Pricing in Microinsurance Markets

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Abstract: Microinsurance markets exhibit strong growth rates in recent years. Large parts of the industry are, however, challenged by the basic fundamentals of providing insurance products, one of the most significant of which is pricing specific risks. To a large degree, this problem is due to constraints on data availability and a lack of suitable actuarial approaches. The lack of precision in setting premiums may expose microinsurers to substantial risk of insolvency in case of *underpricing* risks or make insurance unaffordable by the target population when *overpricing* risks by means of high uncertainty loadings. In this paper, we explicitly analyze the specifics of pricing insurance risk in microinsurance markets and investigate the appropriateness of standard approaches and current practice. Thus, a key contribution of this paper is its investigation of potential solutions for improving the pricing of insurance risk in microinsurance markets.

Keywords: Microinsurance, actuarial pricing, data availability, Bayesian methods

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1 Introduction

This paper investigates actuarial approaches to pricing insurance risk in microinsurance markets. Despite strong growth rates (see Lloyd's and Microinsurance Centre, 2009), these markets are challenged by the basic fundamentals of providing insurance products, one of the most significant of which is pricing specific risks. To a large degree, this problem is due to constraints on data availability and a lack of suitable actuarial approaches.

Microinsurance is commonly 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 Churchill, 2007). Frequently, microinsurers set premiums using rule-of-thumb estimates for expected losses and then add high loadings to correct for the uncertainty of the assessment. In certain cases, premiums are set on the basis that they will not exceed the willingness to pay of the target population. The lack of precision in setting premiums thus exposes microinsurers either to substantial risk of insolvency due to *underpricing* the risks (see, e.g., Dror and Armstrong, 2006), e.g., premiums are set to match willingness to pay, or make insurance unaffordable by the target population due to *overpricing* the risks by means of high loadings. Increased precision in premium setting would allow microinsurers to reduce loadings imposed due to uncertainty and, consequently, increase their ability to offer more competitive prices (see, e.g., Brown and Churchill, 2000) while also enhancing their capability to remain solvent. The current imprecise pricing schemes have the potential to jeopardize confidence in a developing market if they result in microinsurers not having sufficient capital to settle insured losses or the cost of the premiums exceeds the willingness to pay of the target population. Thus, to create and promote a sustainable microinsurance industry, it is necessary to design products, as well as pricing schemes, that will ensure both a low risk of insolvency and that the target population can afford to invest in insurance coverage.

In this paper, we explicitly analyze the specifics of pricing insurance risk in microinsurance markets and investigate the appropriateness of standard approaches and current practice. Despite the growing interest in microinsurance, very few studies provide guidance on pricing in these markets given their specific challenges (see, e.g., Brown and Churchill, 2000; Auray and Fonteneau, 2002).

Results of our research confirm that there are, indeed, significant problems in pricing risk in microinsurance markets (see, e.g., Dlugolecki, 2008; Biener and Eling, 2011). In fact, every component of an actuarial premium presents a difficulty in these markets. In this respect, the biggest problem is data availability. Data restrictions severely limit estimating robust distributions of insured losses and other costs; a situation that needs thorough attention for microinsurance markets to develop on a sustainable basis. Other difficulties involve issues such as how to figure subsidies, which are of limited duration and common in microinsurance, into the price.

Often, in a case where there is limited data on, e.g., frequency and severity distributions of a specific risk, simulation methodologies such as the bootstrap and Monte Carlo can be used to obtain risk estimates. In reality, microinsurers usually have access to at least some information, such as data from different areas or industry- and country-level data, but it is quite likely that none of it is sufficient to provide a sole basis for pricing. Bayesian methodologies, i.e., credibility theory, can be powerful tools for making use of these various sources of information and aid in synthesizing risk characteristics into an actuarial premium (see, e.g., Morris, 1977; Winkler, 1981). Repeated interactions, i.e., claims experience over the contract period, provide further means of deriving more accurate and appropriate premium prices (see, e.g., Cooper and Hayes, 1987). In this respect, Bayesian methodologies are feasible solutions for updating premiums (see, e.g., Hosios and Peters, 1989; Watt and Vazquez, 1997). Since most microinsurance policies are short term and renewed on a regular basis, it is straightforward to adjust premiums on the basis of claims experience over the expired contract period.

