THE PERFORMANCE OF MICROINSURANCE PROGRAMS:

A FRONTIER EFFICIENCY ANALYSIS

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1. Introduction

In this paper, we use frontier efficiency analysis to evaluate the performance of microinsurance programs. Frontier efficiency techniques measure firm performance relative to 'best practice' frontiers comprised of the leading firms in the industry. Typical examples of these techniques are Data Envelopment Analysis (DEA; see Cooper et al., 2006) and Stochastic Frontier Analysis (SFA; see Kumbhakar/Lovell, 2000). Both have been applied in numerous insurance markets (see Eling/Luhnen, 2009b, for an overview), but we are not aware of any research that has been undertaken to evaluate the efficiency of microinsurance programs.

Microinsurance programs need to become viable since in most cases donor or government subsidies are only temporarily available. Without subsidies, all programs are subject to the same economic and market forces as commercial insurance, and this requires them to be managed professionally. Management goals, however, cannot be achieved without constant monitoring and transparent measurement of performance. For these reasons performance measurement and benchmarking is an important issue for microinsurance providers (see Wipf/Garand, 2008).

Research on performance of microinsurance programs, however, is still in its very early stages. Industry practitioners organized in the *Microinsurance Network* have set up a *Performance Indicator Working Group* and developed ten performance ratios during two workshops in 2006 and 2007 that are summarized in a performance indicators handbook (see Wipf/Garand, 2008). The ten performance ratios were also tested on a sample of microinsurance providers. These empirical tests show that the performance indicators can enhance the comparability of different schemes and improve transparency but they cannot capture the large diversity of different microinsurance providers. For example, some programs are small projects in the start-up phase, while others are large, established programs. It is not quite clear what set of indicators signifies poor, average, and excellent performance; the answer depends on many factors including the type of product, operational setup, location, size, and age of the program (see Wipf/Garand, 2008, p. 46). Benchmarking problems as well as differences between microinsurance programs are therefore highlighted in the handbook.

Frontier efficiency techniques might be an ideal tool to assess the performance of microinsurance programs. They are superior to traditional financial ratio analysis because they summarize performance in a single statistic that controls for differences among firms using a multidimensional framework (see Cummins/Weiss, 2000). The techniques are particularly suitable for microinsurance: Frontier efficiency methods were originally developed for benchmarking of non-profit organizations such as schools, because unlike many industries the production function with these institutions is unknown. This is exactly the situation faced by microinsurance providers. Inputs and outputs used in efficiency measurement include financial indicators but the methods can also accommodate social output indicators and thus display the important social function of microinsurance providers. Other advantages of frontier efficiency techniques will be discussed throughout the paper.

This paper uses new data and an innovative methodology. We consider data provided by the *Performance Indicator Working Group* of the *Microinsurance Network*. We analyze an updated dataset on the insurance schemes considered in the performance indicators handbook (see Wipf/Garand, 2008), which contains detailed information on 21 microinsurance programs. With regard to methodology, we use recent innovations from bootstrapping literature to account for the fact that the standard DEA efficiency scores are sensitive to problems of measurement error, especially with smaller data samples. For the first stage determination of DEA efficiency scores, we use the bootstrapping procedure presented in Simar/Wilson (1998). Another important feature of our analysis is that we cross-check the robustness of our findings using stochastic frontier analysis. While most studies use either DEA or SFA, we combine the advantages of both approaches to ensure the methodological robustness of our findings.

This is the first paper to analyze the efficiency of microinsurance programs. We therefore use recent innovations in frontier efficiency methods such as bootstrapping of efficiency scores. On the insurance practitioner front, a contribution is that we extend the existing key performance indicators with a powerful new benchmarking tool that addresses the limitations of the ten ratios currently used in the microinsurance industry. Furthermore, we enhance the comparability of microinsurance programs using a single and simple to interpret performance number. Another aim of this paper is to encourage further research and discussion on benchmarking and performance measurement in microinsurance from the academic and practitioner's perspectives.

The remainder of this paper is structured as follows: Section 2 presents an overview of performance measurement in the field of microinsurance. Section 3 introduces our methodology as well as the data that we use in the empirical part. Section 4 presents the empirical results. Finally, Section 5 concludes.

2. Performance of Microinsurance Programs

In this Section, we shortly describe the state of the art of performance measurement in microinsurance. Microinsurance is insurance for low-income people and businesses in developing countries and characterized by low premiums and low coverage limits. Churchill (2006) defines microinsurance as a financial arrangement to protect low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved. The types of risks covered are life, pension, health, disability, and property (especially crop insurance). Microinsurance can be delivered through a variety of different channels, including commercial insurers, non-governmental organizations (NGOs), mutuals, and small community-based schemes (see Roth et al., 2007). Also large multinational companies such as Allianz or Munich Re are involved in the marketplace. The most important microinsurance markets are in Asia (China, India, among others), Africa (Egypt, Uganda) and South America (Paraguay, Peru). Although the idea of insurance schemes organized as mutuals or community based is nothing new in developing countries, the term microinsurance not came up before the mid-1990's and emerged with the development of microfinance. An increasing number of microinsurance programs have been established as either pilot or as ongoing structures in recent years (Churchill, 2006, and Roth et al., 2007, provide the most comprehensive overviews of the market). Numerous classical problems of insurability including moral hazard, adverse selection, correlated risks, high administration costs, and lack of data (see Levy/Rheinhard, 2007) are inherent in microinsurance markets, making the environment challenging from an economic perspective. Despite the growing policy interest in microinsurance, little academic attention has been focused on this marketplace so that the management of such organizations has not yet been discussed in literature.

