of observations (i.e., bootstrap samples) through sampling from the original yield data with replacement, thus avoid assumptions on the mathematical shape of the loss distribution. This procedure is repeated sufficiently often such that a large number of bootstrap samples is obtained for each of which the relevant statistic – here shortfall probability and expected shortfall – is estimated. Besides the estimates alone, the microinsurer is interested in the accuracy of these estimates to account for through suitable risk-loading on the pure technical premium. The accuracy is defined as the deviation from the bootstrap sample mean values (see Efron & Gong, 1983).

Figure 3
Historical data and bootstrap estimates for maize yields in the Kadiogo province of Burkina Faso



Note: The yield data is publicly available from the Food and Agriculture Organization of the United Nations (FAO, 2012). Figures (a) and (b) show historical annual maize yields (tons per hectare) for the period 1984 to 2009, whereas Figures (c) and (d) show bootstrap estimates of shortfall probabilities and expected shortfalls (solid lines) for various threshold levels along with respective 95% confidence levels (dashed lines). For the bootstrap procedure 10,000 bootstrap samples were computed. The solid vertical lines in each figure represent the threshold yield of the crop insurance policy.

The resulting bootstrap estimates for particular distribution parameters, in this case the shortfall probability and expected shortfall, can subsequently be used to derive an assessment of the variability of the expected loss and thus the premium for the crop insurance policy. To illustrate the variability of the shortfall probabilities and the expected shortfall values, Figures 3 (c) and (d) include 95% confidence intervals.

The virtue of this approach, however, is not that data requirements are negligible, but that it bypasses the disadvantage of making assumptions on the distributional properties of the loss distribution, in case there is only limited data, by creating new data (see Embrechts & Mikosch, 1991).[10]

4.3 Risk management architecture

An extensive body of literature has been dedicated to explaining the benefits of risk management on the corporate level. The rationale is that the variability in the cash flows generated by a corporation holding risk makes external financing costly in the presence of capital and product market imperfections (see, e.g., Froot, Scharfstein, & Stein, 1996). The special sensitivity of insurers to the cost of holding risk results from two fundamental characteristics. The insured pay premiums ex ante to receive a contingent payout in the future. Thus, they are highly sensitive to contractual performance risk, which is the risk of not being reimbursed in case of loss, such that the demand for insurance declines in the riskiness of the insurer. Insurers are furthermore often exposed to catastrophe risk which can have severe effects on the ability to pay out loss compensations in case those risks materialize (see Froot, 2007).

Both of these characteristics are highly relevant in microinsurance markets and make the use of risk management strategies attractive with potential effects on premiums. The techniques used for managing risk can be classified as risk financing and risk control (see, e.g., Rejda, 2011). Risk financing refers to techniques to allocate (finance) the adverse financial outcomes of risk and consists of self-insurance and risk transfer. Risk control signifies the avoidance and mitigation of exposure to losses resulting from risk. The following two sections discuss

[10] It is important that the original sample is not too small and is of good quality, since irregularities may severely bias the estimators. This constraint needs to be carefully addressed when applying bootstrap techniques.

risk management strategies in the context of microinsurance and their consequent effects on premiums.

(a) Risk financing

According to Bühlmann (1985) the higher the initial equity capital of an insurer, the smaller the required premiums for insurance risk. Holding equity capital to bear risk is a means to self-insure against adverse financial outcomes. By setting equity capital levels, microinsurers control their risk of insolvency; thus, a sufficient level of equity capital is required to assure that loss compensations can be paid out with a certain probability. Equity capital can either be raised internally through retained earnings generated from premium income or externally, e.g., through the issue of equity shares or the acquisition of other external capital such as venture capital. Thus, the higher the proportion of equity capital, the lower the risk-loadings on premiums necessary to account for unexpected deviations in loss experience. This lever can be used to decrease premiums especially for start-up and small microinsurers with unstable risk pools, i.e., high standard deviation of mean aggregate loss. According to the law of large numbers, the larger the number of mutually independent exposure units in the insurance risk pool, the more likely it is that mean aggregate loss compensations correspond to expected losses. In large insurance risk pools the standard deviation of mean losses is thus smaller compared to small insurance risk pools and the required equity capital to achieve the determined solvency level is hence lower. With the approach outlined here, high risk-loadings on premiums to achieve a sufficient solvency level are reduced by keeping relatively high proportions of equity capital in relation to total capital. An important constraint is that investors would typically not be satisfied with providing subsidies for insufficient premium income generated by the microinsurer. The specific role of microinsurance in poverty reduction (see, e.g., World Bank, 2001) may, however, provide a rationale for specialized investors such as so-called impact investment funds (e.g. Leapfrog Investments) to provide initial equity capital. Indeed, the market for such investments has increased substantially over the last years (see J.P. Morgan, 2011). In the long term, however, microinsurers need to achieve sufficient scale for premium income to be sufficient to cover costs of capital.