Fuzzy logic may be another useful theoretical approach to pricing microinsurance. This type of approach integrates data that are imprecise or vague and supplementary with statistical data (see Shapiro, 2004).

However, in microinsurance, often there is no data on specific risks. In such cases, surveys, expert opinions, and qualitative data from focus groups may be appropriate sources of information. By obtaining as many estimates as possible from as wide an array of experts as possible, it may be feasible to either synthesize those opinions into consensus estimates using, e.g., Delphi methods (see, e.g., Mehr and Neumann, 1970), or apply Bayesian and maximum likelihood techniques to derive distributions of the specific risks (see, e.g., Auray and Fonteneau, 2002). Results of such ad-hoc methods provide valuable input to Bayesian approaches as they give an intuition or prior knowledge on risk characteristics that can be complemented by other data and condensed to form a distribution of insured losses.

This paper's key contribution is its investigation of potential approaches for more accurately pricing insurance risks in microinsurance markets. The industry investigated in this paper—microinsurance—is still in its infancy, but has huge future potential. We explicitly analyze the specifics of pricing risk in microinsurance markets and inquire the appropriateness of standard approaches and current practice. We take from the actuarial literature to create a toolbox of approaches that have proven successful in solving similar problems in other markets. To our knowledge, this is the first paper that develops actuarially consistent schemes for pricing risk in microinsurance markets. Our findings are thus highly 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.

The remainder of this article is structured as follows. Section 2 provides a review of the actuarial pricing of risks. In Section 3, we discuss challenges in pricing risks in microinsurance markets. A discussion of potential solutions is presented in Section 4. Section 5 concludes.

2 Actuarial pricing of risks

Insurance provides a mechanism to exchange contingent future loss reimbursements against fixed payments – premiums (see Wang, 1995). The actuarial rationale for the determination of premiums 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 risks and defines the *pure insurance premium* as such that the present value of premiums is equal to the present value of expected losses.

For the fundamental approach of pricing insurance risk assume that total losses X from an insured risk in a specified time period are produced by a stochastic process the insurer has no or only limited influence on. The random variable X is i.i.d. with mean μ and standard deviation σ. Since it is the objective of an insurance mechanism to define insurance cover and the corresponding premium π prospectively, it is necessary to provide an estimate of π in advance (see Bühlmann, 1985). Thus, the expectation on losses μ, a point estimate (see Lu, Macdonald, and Wekwete, 2008), is included in the actuarial pure insurance premium.

Since future losses are random and thus not known with certainty and the premium π is set prospectively, the pure insurance premium may not be sufficient to cover all losses and costs in the future with a certain probability. However, insurer can control the risk of insolvency α by adding a *risk-loading* θ to the premium that is dependent on the distribution of losses X. The required actuarial premium π for insurance risks that controls for risk of insolvency α is hence defined by $\pi = (1 + \theta)\mu$.

The *risk-loading* θ can be derived by various principles, all of which aim at limiting the risk of insolvency to a sufficiently small value.[1] If a large enough number of insured n is assumed, the central limit theorem yields $\theta = (z_{1-\alpha}\sigma)/(\mu\sqrt{n})$. Assuming the number of insured being

[1] Premium principles frequently addressed in insurance literature are derived from the equivalence principle or related to quantile principles, utility theory, and the Esscher principle (see, e.g., Embrechts, 2000 for a discussion of premium principles).

independent of the premium, the insurer may control the risk of insolvency by increasing the *risk-loading* θ to a sufficient level (see Kliger and Levikson, 1998).