Microinsurance programs need to become economically viable since in most cases donor or government subsidies are only available over a specific period of time. Without subsidies, all microinsurers are subject to the same market forces as commercial insurance, which requires them to be managed professionally. Professional management, however, requires a constant monitoring and transparent performance measurement. As a first step for developing a transparent performance measurement process, the *Microinsurance Network* (former *CGAP Working Group on Microinsurance*) has set up a *Performance Indicator Working Group*. They developed ten performance ratios during two workshops in 2006 and 2007 that are summarized in a performance indicators handbook (see Wipf/Garand, 2008). The considered indicators are 1) Net income ratio 2) Incurred expense ratio 3) Incurred claims ratio 4) Renewal ratio 5) Promptness of claims settlements 6) Claims rejection ratio 7) Growth ratio 8) Coverage ratio 9) Solvency ratio and 10) Liquidity ratio (see Wipf/Garand, 2008, for the exact definition of these ratios). All these ratios are important indicators of financial strengths and enhance the comparability and transparency of different schemes.

Nevertheless, standard financial ratio analysis cannot capture the large diversity in terms of size, sustainability and other decisive characteristics of microinsurance providers. The choice of a specific set of financial ratios signifying poor, average and excellent performance is challenging and as such implies a trade-off between the importance of specific corporate goals which is provided by the efficiency analysis.

As many microinsurance programs are set up as non-profit organizations and social organizations as well as governments finance a lot of their activities; their objectives thus cannot be limited to financial performance. Like many microfinance institutions, microinsurers have a twofold responsibility with combined financial and social objectives that have to be satisfied efficiently (see Gutiérrez-Nieto et al., 2009). The social function of microinsurers, i.e., providing protection on the individual and firm level and as such strengthening the ability for economic growth, mitigation of poverty, inequality and vulnerability, is a crucial aspect in evaluating performance. The *Performance Indicators Sub-group* discussed four potential indicators to reflect the social function that many microinsurers have (see Wipf/Garand, 2008, p. 50): 1) The social investment ratio defined as total expenditure on information, education, and communication divided by total expenditure of the programme. 2) The percent of insured below the poverty line defined as number of insured below the poverty line divided by total number insured in the scheme. 3) Value of incurred claims in comparison with client annual income. 4) Cost of benefits provided in comparison to the cost of annual premium.

In practice, using such measures would require a clear definition of the poverty line and of what to consider in the annual income since many insured receive benefits in kind and services instead of cash income. Furthermore, we believe that the existing ten performance indicators can also illustrate social performance. For example, the higher the coverage ratio, the higher is the protection in the target audience, the better is the social benefit. Moreover, the social indicator number 4) is very similar to the performance indicator 3), the incurred claims ratio. Yet the above discussed performance ratios cannot capture the diversity of microinsurers with respect to their distinct objectives. An advantage of the frontier efficiency methodology is that it can accommodate traditional indicators reflecting financial performance as well as other indicators, e.g., reflecting social performance. A social output indicator will thus also be part of the efficiency analysis.

3. Methodology and Data

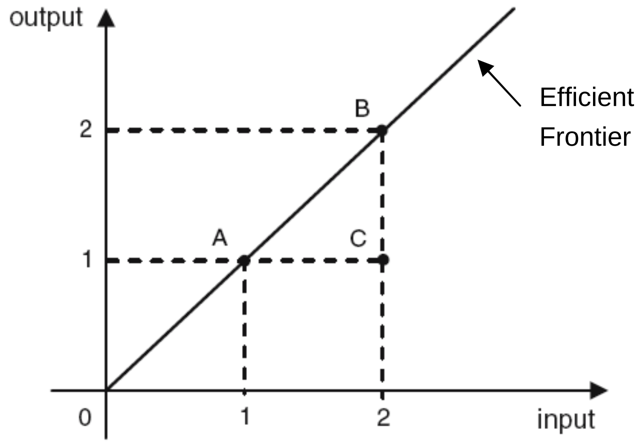
In this Section, we introduce the efficiency methodology and show how to adjust the standard set of input and outputs used in efficiency measurement of commercial insurance companies to accommodate the social function that insurance providers have. Furthermore, we present the dataset provided by the *Performance Indicator Working Group* of the *Microinsurance Network*.