A similar approach is provided by reinsurance schemes in that transferring risk to a reinsurer reduces the risk exposure for microinsurers and hence the required equity capital and risk loadings necessary to remain solvent with a certain probability (see, e.g., Garand, Tatin-Jaleran, Swiderek, & Yang,, 2012). Under the specific assumptions of capital-market imperfections and information asymmetries, the use of risk-transfer via reinsurance can reduce the cost of bearing risk (see, e.g., Froot, 2007), i.e., the reinsurance premium for ceding a risk is lower than the equity capital charge needed to hold the risk. Dror and Armstrong (2006) show that using reinsurance is less expensive than equity capital in a simulation study of micro health insurance schemes.

Besides holding large amounts of equity capital and using reinsurance, some financial instruments give the issuing party the right to issue new equity when a predefined trigger is exceeded in exchange for a predefined issue-price. These contingent capital facilities can be negotiated bilaterally with a single counterparty that agrees to buy newly issued equity directly from the counterparty in the event a trigger is activated (see, e.g., Culp, 2002). They are effective means of accessing capital when it is most needed, and lower the equity capital charge needed to hold risk as with reinsurance.

Both self-insurance and risk transfer through reinsurance and contingent capital, may be attractive for organizations interested in developing viable microinsurance markets such as governments, donor organizations, and reinsurers. Transferring risk through equity capital investments, reinsurance, and other risk transfer techniques are important means to address the high degree of correlated risks in geographically not well diversified microinsurers.

A different approach to risk transfer is to share some of the risk of offering insurance with the insured. Risk is shared by implementing an option into the insurance contract to raise an additional premium at the end of the term or increase premiums for the next term if premium income of the last term was not sufficient to cover the costs generated by the insurance risk pool. Surpluses may be distributed among the insured in good years. Such participating policies can be used to account for unexpected deviations from expected losses and are especially beneficial for new and small microinsurers (see Brown & Churchill, 2000). However, such schemes may undermine the incentives for an efficient management of microinsurance institutions that is important for a viable business model (see Biener & Eling, 2011). Mutual or member-owned microinsurers, as discussed in Fischer and Qureshi (2006) are a natural setting for this type of arrangement because the insured are owners of the microinsurer at the same time (see Brown & Churchill, 2000).

(b) Risk control

The mitigation and avoidance of risk that cannot be sufficiently assessed is an important aspect in the context of product design in microinsurance markets. One straightforward approach could be to design products such that their pricing is consistent with the underlying conditions in microinsurance markets; only product features are included that are not too complex to derive prices under the observed data restrictions. Those requirements may be important levers in the development of microinsurance products for which actuarially consistent prices can be obtained and risk-loadings are relatively low. There is a range of classical product features that can be adapted to simplify pricing risk. These features include the amount insured, the period of coverage, and the number of perils covered. Furthermore tying payments for losses to an index may be advantageous for some risks such as weather related risk. A typical means of reducing problems such as adverse selection and moral hazard is to provide group insurance instead of individual insurance, avoiding many of the related valuation issues.

While the amount insured with microinsurance policies is per definition small, there may arise vast variations in the size of losses that constitute severe problems when historical experience data is scarce. Hence, a microinsurer may choose to mitigate exposure to large losses und decrease the variation in losses by introducing policy limits. Such restrictions can be further relaxed when the microinsurer has more confidence in the data generated from the insurance pool, but provide the microinsurer with a suitable means to keep premiums at an acceptable level.