Beside the total costs of future losses, the insurer has significant additional costs originating in the organization (e.g., distribution, management, settlement) and from financing of the organization, i.e., cost of capital. These costs need to be generated from premium income and are reflected in a *cost-loading* c that equals the present value of expected costs.[2] Thus, the required actuarial premium π for insurance risks controlling for risk of insolvency and including cost is $\pi = (1 + \theta)\mu + c$.

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 as to the application of the equivalence principle. This is mainly due to the different duration of risk coverage. Whereas health, non-life, and some life insurance coverage is usually short-term and renewed or terminated at the end of the term, most life insurance policies are long-term contracts. Thus, we briefly discuss approaches to pricing risks in short- and long-term lines of business.

Premium calculation for short-term insurance

The difficulty in estimating sufficient actuarial premiums in short-term insurance such as health or agricultural insurance is rooted in the stochasticity of losses; both frequency and severity of losses are random. In order to derive average losses μ and *risk-loading* θ, a model is necessary that captures the stochasticity of total losses based on claim frequencies and severities. The collective risk theory models the distribution of total losses X in a specified time period by the compound distribution of loss frequency and severity as $X = \sum_{i=1}^{N} x_i$, with N the

[2] A loading for cost of capital is often critically addressed by the microinsurance community due to reservations against profit maximizing capital markets schemes. However, equity capital is needed to achieve a sufficient degree of solvency. Policyholder benefit from higher security levels of insurers, which provides a rationale for adding the cost-loading to the pure premium. How the cost-loading for cost of capital can be reduced for the policyholder will be discussed in Section 4.

random number of losses and x_i the random loss size of loss $i=1,2,\ldots,N$ in monetary terms.[3] As both loss frequencies and severities are stochastic, assumptions on their respective distributions and parameters are required. Those are usually derived from historical data which is used to determine the distributional properties.[4] The distribution of total losses X will provide the basis to apply premium principles and derive average losses μ and *risk-loading* θ to calculate π.

Premium calculation for long-term insurance

In contrast to short-term insurance where both frequency and severity of losses are random, long-term insurance such as life insurance primarily deals with insurance where the randomness of losses is related to an individuals' mortality (see Bowers, 1986). The size of losses but not the time of occurrence is typically known with certainty. This implies the necessity to incorporate the time-value of money in terms of interest rates and mortality into the calculation of actuarial premiums. The modeling of loss severity is, however, not required for long-term insurance.

Rather than estimating expected loss μ and *risk-loading* θ for π from the distribution of total losses of an insurance pool as in short-term insurance, long-term insurance expected losses are based on the individual actuarial present value of losses dependent on actual mortality, interest rates, and a loading for the variation in actual mortality rates. Mortality, interest rates, and costs are thus the calculation basis for most long-term insurance policies for which assumptions are needed. As with short-term insurance, those assumptions are usually derived from historical data.

[3] Individual risk theory differs from collective risk theory in that it considers individual exposure units rather than looking at the insurance pool as a collective. However, when analyzing real-world insurance pools, the collective risk theory model is usually preferred, since it provides more reliable estimates for smaller time-series of loss data (see Cummins, 1991). This is especially relevant for microinsurance due to prevalent data restrictions.

[4] The compounding process can be problematic in practice, since closed form solutions only exist for a limited number of combinations of frequency and severity distributions (see Cummins, 1991). However, different approximation approaches exist for these cases.

3 Challenges in pricing risks in microinsurance markets

Research on microinsurance confirms that there exist significant problems in pricing risk in microinsurance markets (see, e.g., Dlugolecki, 2008). In this respect, the biggest problem is data availability (see, e.g., Biener and Eling, 2011).

The reasons for data restrictions originate from several issues. (1) Microinsurance markets exhibit a limited record of providing insurance to low-income people because the industry is relatively young. Thus, limited historical experience data on risks is available from the industry. (2) Many microinsurers are relatively small such that experience data generated from insurance pools is insufficient for statistical analysis and premium calculation. (3) Internal and external reporting standards as well as data collection from insured is often poor in microinsurance markets, limiting the capacity to analyze risks. (4) Poor infrastructure in many developing countries and dependence on third-party data impede the utilization of important macro-level data such as inflation, demographics, meteorological data, and health costs. Data restrictions, thus, severely limit estimating robust distributions of losses and other costs.