3.1 Methodology

Under the concept of efficiency the performance of a company is measured relative to a "best practice" frontier, which is determined by the most efficient companies in the industry. Modern frontier efficiency methods, similar to more traditional techniques such as financial ratio analysis, thus aim at benchmarking firms of an industry against each other. These methods are considered superior to other techniques because they integrate different measures of firm performance into a single and thus easily comparable statistic that differentiates between companies based on a multidimensional framework (see Cummins/Weiss, 2000). The efficiency statistic is standardized between 0 and 1, with the most (least) efficient firm receiving the value of 1 (0). The difference between a company's assigned value and the value of 1 determines the company's improvement potential in terms of efficiency (see, e.g., Cooper et al., 2006).

Different types of efficient frontiers can be estimated. In the simplest case, a production frontier is estimated, assuming that companies minimize inputs conditional on a given level of outputs (input orientation) or maximize outputs conditional on given level of inputs (output orientation). The basic case for input orientation is illustrated in Figure 1.

Figure 1: Efficient frontier example for one input, one output and CRS



In this example, we assume constant returns to scale (CRS) and employ one type of input and one type of output. Firms A and B dominate Firm C in terms of efficiency, since they only consume 1 input to produce 1 output. They build the efficient frontier and are assigned an efficiency score of 1. Firm C uses 2 inputs to produce 1 output. Its efficiency score is determined by dividing the optimally needed amount of inputs to produce 1 output (1 in this case) by the actually consumed amount of inputs (2 in this case). The resulting score is 0.5. Firm C is therefore half as efficient as Firms A and B. The production frontier can be interpreted to measure a company's success in employing technology. In this case, an inefficient firm should move closer to the efficient frontier, i.e., improve its efficiency, by upgrading its technology to state of the art.

There are two main approaches in efficient frontier analysis: the econometric approach and the mathematical programming approach. We shortly introduce these two approaches (including references to detailed overviews) and discuss their application to the insurance field.[1]

Econometric Approach

The econometric approaches specify a production, cost, revenue, or profit function with a specific shape and make assumptions about the distributions of the inefficiency and error terms. The most commonly used econometric approach is *stochastic frontier analysis* (SFA),

1 Due to space constraints we restrict ourselves to a basic description of the methodologies. An extended version of this paper that contains more details on the different methodologies is available upon request.

which was first proposed by Aigner et al. (1977). SFA is usually applied in two steps: In the first step, a production, cost, revenue, or profit function is estimated, determining the efficient frontier. In the second step deviations from the efficient frontier due to inefficiency and a random error are calculated for individual firms (see Cummins/Weiss, 2000).

There are two configuration decisions that must be made when employing SFA: (1) The choice of the functional form to approximate the real underlying production, cost, revenue, or profit function, and (2) the distributional assumption for the inefficiency term. The translog is an accepted and widely used functional form, but there are a variety of other options, including the Cobb-Douglas, Fuss normalized quadratic (see Morrison/Berndt, 1982), and generalized translog (see Caves et al., 1980). The composite cost (see Pulley/Braunstein, 1992) or the Fourier flexible form (see Gallant, 1982) have also been applied in the financial services industry. While the random error term is usually assumed to be distributed normally, the inefficiency term has been specified to have different distributions, such as half-normal, truncated normal, exponential, or gamma (see, e.g., Berger/Humphrey, 1997).

Mathematical programming approaches

The most widespread mathematical programming approach is *data envelopment analysis* (DEA), which uses linear programming to measure the relationship of produced goods and services (outputs) to assigned resources (inputs). Compared with the econometric approaches, the mathematical programming approaches put significantly less structure on the specification of the efficient frontier and do not decompose the inefficiency and error terms. DEA determines the efficiency score as an optimization result. DEA models can be specified under the assumption of constant (CRS) or variable returns to scale (VRS) and can be used to decompose cost efficiency into its single components—technical, pure technical, allocative, and scale efficiency (see Cooper et al., 2006).

Frontier efficiency techniques have already been applied to numerous insurance markets. In fact, efficiency measurement is one of the most rapidly growing streams of literature and the insurance sector in particular has seen extreme growth in the number of studies applying frontier efficiency methods. Eling/Luhnen (2009a) surveyed 95 studies on efficiency measurement in the insurance industry. Recent work in the field has refined methodologies, addressed new topics (e.g., market structure and risk management), and extended geographic coverage from a previously US-focused view to a broad set of countries around the world, including emerging markets such as China and Taiwan. None of the 95 papers attempts to incorporate microinsurance in an efficiency analysis. The only paper that uses frontier efficiency techniques but in a microfinance (and not a microinsurance) context is Gutiérrez-Nieto et al. (2009). They rely upon the *Microfinance Information eXchange* database and show the advantages of DEA for measuring efficiency in banking.

Advantages of Frontier Efficiency for Microinsurance

Frontier efficiency techniques might be an ideal tool to assess the performance of microinsurance programs for the following reasons:

1) Frontier efficiency methods were originally developed for benchmarking of non-profit organizations such as schools, because unlike many industries the production function with these institutions is unknown. This is exactly the situation faced by microinsurance providers.