The period of coverage is yet an important way to ensure predictability of risk. Microinsurance policies today are mostly short-term, thus limiting the impact of changes in inflation, interest rates, risk factors, and model assumptions that are hard to derive when data availability limits the ability to identify major risk characteristics. Thus, short-term policies decrease risk-loadings compared to policies with longer terms. Furthermore short-term polices may be especially applicable in microinsurance markets. In developed insurance markets, long-term insurance such as disability or term life insurance is constructed such that premiums are relatively high compared to the actual risk at the beginning of the policy term when the insured is young and relatively low compared to the actual risk at the end of the policy term when the insured is older. As a consequence, premiums are constant over the contract period and ensure affordability as the insured gets older and constitutes a higher risk. In microinsurance markets this mechanism may not appeal to the target population since it increases the premium for young low-risk individuals. Those individuals may profit more from lower and affordable premiums when they are young to decrease the variability in income and avoid falling below the poverty line.[11] By stabilizing the income, individuals may then be able to pay higher premiums in the future.

[11] The poverty line defines the required minimum level of income to achieve an adequate standard of living (see, e.g., Ravallion, 1992).

The number of perils covered under an insurance policy is of utmost importance, not only for pricing. Microinsurance markets are developing at high rates; however, experience with insurance products and financial literacy is still limited, requiring products that are easy to understand. In an environment with low experience and data on risk properties, single-peril insurance policies have advantages over multi-peril policies because they restrict the complexity of the estimation and thus decrease the uncertainty and subsequently the related risk-loading. Even more, Sinha, Ranson, and Mills (2007) show that the provision of multi-peril insurance policies may have unfavorable distributional impacts for urban and rural insured populations.

Index-based insurance has received some attention in microinsurance markets (see, e.g., Barnett, Barrett, & Skees, 2008; Meze-Hausken, Patt, & Fritz, 2009; Skees, 2008). Particularly, risks considered for index-based insurance are weather-related agricultural risks. Agriculture is a central economic activity in most developing countries but at the same time it is especially vulnerable to extreme weather and price risk (see, e.g., Karlan, Kutsoati, McMillan, & Udry, 2011). Thus, insurance covering weather-related agricultural risk is highly desirable from a development economics perspective. These markets are, however, challenged by unpredictable individual risk exposures – due to inadequate data and climatic change – requiring microinsurance schemes to hold large amounts of equity capital to account for large unexpected losses. As a consequence, microinsurers need high risk-loadings, making coverage unaffordable in many cases. Private microinsurers therefore play a small role in these markets (see Meze-Hausken et al., 2009). Index-based insurance policies are especially interesting because they avoid several problems in the provision of agricultural weather-related coverage compared to indemnity-based insurance policies. The payout of index-based insurance policies does not depend on the loss of an individual insured but is tied to an index that is linked to the actual risk insured. Index-based insurance policies thus circumvent data restrictions by tying loss compensation to an observable index for which sufficient data exists.

The pricing of such insurance policies can thus be based on robust data mitigating the risk associated with assessing individual risk exposure based on restrictive data. Loss assessment and settlement for agricultural indemnity-based insurance is prohibitively expensive compared to the values insured. Index-based insurance policies avoid expensive loss assessments and pay a specified compensation based on a predefined index level. Moreover, these products minimize moral hazard and adverse selection problems at the same time (see Giné, Townsend, & Vickery, 2008). Individual losses may, however, not be perfectly correlated with the index and consequent compensation from the index policy, an issue referred to as basis risk (see, e.g., Linnerooth-Bayer & Mechler, 2006). The disadvantage of index-based insurance thus is that due to basis risk, the insured may contest the deficiency of payouts when losses occur that do not trigger a payment.

Categorizing risks into groups that exhibit a high degree of homogeneity within and a high degree of heterogeneity between is especially challenging in microinsurance markets where little is known about risk factors. Thus, premiums that sufficiently reflect the individual risk are infeasible. However, charging a flat premium for all individuals may lead to adverse selection in some cases. Instead of individuals with group insurance, groups of people such as a family, a village, or the members of an association are insured against a predefined risk. Group insurance circumvents the problem of differentiating among categories of risk by creating groups of insured that are not limited to high-risk individuals. The use of group policies can mitigate the potential for moral hazard since mutual monitoring is inherent in such schemes (see, e.g., Biener & Eling, 2012; Dercon, de Weerdt, Bold, & Pankhurst, 2006).