Standard actuarial approaches to pricing insurance risks as presented in Section 2 require large sets of data and statistical information. Those range from assumptions on interest rates to more complex issues such as 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 and Churchill, 2000). This is especially important when tailoring insurance coverage to the low-income population of microinsurance markets.

Compared to regular insurance market, microinsurance market's institutions face a dilemma. Microinsurance aims at providing insurance coverage to the low-income population with limited willingness to pay.[5] Despite lower expected losses from this segment, microinsurers are required to add high risk-loadings for uncertainty in the estimation of expected losses due to data constraints. Consequently, the relative markup for uncertainty on the pure premium is higher in microinsurance markets compared to regular insurance markets, making insurance relatively more expensive and thus less attractive to the low-income population.[6]

From this follows that, when selling insurance at the estimated actuarial premium, microinsurers run the risk of overpricing risks and thus making the coverage unattractive, and when adapting the actuarial premium to the willingness to pay of the low-income population, microinsurers may increase the risk of insolvency because premiums are not sufficient to cover expected costs. If willingness to pay is assumed to be a constant and not modifiable, the dilemma needs to be approached either by increasing confidence in the calculation of premiums, thus reducing the risk-loading, or by utilizing other institutional arrangements.

In this paper, both approaches are analyzed in that we present methodologies that can be used to make best use of the available information, increase information, and utilize institutional arrangements.

4 Discussion of potential solutions

As outlined in Section 2, actuarial consistent pricing of insurance risks requires large sets of reliable data to obtain estimates of expected losses, risk-loading, and cost-loading. For short-term insurance, the former two are derived from the distribution of loss frequency and severity due to the random character of both of these variables. For long-term insurance, it is primarily the individual mortality and interest rates for which estimates are needed because of

[5] See Biener and Eling (2011) for a literature review.

[6] We assume that there exists no such thing as the correct price for insurance, but only a market price that is "high enough to bring forth sellers, and low enough to induce buyers." (see Finn and Lane, 1997).

the longer duration of insurance coverage and typical non-randomness of loss severity. Section 3 illustrates the dilemma associated with the necessity to precisely price insurance risks and the data restrictions observed in microinsurance markets. In this section, approaches to advance the precision in calculating insurance premiums are considered.

Microinsurers usually have access to some information on risk properties, such as experience data from recent years or different geographical areas. Also, macro-level data such as industry- and country-level data may be available to some extent. Over time, microinsurers also collect further data on their own risk pool. However, it is likely that none of the available data itself is sufficient to provide a sole basis for pricing insurance risk. Modeling and Bayesian approaches efficiently process the available information to obtain estimates when data availability is restricted. Fuzzy logic may integrate data that are imprecise or vague and supplementary with statistical data. It is evident that meaningful estimates for pricing insurance risks cannot be derived without a minimum of reliable data. Despite improving the efficient use of all available information, the above described methods for data analysis with small samples cannot substitute the accumulation of experience data at the micro-level; i.e., the individual microinsurer. However, the employment of ad-hoc methods such as surveys and the inclusion of expert experience can significantly improve the accuracy of pricing insurance risk. In addition, particular institutional arrangements may add to decrease excessive risk-loadings that will remain prerequisite in the presence of informational restrictions. Those measures are important levers in the development of actuarial pricing schemes when affordability of premiums is an important condition as it is in microinsurance markets.

Modeling techniques

Modeling techniques can be suitable approaches to pricing insurance risk and utilize the data available to capture complex interactions of pricing parameters (see Wipf and Garand, 2006). Often, in a case where there is limited data on specific risks, e.g., loss statistics, simulation

methodologies such as the bootstrap or Monte Carlo can be used to obtain estimates of distribution parameters of insured losses. Simulation methodologies can also be applied to analyze the effects of various modifications in insurance product specifics such as waiting times or caps on the maximum age to be covered with life insurance (see Wipf and Garand, 2006).