2) The methods are superior to traditional financial ratio analysis because they summarize performance in a single statistic that controls for differences among firms using a multidimensional framework (see Cummins/Weiss, 2000). Instead of ten different indicators we thus have one easy to use and easy to interpret performance indicator.

3) As mentioned, inputs and outputs used in efficiency measurement include financial indicators but the methods can also accommodate social output indicators and thus display the important social function of microinsurance providers.

4) The techniques measure efficiency and identify areas in which a program has strengths relative to other programs as well as areas in which the firm is weak. It is possible to identify performance targets for inefficient units, i.e., the results directly indicate the direction in which resources need to be located in order to improve efficiency.

5) From an economic point of view, several useful parameters (that have not yet been analyzed in microinsurance) can be generated, such as the marginal rate of substitution, marginal productivity, and the marginal rate of transformation. All these measures can be helpful in evaluating the effects of different business decisions on the performance.

6) With SFA we can isolate and directly model the effects of organizational forms, company sizes, solvency, time and many other factors on efficiency, all of which are important determinants in microinsurance, using the conditional mean approach (see, e.g., Greene/Segal, 2004).

7) The data requirements are not too exhaustive, which is extremely relevant given the limited availability and quality of data in this emerging field of research. Different methodologies might be used to account for data of varying quality. When data is known to be noisy, SFA might for example be appropriate, because it distinguishes between random deviations from the efficient frontier and deviations due to inefficiency.

Frontier efficiency analysis might thus be a powerful performance measurement technique for microinsurance and a valuable addition to the existing performance measures in the field of microinsurance.

3.2 Data and Configuration of Efficiency Analysis

We received data on 21 microinsurance schemes providing mostly life and health insurance form the *Microinsurance Network*. The data contains balance sheet and statement of income information from 2004 to 2008. We do not have data for all years for all companies; we thus consider unbalanced panel data. In total we have 78 firm years available for this analysis. This setup provides an ideal basis for efficiency analysis as most of the inputs and outputs used in efficiency analysis rely upon data provided in the balance sheet and the statement of income. We have seven companies from Africa, Asia and Latin America each.

There is widespread agreement in literature with regard to the choice of inputs (see Cummins/Rubio-Misas/Zi, 2004). We thus use *labor*, *business services and material*, *debt capital*, and *equity capital* as inputs. Due to data availability, it was necessary to simplify this scheme by combining labor and business services as only operating expenses (including commissions). This simplification is a common practice in many international efficiency comparisons (see Diacon/Starkey/O'Brien, 2002; Fenn et al., 2008), usually for reasons similar to ours. Furthermore, Ennsfellner/Lewis/Anderson (2004) argue that the operating expenses should be treated as a single input in order to reduce the number of parameters that will need to be estimated. We thus use operating expenses to proxy both labor and business services and handle these as a single input in the following analysis.

Cummins/Weiss (2000) showed in their analysis of operating expenses in the US insurance market that these are mostly labor related, i.e., in both life and non-life insurance, the largest expenses are employee salaries and commissions. We therefore concentrate on labor to determine the price of the operating-expenses-related input factor. The *price of labor* is determined using the ILO Main Statistics and October Inquiry, worldwide surveys of wages and hours of work published by the International Labour Organization (ILO; see http://laborsta.ilo.org/) and used in a variety of efficiency applications (see, e.g., Fenn et al., 2008). The *price of debt capital* is proxied using region-specific bond indices for each year of the sample period. The *price of equity capital* is determined using rolling window 5-year-averages of the yearly rates of total return of regional MSCI Emerging Markets Indices (all data were obtained from the Datastream database; see Cummins/Rubio-Misas (2006) for a comparable selection and a discussion on selection depending on the insurer's capital structure and portfolio risk). To ensure that all monetary values are directly comparable, we deflate each year's value by the *consumer price index* to the base year 2004 (see Weiss, 1991; Cummins/Zi, 1998). Country-specific consumer price indices were obtained from the International Monetary Fund (IMF) database.

As done in most studies on efficiency in the insurance industry, we use the value-added approach (also called the production approach; see Grace/Timme, 1992; Berger et al., 2000) to determine the outputs. We thus distinguish between the three main services provided by insurance companies—risk-pooling/-bearing, financial services, and intermediation. According to Yuengert (1993), a good proxy for the amount of risk-pooling/-bearing and financial services is the value of real incurred losses, defined as current losses paid plus additions to reserves. As most of the microinsurance programs included in the database provide life and health insurance coverage we use the present value of *net incurred benefits* as a proxy for the risk-pooling/-bearing and financial services output. The output variable, which proxies the intermediation function, is the real value of *total investments*. The cost variable necessary for the calculation of SFA cost efficiency is calculated following Choi/Weiss (2005) as operating expenses plus cost of capital.[2] To obtain present values we again deflate each year's value using the consumer price indices.