5 Interaction of premiums, demand, and behavior

As discussed, the supply side is restrained by persistent uncertainty in pricing risk leading to high loadings on the pure technical premium and making insurance relatively expensive and less attractive to the low-income population. On the demand side, microinsurance markets exhibit low willingness to pay and high price sensitivity with individuals facing the decision to buy insurance (see, e.g., Biener & Eling, 2012; Cole et al., 2010). In the preceding section, we address the mismatch of supply and demand from the supply side by identifying ways to reduce excessive risk-loadings and thus reducing premiums for microinsurance. However, addressing demand-side specific effects when introducing microinsurance is important to consider in the process of pricing risk. In this respect, changed incentives through microinsurance coverage and marketability of microinsurance premiums are seemingly important.

The former relates to behavioral changes and expected trends in the observed frequency and severity of losses. For a variety of reasons, losses may be significantly higher within the insured risk pool than in the total population. For health microinsurance, many studies find that increasing healthcare costs and a higher than expected use of health services are characteristic of microinsurance schemes (see, e.g., Jütting, 2004). For a broad share of the low-income population, health services are not accessible because treatment costs are not affordable. Health microinsurance coverage provides access to these services. This complementary value of health microinsurance provides the rationale for an important differentiation regarding increasing utilization rates. The higher probability of using medical services when one has health insurance may be ascribed to either taking care of health needs that are not affordable in the absence of health insurance or an overuse of not strictly necessary medical services (see Biener & Eling, 2012). Unless the microinsurer is able to control for these issues, both of these trends need to be reflected in the premiums. During the initial phase of microinsurance programs, opposite effects might also be observed due to the opportunity costs of using medical services such as the loss of income for the time needed to visit a doctor. In cases where insurance coverage is mandatory, coverage is often not communicated such that utilization is low (see Garand et al., 2012). These factors need to be carefully assessed.

Studies of microinsurance in developing countries suggest that individual and household insurance demand is extremely low due to limited willingness to pay. Some authors explain this observation by a lack of trust between the potential insured and the microinsurance provider (see, e.g., Cole et al., 2010; Ito & Kono, 2008). More specifically, people unfamiliar with microinsurance regard insurance policies as a risky investment (see Giné, et al., 2008; Giesbert, Steiner, & Bendig, 2011) thus adding a discount to their willingness to pay. Willingness to pay, however, also depends on various other factors such as risk perception, the allocation of resources, the insurance product design, and other cultural characteristics of the low-income population. A suitable insurance product needs to account for all such factors. A mere downscaling of insurance products known in developed insurance markets will not create sufficient willingness to pay for microinsurance (see Cohen & Sebstad, 2005). The consequence of a lack of trust and other factors reducing the perceived value from a customer's perspective is that willingness to pay would be potentially lower than the technical insurance premium and result in low take-up rates. This is a significant constraint for product development and pricing. Actuarial techniques may, however, provide some important contribution to adapt products and premiums. Ways to approach a gap between willingness to pay and the actuarial premium is to adapt product features, increase the risk pool, and hold sufficient equity capital (see Section 4.3). For a careful assessment of these measures' effects, actuarial techniques are necessary. There are some promising initiatives to adapt products to the needs of the low-income population in microinsurance markets such as accepting premium payments in-kind, using the interest earned on a savings account to cover the premium, and scheduling premium payments according to household cash flows (see, e.g., Brown & Churchill, 2000).

6 Conclusion

This paper's key contribution is its investigation of potential approaches for more accurately pricing insurance risk and obtaining technical premiums in microinsurance markets. The analysis of the specifics in microinsurance markets indicates that standard approaches and current practice are not an appropriate basis for pricing insurance risk. Indeed, data restrictions severely limit the applicability of standard estimators of risk used for pricing insurance. We show particular techniques that have solved similar problems in other markets. We also investigate possible explanations of the mismatch between technical and market premiums in microinsurance markets.