When pricing insurance risk, despite estimating the expected loss through point estimators such as the mean loss, it is essential to know the variability of the expected loss to account for through the risk-loading. In finite, often small samples of original loss data that we find in microinsurance markets, bootstrap techniques bypass the disadvantage of estimating the variability of mean loss from a small sample of data by creating new data (see Embrechts and Mikosch, 1991). The bootstrap is a technique to make inference on the accuracy, i.e., the standard deviation, of particular estimates of distribution parameters through resampling from the original data. As such, it offers a means to strengthen the basis for making inference on parameters relevant for pricing insurance risk in microinsurance markets.

Consider a simple crop insurance policy that compensates a farmer in case of loss of crops due to multiple perils (e.g., drought, flood) in a particular region. A microinsurer has some limited data on random crop losses $X=(x_1, x_2,\ldots,x_n)$ with n the number of observations and utilizes this information to obtain an estimate of mean crop losses. Besides the estimator of the mean, nonparametric methods can be used to obtain its standard deviation necessary to derive a suitable risk-loading on the pure premium. Assume that the observations, i.e., crop losses, are independent and stem from some probability distribution F of which the true standard deviation $\sigma(F)$ is not known. The distribution of F can, however, be estimated by its empirical distribution function $\hat{F}$ with equal probability $1/n$ of each observation x_i with $i=1,2,\ldots,n$. The subsequent bootstrap estimate of $\sigma(F)$ would be $\widehat{\sigma_B} = \sigma(\hat{F})$. The estimator for $\widehat{\sigma_B}$ can be approximated by the use Monte Carlo methods using the empirical distribution function $\hat{F}$ to draw a random bootstrap sample $x_1^*, x_2^*, \ldots, x_n^*$ from which $\hat{\mu}^* = \hat{\mu}(x_1^*, x_2^*, \ldots, x_n^*)$ is computed. This procedure, that is randomly drawing samples and computing $\hat{\mu}^*$, is repeated

for a sufficiently large number of B such that an independent number of bootstrap approximations $\hat{\mu}^{*1}, \hat{\mu}^{*2}, \dots, \hat{\mu}^{*B}$ is obtained. The estimator for $\widehat{\sigma_B}$ is then defined as the standard deviation of the bootstrap approximations $\hat{\mu}^{*1}, \hat{\mu}^{*2}, \dots, \hat{\mu}^{*B}$ (see Efron and Gong, 1983).

The resulting bootstrap estimates for particular distribution parameters, in this case expected loss and standard deviation, can then be used to derive the premium for the crop insurance policy. However, it is important that the original sample is not too small and of good quality, since irregularities may severely bias the estimators. This is an important constraint that needs to be carefully addressed when applying simulation techniques.

Bayesian methodologies

Bayesian methodologies can be powerful tools for making use of various sources of information and aid in synthesizing risk characteristics into an actuarial premium (see, e.g., Morris, 1977; Winkler, 1981). Repeated interactions, i.e., claims experience over the contract period, provide further means of deriving more accurate and appropriate premium prices over time (see, e.g., Cooper and Hayes, 1987). In this respect, Bayesian methodologies are feasible solutions for updating premiums (see, e.g., Hosios and Peters, 1989; Watt and Vazquez, 1997). Since most microinsurance policies are short-term and renewed on a regular basis, it is straightforward to adjust premiums on the basis of loss experience over the expired contract period.

The process of estimating premiums needs to utilize all information available on the properties of the risks to be insured. This is of particular relevance in microinsurance markets where data is scarce. Thus, when distributions of risks can be derived from different sources of information, those need to be condensed to a single distribution (see Winkler, 1981). Microinsurers' actuaries and experts may have an intuition or belief on the frequency and severity of specific risks based on experience from various sources. This knowledge should be included in the pricing model and updated by additional information. Bayesian methodologies provide

a natural setting to include information different from an insurers' individual loss data in an actuarial model for pricing insurance risk.