In an additional model we complement the analysis of technical efficiency with the implementation of a further output variable that represents the social function of the microinsurer. For this purpose we selected an indicator that is able to display the capacity of microinsurers to reach their target population. Along with the definition of a coverage ratio by the *Performance Indicator Working Group* of the *Microinsurance Network* (see Wipf/Garand, 2008) we defined the additional output as the number of people insured relative to the target population defined by the respective microinsurer. Note that the coverage ratio is one of the ten key performance indicators in the performance indicators handbook and not one of the four additional social indicators. We believe, however, that the coverage ratio is the social output indicator best reflecting the service function of non-profit insurance companies. For the efficiency analysis it would also be feasible to implement one of the four additional social indicators

[2] Contrary to DEA, SFA cost efficiency estimation requires the pre-specification of a cost variable reflecting total observed costs of the respective microinsurer as dependent variable in the regression. DEA computes a cost minimizing vector of input quantities as optimization solution from which cost efficiency can be calculated dividing it by the actual consumed quantities. As such a pre-specified cost variable is not required in the case of DEA.

from the performance indicators handbook or any other indicator which might best fit the social performance of microinsurance providers.[3]

Panel A of Table 1 presents an overview of the inputs, outputs and prices used in this analysis. Panel B of Table 1 contains summary statistics on the variables employed. For comparative purposes, all numbers were deflated to 2004 using the IMF consumer price indices and converted into US dollars using the exchange rates published in the Datastream database.

Table 1: Inputs and outputs

Panel A: Overview	
Inputs	Proxy
Labor and business service	Operating expenses / ILO Inquiry wage per year
Debt capital	Total liabilities
Equity capital	Capital & surplus
Input prices	
Price of labor	Regional ILO Inquiry wage per year
Price of debt capital	Annual return of regional JPM EMBI GLOBAL indices
Price of equity capital	5-year-average of yearly total return rates of regional MSCI EM indices
Outputs	
Benefits + additions to reserves	Net incurred benefits + additions to reserves
Investments	Total investments
Social Output Indicator	Ratio of number of insured to target population

Panel B: Summary statistics for variables used					
Variable	Unit	Mean	St. Dev.	Min.	Max.
Labor and business service	Quantity	80	189	0.78	1,341
Debt capital	US $	10,065,467	33,935,375	1.00	188,959,766
Equity capital	US $	1,981,454	4,296,873	1.00	20,364,679
Price of labor	US $	7,925	1,281	5,822.30	10,202
Price of debt capital	%	8.25	4.58	1.82	19.61
Price of equity capital	%	16.43	7.18	3.40	29.27
Benefits + additions to reserves	US $	113,471	339,132	1.00	1,701,119
Investments	US $	9,511,065	30,080,861	1.00	169,577,686
IMF consumer price index	%	13.76	15.76	0.00	89.22
Social Output Indicator	%	55.05	32.24	0.53	100

[3] A related discussion from insurance literature is the question of different organizational types (stocks and mutuals), their main types of goals, and resulting agency conflicts. The two principal hypotheses in this area are the expense preference hypothesis (see Mester, 1991) and the managerial discretion hypotheses (see Mayers/Smith, 1988; see Cummins/Weiss, 2000 for more details on both these hypotheses). While the stock insurers primary goal is to ensure high profits with a given solvency level set by regulator or rating agency, the primary goal of a mutual insurer is the fulfillment of demand for the owners and a high service quality. The fulfillment of demand for the owners is comparable to the coverage ratio. Again, however, an advantage of frontier efficiency methods is that it does not matter whether these are considered as financial or social goals.

In the next section, we analyze technical and cost efficiency considering two methodologies (DEA, SFA), three regions (Asia, Africa, Latin America), three company sizes (large, medium, small) and two organizational forms (non-profit, profit). Total assets is a widespread measure of insurer size (see, e.g., Cummins/Zi, 1998; Diacon/Starkey/O'Brien, 2002). For comparison of different company sizes, we subdivide all companies by their total assets into large (total assets larger than \$1,737,989), medium, and small (total assets smaller than \$5,611) insurers. Although the comparability of findings from different efficiency studies is limited, e.g., due to different sample compositions and time horizons, we try to integrate our empirical results into the existing literature whenever possible.

4. Empirical Results

Data envelopment analysis (model without social output indicator)

In a first step we analyze the model without the social output indicator. For data envelopment analysis, we calculate efficiency values assuming input orientation and variable returns to scale. As the standard DEA approach is sensitive to problems of measurement error, we use the bootstrapping procedure presented in Simar/Wilson (1998). Table 2 sets out the bias-corrected DEA efficiency scores for technical and cost efficiency.[4] For comparison purposes, the average annual values are presented in the last line of the table and the average values for the respective microinsurer on the two last columns on the right hand side of the table. We also display mean technical and cost efficiency estimates for each of the regions in the panel.

[4] The DEA results in Table 2 are based on a one-world frontier and estimated separately for all years, while we present results for an unbalanced panel for the SFA analysis (Table 3). Our DEA implementation only allows a pooled estimation using balanced panel data and we did that to check the robustness of our results. We find comparable results considering the pooled sample and the results for separate years. However, for methodological consistency, our estimation on time trend is presented with the SFA results.