Meaningful technical premium estimates cannot be derived without a minimum of reliable data. However, microinsurers typically have access to macro- and meso-level data, industry data, and data from neighboring regions, competitors, and reinsurers that allow inferences on risk properties. Microinsurers can apply ad hoc methods to generate data relevant for pricing insurance risk through surveys and expert opinions. Methodologies that efficiently process the available data and that use multiple sources simultaneously are desirable in cases where none of the available data itself is sufficient as a sole basis for pricing. In this respect, we discuss the application of transition approaches that adapt risk patterns from other regions, where more data is available, to the region of interest. Credibility models can take advantage of these sources of information, synthesize risk characteristics into a technical premium, and update premiums when more loss experience becomes available over the contract period. In small samples of original loss data as prevalent in microinsurance, bootstrap techniques can compensate for the disadvantage of estimating the variability of mean loss from a small sample of data. The application of risk management strategies is a way to adapt to the environment of microinsurance markets and decrease excessive risk-loadings. By focusing on the interaction of premiums with demand and behavior, we find that there is a significant need to consider behavioral changes in the presence of microinsurance coverage in the pricing process. Furthermore, actuarial techniques provide important contributions to adapt products and premiums when willingness to pay and actuarial premiums differ.

A next step for future research would be to empirically test the methodologies suggested for the estimation of technical premiums in this paper. The identification of risk patterns and the collection of data on insurance risk is an important precondition for insuring risk in microinsurance markets. Further research could answer research questions in a more interdisciplinary manner since different fields have many of the same challenges. For example, the identification of mortality and morbidity patterns is relevant both to insurance science and to the medical sciences; the analysis of climate change affects several streams of research. Another promising avenue for future research is the empirical analysis of behavioral aspects of microinsurance demand that may provide valuable insights into the perception of microinsurance and decision under uncertainty in microinsurance markets. The results may identify levers that have the potential to better balance supply and demand.

References

Actuarial Standards Board (2011). Data Quality, Actuarial Standard of Practice No. 23. Washington DC.

Akerlof, G. A. (1970). The market for “lemons”: Quality uncertainty and the market Mechanism. *Quarterly Journal of Economics*, *84*(3), 488–500.

Auray, J. P., & Fonteneau, R. (2002). Local consensus and estimates of medical risk. In D. M. Dror & A. S. Preker (Eds.), *Social reinsurance: A new approach to sustainable community health financing* (pp. 187–201). Washington, DC.: World Bank.

Barnett, B. J., Barrett, C. B., & Skees, J. R. (2008). Poverty traps and index-based risk transfer products. *World Development*, *36*(10), 1766–1785.

Bates, I., Fenton, C., Gruber, J., Lalloo, D., Lara, A. M., Squire, S. B., Theobald, S., Thomson, R., & Tolhurst, R. (2004a). Vulnerability to malaria, tuberculosis, and HIV/AIDS infection and disease. Part I: Determinants operating at individual and household level. *The Lancet Infectious Diseases*, *4*(5), 267–277.

Bates, I., Fenton, C., Gruber, J., Lalloo, D., Lara, A. M., Squire, S. B., Theobald, S., Thomson, R., & Tolhurst, R. (2004b). Vulnerability to malaria, tuberculosis, and HIV/AIDS infection and disease. Part II: Determinants operating at environmental and institutional level. *The Lancet Infectious Diseases*, *4*(6), 368–375.

Bennett, S., & Gotsadze, G. (2002). Building capacity and strengthening implementation at the community level. In D. M. Dror, & A. S. Preker (Eds.), *Social reinsurance: A new approach to sustainable community health financing* (pp. 225–243). Washington, DC: World Bank.

Biener, C., & Eling, M. (2011). The performance of microinsurance programs: A data envelopment analysis. *Journal of Risk and Insurance, 78*(1), 83–115.

Biener, C., & Eling, M. (2012). Insurability in microinsurance markets: An analysis of problems and potential solutions. *Geneva Papers on Risk and Insurance*, *37*(1), 77–107.