Bayesian methodologies include knowledge on the distribution of risks in a prior distribution $\vartheta(\theta)$ that represents an opinion concerning the relative chance of parameter values of θ being the true value. Prior distributions can be based on various sources such as expert experience discussed later in this section or based on existing loss experience with other markets and risks.[7] When additional knowledge on the risk is obtained by observations *x*, it is worthwhile to reconsider the assumption made in the prior loss distribution and re-evaluate the risk in terms of the distribution of experienced losses conditional on the prior distribution, i.e., the posterior distribution $\vartheta(\theta|x)$. According to the Bayes' theorem, the posterior distribution is derived by $\vartheta(\theta|x) = \frac{f(x|\theta)\vartheta(\theta)}{\int f(x|\theta)\vartheta(\theta)d\theta}$, whereas $f(x|\theta)$ represents the likelihood of various observations x given that θ is the true set of parameter values (see, e.g., Klugman, 1992). In some cases, the posterior distribution can be derived in closed form. This is, however, rarely the case in practice since a closed form solution exists for only a small number of combinations of prior and model distributions. Thus, estimators of the posterior distribution are required. Numerical as well as linear credibility methods are applied to provide solutions to the estimation of model parameters.

Bayesian methodologies were first applied to problems in insurance pricing by Bühlmann (1967, 1969) 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, and Liu, 1996). In the classical linear approximation of the Bayesian pure premium, Bühlmann (1967) relates the estimator for expected losses μ to the prior mean loss $\overline{X}$, e.g., based on the prior data or opinion, and the mean loss from the additional data $\overline{X}_i$, e.g. current observations *i*, in a linear model and defines the credibility adjusted pure premium as

[7] Garthwaite et al. (2005) provide an overview on various approaches to derive prior distributions based on expert knowledge.

$\mu = (1-\omega)\overline{X} + \omega\overline{X}_i$, whereas ω represents the credibility factor that is given to the additional data $\overline{X}_i$ and is defined by $\omega = n/(n+k)$, with n the number of exposure units of current observations and the credibility coefficient $k = \sigma^2/\tau^2$. The variance factor σ^2 is the expected variance of additional loss data conditional on the combination of risk characteristics θ. It is defined by $\sigma^2 = E[Var(X_i|\theta)]$. The factor τ^2 is the variance of the expected average loss of additional data conditional on the combination of risk characteristics θ and is defined by $\tau^2 = Var[E(X_i|\theta)]$. The posterior distribution of expected losses μ is thus a linear estimate based on the prior loss distribution $\overline{X}$ and the model distribution $\overline{X}_i$ based on additional experience. It can be shown that the Bühlmann (1967) model is the best linear approximation of the Bayesian pure premium (see, e.g., Makov, Smith, and Liu, 1996; Herzog, 1989).

We may distinguish at least two possible situations in which credibility theory as proposed by Bühlmann (1967) can be applied to condense information from different sources to a single distribution in 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 young 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] The second situation may refer to microinsurers having no or only very limited information on the risk to be insured, e.g., establishing new microinsurers, expanding operations to new regions or risks. Here, various sources of information such as demographics, survey data, and expert knowledge can be of relevance and included in the prior distribution of $\overline{X}$.

For both situations Bayesian methodologies provide a means to condense information from additional sources and derive meaningful premiums. Morris (1977) and Winkler (1981) show,

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

[9] Churchill et al. (2003) provide a detailed description of applying a simplified implementation of credibility theory to microinsurance operations.

how Bayesian approaches can be applied to integrate conflicting assessments of various experts. Ker and Goodwin (2000) apply a Bayesian 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 and supplementary with statistical data. Ostaszewski and Karwowski (1992) consider an insurer having experience in particular geographical areas extending the provision of insurance services to another area. 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.