Table 2: Results of the data envelopment analysis (model without social output indicator)

		Technical efficiency (TE)						Cost efficiency (CE)					
	Microinsurer	2004	2005	2006	2007	2008	Mean	2004	2005	2006	2007	2008	Mean
Africa	1	n/a	n/a	0.88	0.87	0.95	0.90	n/a	n/a	1.00	1.00	1.00	1.00
	2	0.90	0.95	0.97	0.95	n/a	0.94	0.02	0.05	0.03	0.03	n/a	0.03
	3	n/a	n/a	0.88	0.87	n/a	0.88	n/a	n/a	1.00	1.00	n/a	1.00
	4	n/a	0.88	0.93	0.95	0.95	0.93	n/a	0.95	0.89	0.76	0.90	0.88
	5	0.80	0.86	0.88	0.87	0.95	0.87	1.00	1.00	0.70	0.56	0.69	0.79
	6	n/a	n/a	n/a	0.89	0.95	0.92	n/a	n/a	n/a	1.00	1.00	1.00
	7	0.82	0.90	0.93	0.78	n/a	0.86	1.00	0.98	0.87	0.74	n/a	0.90
	Mean	0.84	0.90	0.91	0.88	0.95	**0.90**	0.67	0.74	0.75	0.73	0.90	**0.80**
Asia	8	0.79	0.86	0.88	0.87	n/a	0.85	0.45	0.44	0.39	0.39	n/a	0.42
	9	0.79	0.77	0.76	0.91	n/a	0.81	0.99	0.46	0.47	0.63	n/a	0.64
	10	n/a	n/a	0.88	0.87	0.95	0.90	n/a	n/a	1.00	1.00	0.74	0.91
	11	n/a	n/a	0.95	0.87	0.95	0.92	n/a	n/a	0.75	0.61	1.00	0.78
	12	n/a	0.86	0.90	0.86	0.95	0.89	n/a	0.47	0.53	0.15	1.00	0.54
	13	0.79	0.87	0.88	0.93	0.95	0.88	1.00	1.00	1.00	1.00	1.00	1.00
	14	n/a	n/a	n/a	0.90	0.95	0.93	n/a	n/a	n/a	0.17	0.24	0.21
	Mean	0.79	0.84	0.87	0.89	0.95	**0.88**	0.81	0.59	0.69	0.56	0.80	**0.64**
Latin America	15	0.80	0.87	0.88	0.88	0.95	0.88	1.00	1.00	1.00	1.00	1.00	1.00
	16	n/a	n/a	0.94	0.88	n/a	0.91	n/a	n/a	0.85	1.00	n/a	0.93
	17	0.78	0.87	0.88	0.87	n/a	0.85	1.00	1.00	1.00	1.00	n/a	1.00
	18	0.83	0.88	0.63	0.53	0.95	0.76	0.64	0.72	0.47	0.44	1.00	0.66
	19	0.11	0.28	0.06	0.08	n/a	0.13	0.08	0.17	0.06	0.07	n/a	0.10
	20	0.85	0.91	0.91	0.72	0.68	0.81	0.86	0.99	0.83	0.68	0.19	0.71
	21	0.79	0.86	0.87	0.87	n/a	0.85	1.00	1.00	1.00	1.00	n/a	1.00
	Mean	0.69	0.78	0.74	0.69	0.86	**0.74**	0.76	0.81	0.75	0.74	0.73	**0.77**
Mean		0.75	0.83	0.84	0.82	0.93	**0.83**	0.75	0.73	0.73	0.68	0.81	**0.73**

Overall, the DEA efficiency estimates are relatively high compared to those of other studies with Africa (0.90) and Asia (0.88) being the most technical efficient markets. The African microinsurers also show relatively high cost efficiency values (0.80) followed by Latin America (0.77) and Asia (0.64) as least cost efficient market. Results of technical and cost efficiency are relatively consistent within the sample. As an example we consider the microinsurance program #10 which ranked high with a technical efficiency score of 0.90. The insurer is especially gaining efficiency by good values in incurred benefits (top 35%, meaning the relative position of microinsurer #10 in the sample, i.e. 65% of the microinsurers have lower values), operating expenses (top 31%) and equity capital (top 12%). As is visible from these values, not the single outcome in either input or output variables results in high efficiency scores but the efficient combination of both. The estimates from the efficiency analysis are also consistent with traditional financial ratio analysis. For example, microinsurer #10 has good values in incurred expense ratio, incurred claims ratio, operating margin and return on assets. The effect of input and output values on technical efficiency is further illustrated by the least efficient microinsurer #19 (technical efficiency 0.13). Although we find relatively good results for incurred benefits, the efficiency is very low due to poor input values; only 5-20% of the sample have inferior values. Financial ratio analysis supports the efficiency result with poor net income ratio, incurred claims ratio, operating margin and return on assets for microinsurer #19. A possible explanation for the relatively high DEA estimates on the aggregate level might be that the sample is rather heterogeneous, consisting of a variety of different insurance schemes with different organizational forms, regional focus, persistence, product range and client structure. We also face a dataset of varying quality and consistency such that noise is likely to alter the quality of our analysis. Moreover the sample is relatively small and as such may be biased upward, taking the effect of sample size on average efficiency scores outlined by Zhang and Bartles (1998) into consideration. It might thus be promising to complement the mathematical programming method (data envelopment analysis) with an econometric frontier efficiency method (stochastic frontier analysis) that is able to distinguish between random departures from efficiency such as noise and departures due to inefficiency.