Bowers, N. L., Gerber, H. U., Hickman, J. C., Jones, D. A., & Nesbitt, C. J. (1986). *Actuarial mathematics*. Itasca, IL: The Society of Actuaries.

Brass, W. (1971). On the scale of mortality. In W. Brass (Ed.), *biological aspects of demography* (pp. 86–110). London: Taylor & Francis.

Brown, W., & Churchill, C. F. (2000). Insurance provision in low-income communities: Part II: Initial lessons from microinsurance experiments for the poor. Bethesda, MD: Development Alternatives Inc. and USAID.

Bühlmann, H. (1967). Experience rating and credibility. *ASTIN Bulletin*, *4*(3), 199–207.

Bühlmann, H. (1985). Premium calculation from top down. *ASTIN Bulletin*, *15*(2), 89–102.

Bühlmann, H., & Straub, E. (1970). Glaubwürdigkeit für Schadensätze. *Bulletin of the Swiss Association of Actuaries*, *70*, 111–133.

Christopherson, S., & Werland, D. L. (1996). Using a Geographic Information System to identify territory boundaries. Casualty Actuarial Society Forum, 191–211.

Churchill, C. (2007). Insuring the low-income market: challenges and solutions for commercial insurers. *Geneva Papers on Risk and Insurance – Issues and Practice*, *32*(3), 401–412.

Churchill, C., Liber, D., McCord, M. J., & Roth, J. (2003). *Making insurance work for microfinance institutions: A technical guide to developing and delivering microinsurance*. Geneva: International Labour Organization.

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

Clarke, D., Mahul, M. & Verma, N. (2012). Index-based crop insurance product design and ratemaking: The case of modified NAIS in India. *Policy Research Working Paper 5986*, Washington, DC: World Bank.

Coale, A., & Demeny, P. (1966). *Regional model life tables and stable populations.* Princeton, NJ: Princeton University Press.

Cohen, M., & Sebstad, J. (2005). Reducing vulnerability: The demand for microinsurance. *Journal of International Development*, *17*(3), 397–474.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickrey, J. (2010). Barriers to household risk management: Evidence from India. *Policy Research Working Paper 5504*, Washington, DC: World Bank.

Cooper, R., & Hayes, B. (1987). Multi-period insurance contracts. *International Journal of Industrial Organization*, *5*(2), 211–231.

Culp, C. L. (2002). Contingent capital: Integrating corporate financing and risk management decisions. *Journal of Applied Corporate Finance, 15*(1), 46–56.

Cummins, D. (1991). Statistical and financial models of insurance pricing and the insurance firm. *Journal of Risk and Insurance*, *58*(2), 261–302.

Dercon, S., de Weerdt, J., Bold, T., & Pankhurst, A. (2006). Group-based funeral insurance in Ethiopia and Tanzania. *World Development*, *34*(4), 685–703.

Dlugolecki, A. (2008). Climate change and the insurance sector. *Geneva Papers on Risk and Insurance – Issues and Practice*, *33*(1), 71–90.

Dror, D. M., & Armstrong, J. (2006). Do micro health insurance units need capital or reinsurance? A simulated exercise to examine different alternatives. *Geneva Papers on Risk and Insurance – Issues and Practice*, *31*(4), 739–761.

Dror, D. M., Radermacher, R., Khadilkar, S. B., Schout, P., Hay, F. X., Singh, A., & Koren, R. (2009). Microinsurance: Innovations in low-cost health insurance. *Health Affairs*, *28*(6), 1788–1798.

Dror, D. M., van Putten-Rademaker, O., & Koren, R. (2008). Cost of illness: Evidence from a study in five resource-poor locations in India. *Indian Journal of Medical Research, 127*(4), 347–361.

Efron, B., & Gong, G. (1983). A leisurely look at the bootstrap, the jackknife, and cross-validation. *American Statistician*, *37*(1), 36–48.

Embrechts, P. (2000). Actuarial versus financial pricing of insurance. *Journal of Risk Finance*, *1*(4), 17–26.

Embrechts, P., & Mikosch, T. (1991). A bootstrap procedure for estimating the adjustment coefficient. *Insurance: Mathematics and Economics*, *10*(3), 181–190.