Modeling mortality tables

Beside interest rates and costs, mortality tables are the most important source of information for pricing insurance risk in long-term insurance. In most developing countries, however, the vast population data necessary to derive sensible estimates for mortality tables is not available due to a lack of a functioning registration system or insufficient quality of data (see Murray et al., 2000). Instead of directly estimating mortality rates from original population data, indirect approaches may be applied to obtain model mortality estimates based on mortality determinants. Those can be derived from existing mortality tables in a set of countries through various techniques. The rationale for this approach lies in observed similarities in the age-structures of mortality for different populations, such that particular environmental parameters such as economic development (see Lorentzen et al., 2008) can be defined that influence mortality rates.

The United Nations (UN) was the first organization to develop such mortality tables for developing countries to analyze dynamics of populations in various countries. Existing tech-

niques range from the adoption of mortality structures of neighboring populations with similar characteristics, to the application of sophisticated models (see Murray et al., 2003 for an overview of various approaches). The objective in establishing model mortality tables is to obtain a set of parameters that capture the level and age-structure of mortality to derive mortality estimates differentiated by age and gender (see Murray et al., 2003).

Despite different objectives, such approaches can also be functional to develop mortality tables for pricing microinsurance. Indeed, mortality tables of the UN provided by the World Health Organization (WHO) include all necessary information for evaluating mortality risk with long-term insurance.[10] 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 from, predominantly, developed economies. Predicted age mortality structures may thus not adequately represent the specifics of developing countries. Especially high and highly dynamic AIDS/HIV rates can cause problems and lead to an underestimation of mortality patterns. A bias resulting from dynamic AIDS/HIV rates can, however, not be tested owing to the lack of data (see Murray et al., 2003). Microinsurers need thus be careful when applying such approaches.

Generating data

In microinsurance markets, often there exist no relevant primary (e.g., historical loss data) and secondary data (e.g., health costs) for pricing specific insurance risks. In such cases, microinsurers are required to obtain an evaluation of the risks to be insured. In those cases, quantitative estimates from experts, household and provider surveys, and qualitative data from focus groups may be appropriate sources of information.

[10] 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 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).

Expert opinions can be used to synthesize a wide array of opinions on, e.g., loss probabilities, into consensus estimates using, e.g., Delphi and nominal group methods (see, e.g., Mehr and Neumann, 1970), or apply nonconsensual Bayesian and maximum likelihood techniques to derive distributions of the specific risks (see, e.g., Auray and 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, e.g., 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. In the process of repeatedly re-evaluating expert estimates in an iterative loop, expert estimates converge. The resulting estimate 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 prone 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 and Neumann, 1970). Regardless of the method used both Delphi and nominal group technique result in a synthesized expert estimator of the quantity of interest; hence, these methods are especially beneficial if no reliable information exists (see Auray and 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 provide no rationale for why the resulting estimate should sufficiently reflect reality (see, e.g., Morris, 1977). In cases when microinsurers have some initial information on the insurable risk, nonconsensual methodologies provide means to give more

weight to the most credible expert estimate and derive point estimates of the quantity of interest such as loss probabilities. When particular distributions of specific risks can be assumed, the range of different expert opinions can be used to fit the distribution parameters. Suitable approaches for point estimates are the maximum likelihood estimator and Bayesian methods (see, e.g., Morris, 1977; Winkler, 1981; Auray and Fontenau, 2002).

When no other reliable data is available, judgments of experts are suitable means to provide estimates of risk. Moreover, estimates obtained by Delphi, nominal group techniques, and nonconsensual methodologies can be used to obtain prior distributions of parameters in the Bayesian framework discussed earlier in this section. However, the choice of credible experts and the ambiguity of questions posed are inherent problems of consensual and nonconsensual estimates based on expert assessments.

Household and provider surveys are popular means to provide estimates of risks and costs from primary sources. These techniques are frequently applied in microinsurance markets and are successful in supporting microinsurance start-ups in estimating average losses from a subsample of the target population (see, e.g., Auray and Fonteneau, 2002; Dror et al., 2008, 2009). Despite the valuable information on relevant pricing parameters, those approaches are particularly expensive and thus only feasible for a relatively limited sample. To obtain reliable estimates of risks and costs for pricing of insurance risks, however, a sufficiently large sample would be necessary. Donor organizations and reinsurers may play an essential role in supporting the collection of primary quantitative data to provide a foundation for actuarial premium calculation in microinsurance markets. Existing initiatives such as the INDEPTH Network for health data or data collection efforts of the World Bank are promising approaches in this respect.[11]

[11] For further information see http://www.indepth-network.org and http://www.worldbank.org.