Stochastic frontier analysis

For the calculation of *technical efficiency*, we specify a translog stochastic input distance function. The distance function formulation was chosen so as to accommodate multiple outputs and multiple inputs (see, e.g., Coelli/Perelman, 1996; Coelli, 2005). To calculate *cost efficiency,* a translog stochastic cost function was specified. The inefficiency term is assumed to follow a truncated normal distribution. The random error term is assumed to be normally distributed. For more details on the SFA specification (which follows Battese/Coelli, 1995), the reader is referred to the Appendix of the paper.

Table 3: Results of the stochastic frontier analysis (model without social output indicator)

		Technical efficiency (TE)						Cost efficiency (CE)					
	Microinsurer	2004	2005	2006	2007	2008	Mean	2004	2005	2006	2007	2008	Mean
Africa	1	n/a	n/a	1.00	0.45	0.36	0.60	n/a	n/a	0.45	0.66	0.65	0.58
	2	0.57	0.06	0.57	0.05	n/a	0.31	0.00	0.00	0.00	0.00	n/a	0.00
	3	n/a	n/a	0.59	0.51	n/a	0.55	n/a	n/a	0.85	0.97	n/a	0.91
	4	n/a	0.86	1.00	0.81	0.95	0.91	n/a	0.40	0.22	0.16	0.13	0.23
	5	1.00	0.76	0.55	0.54	0.72	0.71	0.23	0.70	0.15	0.12	0.05	0.25
	6	n/a	n/a	n/a	0.78	1.00	0.89	n/a	n/a	n/a	0.11	0.72	0.41
	7	0.15	0.22	0.13	0.10	n/a	0.15	0.45	0.98	0.16	0.85	n/a	0.61
	Mean	0.57	0.48	0.64	0.46	0.76	**0.59**	0.23	0.52	0.30	0.41	0.39	**0.43**
Asia	8	1.00	0.84	0.99	1.00	n/a	0.96	0.01	0.17	0.06	0.03	n/a	0.07
	9	1.00	0.73	0.99	0.75	n/a	0.87	0.08	0.08	0.13	0.14	n/a	0.11
	10	n/a	n/a	0.92	1.00	1.00	0.97	n/a	n/a	0.07	0.25	0.98	0.43
	11	n/a	n/a	0.76	1.00	0.86	0.87	n/a	n/a	0.06	0.31	0.15	0.17
	12	n/a	0.49	1.00	0.20	0.31	0.50	n/a	0.05	1.00	0.07	0.08	0.30
	13	1.00	1.00	0.98	0.96	1.00	0.99	0.51	0.34	0.96	0.71	0.32	0.57
	14	n/a	n/a	n/a	0.97	0.74	0.86	n/a	n/a	n/a	0.02	0.04	0.03
	Mean	1.00	0.76	0.94	0.84	0.78	**0.86**	0.20	0.16	0.38	0.22	0.32	**0.24**
Latin America	15	1.00	0.99	0.98	0.96	0.96	0.98	0.88	0.66	0.91	0.92	0.83	0.84
	16	n/a	n/a	0.36	0.46	n/a	0.41	n/a	n/a	0.13	0.23	n/a	0.18
	17	0.66	0.54	0.35	0.35	n/a	0.47	0.92	0.93	0.35	0.43	n/a	0.66
	18	0.14	0.15	0.13	0.17	0.23	0.16	0.12	0.14	0.05	0.08	0.09	0.10
	19	0.03	0.02	0.03	0.03	n/a	0.03	0.01	0.01	0.02	0.02	n/a	0.02
	20	0.92	0.86	0.84	0.88	1.00	0.90	0.06	0.07	0.05	0.04	0.00	0.04
	21	1.00	0.98	0.95	0.99	n/a	0.98	0.93	0.71	0.53	0.53	n/a	0.67
	Mean	0.62	0.59	0.52	0.55	0.73	**0.56**	0.49	0.42	0.29	0.32	0.31	**0.36**
Mean		0.70	0.61	0.69	0.62	0.76	**0.67**	0.35	0.37	0.32	0.32	0.34	**0.34**