Food and Agriculture Organization of the United Nations (2012). FAOSTAT. Available from http://faostat.fao.org/site/567/default.aspx.

Froot, K. A. (2007). Risk management, capital budgeting, and capital structure policy for insurers and reinsurers. *Journal of Risk and Insurance*, *74*(2), 273–299.

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1996). Risk management: Coordinating corporate investment and financing policies. *Journal of Finance*, *48*(5), 1629–1658.

Garand, D., Tatin-Jaleran, C., Swiderek, D., & Yang, M. (2012). Pricing of microinsurance products. In C. Churchill, & M. Matul (Eds.), *Protecting the poor: A microinsurance compendium. Volume II* (pp. 464–483). Geneva: International Labour Organization.

Garthwaite, P. H., Kadane, J. B., & O'Hagan, A. (2005). Statistical methods for eliciting probability distributions. *Journal of the American Statistical Association*, *100*(470), 680–700.

Giesbert, L., Steiner, S. & Bendig, M. (2011). Participation in micro life insurance and the use of other financial services in Ghana. *Journal of Risk and Insurance*, *78*(1), 7–35.

Giné, X., Townsend, R., & Vickery, J. (2008). Patterns of rainfall insurance participation in rural India. *World Bank Economic Review*, *22*(3), 539–566.

Haggerty, J. & Reid, T. (2002). Epidemiological data on health risks in the Philippines. In D. M. Dror, & A. S. Preker (Eds.), *Social reinsurance: A new approach to sustainable community health financing* (pp. 353–376). Washington, DC: World Bank.

Hosios, A. J., & Peters, M. (1989). Repeated insurance contracts with adverse selection and limited commitment. *Quarterly Journal of Economics*, *104*(2), 229–253.

Inui, K., & Kijima, M. (2005). On the significance of expected shortfall as a coherent risk measure. *Journal of Banking & Finance*, *29*(4), 853–864.

Ito, S. & Kono, H. (2008). Why is the take-up of microinsurance so low? Evidence from a health insurance scheme in India. *Developing Economies*, *48*(1), 74–101.

J.P. Morgan (2011). Insight into the impact investment market: An in-depth analysis of investor perspectives and over 2,200 transactions. J.P. Morgan Social Finance Research Report, New York.

Jüting, J. P. (2004). Do community-based health insurance schemes improve poor people's access to health care? Evidence from rural Senegal. *World Development*, *32*(2), 273–288.

Karlan, D., Kutsoati, E., McMillan, M., & Udry, C. (2011). Crop price indemnified loans for farmers: A pilot experiment in rural Ghana. *Journal of Risk and Insurance*, *78*(1), 37–55.

Ker, A. P., & Goodwin, B. K. (2000). Nonparametric estimation of crop insurance rates revisited. *American Journal of Agricultural Economics*, *82*(2), 463–478.

Kliger, D., & Levikson, B. (1998). Pricing insurance contracts – An economic viewpoint. *Insurance: Mathematics and Economics*, *22*(3), 243–249.

Ledermann, S. (1969). *Nouvelles tables-type de mortalité: travaux et document*. Paris: Institut National d'Etudes Demographiques.

Linnerooth-Bayer, J. & Mechler, R. (2006). Insurance for assisting adaptation to climate change in developing countries: A proposed strategy. *Climate Policy*, *6*(6), 621–636.

Linnerooth-Bayer, J., Warner, K., Bals, C., Höppe, P., Burton, I., Loster, T., & Haas, A. (2009). insurance, developing countries and climate change. *Geneva Papers on Risk and Insurance*, *34*(3), 381–400.

Lopez, A. D., Ahmad, O. B., Guillot, M., Ferguson, B. D., Salomon, J. A., Murray, C. J. L., & Hill, K. (2002). *World mortality in 2000: Life tables for 191 countries*. Geneva: World Health Organization.

Lorentzen, P., McMillan, J., & Wacziarg, R. (2008). Death and development. *Journal of Economic Growth*, *13*(2), 81–124.

Makov, U. E., Smith, A. F. M., & Liu, Y.-H. (1996). Bayesian methods in actuarial science. *The Statistician*, *45*(4), 503–515.