Institutional arrangements

In the preceding discussion of Section 3 we state that beside improving the utilization of available data and generating new data, microinsurers can influence premiums for insurance risks by adapting institutional arrangements to fit the demand in microinsurance markets. By institutional arrangements, we primarily refer to arrangements such as the provision of risk capital and risk-sharing schemes that provide potential means to reduce excessive risk-loadings that will remain prerequisite in the presence of informational restrictions. Those measures are important levers in the development of actuarial pricing schemes when affordability of premiums is an important condition as it is in microinsurance markets.

According to Bühlmann (1985) the higher the initial equity capital of an insurer, the smaller the required premiums for insurance risks. This relation provides a promising lever to decrease premiums in microinsurance markets through initial investments in microinsurers' equity capital. The equity capital provides the microinsurer with the required solvency level that would otherwise be expensive to achieve through high risk-loadings on premiums for small microinsurers. Investment in initial equity capital can thus be used to decrease premiums for start-up and small microinsurers until risk pools are stable; i.e., the standard deviation of mean losses is reduced to a reasonable level. However, it is important that subsidies are used only to reduce the risk-loading and not the pure premium. Over time, the stability of the insurance pool provides a lever for decreasing risk-loadings according to the law of large numbers but not for reducing the pure premium that will not be affected by increasing pool size. Latortue (2006) provides examples of problems related to subsidizing insurance premiums that result in significant price increases and subsequent reduced take-up rates when subsidies are withdrawn. With the approach outlined here, equity capital can be withdrawn in relation to reduced standard deviation of mean losses; hence, premiums may remain constant, assuming that mean losses stay constant. A similar approach is provided by reinsurance schemes in that transferring risks to a reinsurer reduces the risk exposure for microinsurers and hence the re-

quired equity capital necessary to remain solvent. Dror and Armstrong (2006) show that using reinsurance is less expensive than equity capital in a simulation study of micro health insurance schemes. However, both approaches investment in equity capital and subsidizing reinsurance may be interesting for organizations interested in developing viable microinsurance markets such as governments, donor organizations, and reinsurers. A different approach discussed in Biener and Eling (2011) is the consolidation of various microinsurers to a cooperative that provides a means for wider risk sharing and the joint use of resources for risk diversification and data utilization.

5 Conclusion

This paper's key contribution is its investigation of potential approaches for more accurately pricing insurance risks in microinsurance markets. The analysis of the specifics in microinsurance markets indicates that standard approaches and current practice do not provide an appropriate basis for pricing insurance risk. Indeed, data restrictions severely limit the applicability of standard estimators of risk used for pricing insurance risk. We show particular techniques suitable to account for some problems related to this issue that have proven successful in solving similar problems in other markets.

We illustrate the applicability of simulation methodologies such as the bootstrap and Monte Carlo in cases where some loss experience data is available. For situations in which microinsurers have access to data other than own loss experience such as data from different areas or industry- and country-level data, those can be condensed using Bayesian methodologies. Fuzzy logic may be another useful theoretical approach in the context of pricing microinsurance. Microinsurer can apply ad-hoc methods to generate data relevant for pricing insurance through surveys, expert opinions, and qualitative data from focus groups. By obtaining as many estimates as possible from as wide an array of experts as possible, it may be feasible to either synthesize those opinions into consensus estimates, or derive distributions of the specif-

ic risks. At the same time, results of such ad-hoc methods provide valuable input to Bayesian approaches as they give an intuition or prior knowledge on risk characteristics that can be complemented by other data and condensed to form a distribution of insured losses.

The microinsurance industry is still in its infancy, but has huge future potential. As such, our findings are highly 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.

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