Mehr, R. I., & Neumann, S. (1970). Delphi forecasting project. *Journal of Risk and Insurance*, *37*(2), 241–246.

Meze-Hausken, E., Patt, A., & Fritz, S. (2009). Reducing climate risk for micro-insurance providers in Africa: A case study of Ethiopia. *Global Environmental Change*, *19*(1), 66–73.

Morris, P. A. (1977). Combining expert judgments: A Bayesian approach. *Management Science*, *23*(7), 679–693.

Murray, C. J. L., Ahmad, O., Lopez, A. D., & Salomon, J. A. (2000). WHO system of model life tables, GPE Discussion Paper No. 8. Geneva: World Health Organization.

Murray, C. J. L., Ferguson, B. D., Lopez, A. D., Guillot, M., Salomon, J. A., & Ahmad, O. (2003). Modified logit life table system: Principles, empirical validation, and application. *Population Studies*, *57*(2), 165–182.

Omran, A. R. (1971). The epidemiological transition: A theory of the epidemiology of population change. *Milbank Memorial Fund Quarterly*, *49*(4), 509–538.

Ostaszewski, K., & Karwowski, W. (1992). An analysis of possible applications of fuzzy set theory to the actuarial credibility theory. Proceeding of the Annual Meeting of the North American Fuzzy Information Processing Society, Puerto Vallaria.

Ravallion, M. (1992). *Poverty comparisons: A guide to concepts and methods*. Washington, DC: World Bank.

Raviv, A. (1979). The design of an optimal insurance policy. *American Economic Review*, *69*(1), 84–96.

Rejda, G. E. (2011). *Principles of risk management and insurance.* 11th edition*.* Boston, MA: Prentice Hall.

Rowe, G., & Wright, G. (1999). The Delphi technique as a forecasting tool: Issues and analysis. *International Journal of Forecasting*, *15*(2), 353–375.

Shapiro, A. F. (2004). Fuzzy logic in insurance. *Insurance: Mathematics and Economics*, *35*(2), 399–424.

Sinha, T., Ranson, M. K., & Mills, A. J. (2007). Protecting the poor? The distributional impact of a bundled insurance scheme. *World Development*, *35*(8), 1404–1421.

Sloan, F. A. (1990). Experience rating: Does it make sense for medical malpractice insurance? *American Economic Review*, *80*(2), 128–133.

Skees, J. R. (2008). Innovations in index insurance for the poor in lower income countries. *Agricultural and Resource Economics Review*, *37*(1), 1–15.

Taylor, G. (2001). Geographic premium rating by Whittaker spatial smoothing. *ASTIN Bulletin*, *31*(1), 147–160.

Vaté, M., & Dror, D. M. (2002). To insure or not to insure? reflections on the limits of insurability. In D. M. Dror, & A. S. Preker (Eds.), *Social reinsurance: A new approach to sustainable community health financing* (pp. 125–148). Washington, DC: World Bank.

Wang, S. (1995). Insurance pricing and increased limits ratemaking by proportional hazards transforms. *Insurance: Mathematics and Economics*, *17*(1), 43–54.

Watt, R., & Vazquez, F. J. (1997). Full insurance, Bayesian updated premiums, and adverse selection. *Geneva Papers on Risk and Insurance – Theory*, *22*(2), 135–150.

Werner, G., & Modlin, C. (2010). Ratemaking data. In G. Werner, & C. Modlin (Eds.), *Basic ratemaking* (pp. 36–49). Arlington, VA: Casualty Actuarial Society.

Winkler, R. L. (1981). Combining probability distributions from dependent information sources. *Management Science*, *27*(4), 479–488.

Wipf, J., & Garand, D. (2006). Pricing microinsurance products. In C. Churchill (Ed.), *Protecting the poor: A microinsurance compendium* (pp. 238–453). Geneva: International Labour Organization.

World Bank (2001). *World development report 2000/2001: Attacking poverty.* Oxford: Oxford University Press.

World Health Organization (2009). Life tables for WHO Member States. Available from http://www.who.int/healthinfo/statistics/mortality_life_tables/en/index.html.

World Health Organization (2010). Life Tables for 2008, 2000 and 1990: Summary of data and methods used. Geneva: World Health Organization.