The results of the stochastic frontier analysis displayed in Table 3 reflect the effects of noise inherent in the data. Technical and cost efficiency estimates are in general lower than those estimated using data envelopment analysis. Efficiencies show much more variation in time as well as among different entities. On the aggregated level Asia displays the highest average technical efficiency with 0.86 at the same time being the least cost efficient region with 0.24. In terms of technical efficiency Asia is followed by Africa (0.59) and Latin America (0.56). The analysis of cost efficiency estimates reveals the same separation as in the data envelopment analysis, with Africa being the most efficient region (0.43), followed by Latin America (0.36) and Asia (0.24). Rank correlation of the technical efficiency scores received by SFA and DEA is very low compared to the observations found in other studies. Cost efficiency rank correlation on the other hand receives a value of 0.70 which is consistent with results from other studies (Borger/Kerstens (1996) find a rank correlation of 0.83, Cummins/Zi (1998) find a rank correlation of 0.58. Hjalmarsson/Kumbhakar/Heshmati (1996) find a rank correlation in the range of 0.65 to 0.73). One possible explanation for these results lies in the treatment of noise in the data that differentiates the results of the SFA from the DEA. Since price information is rather stable compared to balance sheet data in our sample we can easily explain the more consistent cost efficiency results in rank correlation. Considering time as being an important factor in the progress of efficiency in insurance markets we can yet not observe a clear trend towards improvements over time in terms of technical as well as cost efficiency on the aggregate level.

DEA and SFA model with social output indicator

To capture the social performance of microinsurers we incorporated a supplementary output variable in our analysis. For this purpose we relied on the capacity of microinsurers to reach their target population defined as the number of people insured relative to the target population (given by the microinsurer). Table 4 displays the technical efficiency estimates of microinsurers after the incorporation of the social performance variable.

Table 4: Technical efficiency incorporating social performance

	Microinsurer	DEA technical efficiency 2004	2005	2006	2007	2008	Mean	SFA technical efficiency 2004	2005	2006	2007	2008	Mean
Africa	1	n/a	n/a	0.91	0.89	0.95	0.92	n/a	n/a	0.99	0.59	0.57	0.71
	2	0.89	0.90	0.97	0.95	n/a	0.93	0.58	0.10	0.94	0.22	n/a	0.46
	3	n/a	n/a	0.91	0.88	n/a	0.90	n/a	n/a	0.60	0.92	n/a	0.76
	4	n/a	0.90	0.94	0.96	0.95	0.94	n/a	0.78	0.91	1.00	1.00	0.92
	5	0.79	0.90	0.88	0.88	0.96	0.88	0.89	0.65	0.95	0.98	0.75	0.84
	6	n/a	n/a	n/a	0.91	0.96	0.93	n/a	n/a	n/a	0.99	0.67	0.83
	7	0.82	0.93	0.95	0.79	n/a	0.87	0.18	0.29	0.24	0.13	n/a	0.21
	Mean	0.84	0.91	0.93	0.89	0.96	**0.91**	0.55	0.45	0.77	0.69	0.75	**0.68**
Asia	8	0.79	0.90	0.91	0.88	n/a	0.87	1.00	0.80	0.93	0.98	n/a	0.93
	9	0.79	0.90	0.91	0.92	n/a	0.88	0.99	0.65	0.92	0.97	n/a	0.88
	10	n/a	n/a	0.91	0.88	0.96	0.91	n/a	n/a	0.45	0.98	0.97	0.80
	11	n/a	n/a	0.96	0.89	0.95	0.93	n/a	n/a	1.00	0.57	0.93	0.83
	12	n/a	0.90	0.92	0.88	0.96	0.92	n/a	0.45	1.00	0.13	0.15	0.43
	13	0.79	0.90	0.91	0.88	0.95	0.89	0.61	0.60	0.78	0.90	0.97	0.77
	14	n/a	n/a	n/a	0.88	0.95	0.92	n/a	n/a	n/a	0.98	0.97	0.98
	Mean	0.79	0.90	0.92	0.89	0.95	**0.90**	0.87	0.63	0.85	0.79	0.80	**0.80**
Latin America	15	0.80	0.91	0.91	0.88	0.96	0.89	0.99	0.96	0.98	0.92	0.98	0.97
	16	n/a	n/a	0.92	0.89	n/a	0.90	n/a	n/a	0.54	0.76	n/a	0.65
	17	0.80	0.90	0.91	0.88	n/a	0.87	0.67	0.70	0.74	1.00	n/a	0.78
	18	0.82	0.91	0.92	0.54	0.95	0.83	0.27	0.29	0.25	0.29	0.65	0.35
	19	0.14	0.37	0.31	0.16	n/a	0.25	0.03	0.02	0.04	0.04	n/a	0.03
	20	0.86	0.93	0.94	0.72	0.68	0.82	0.96	0.93	0.98	0.99	0.96	0.96
	21	0.80	0.90	0.91	0.88	n/a	0.87	0.32	0.42	0.60	0.99	n/a	0.58
	Mean	0.70	0.82	0.83	0.71	0.86	**0.78**	0.54	0.55	0.59	0.71	0.86	**0.62**
Mean		0.76	0.87	0.89	0.83	0.93	**0.86**	0.63	0.55	0.73	0.73	0.80	**0.70**

Both methodologies, data envelopment analysis and stochastic frontier analysis show slight upward variations on the aggregate level compared to the setup not considering social performance which are generally consistent with results obtained by the previous analysis. Asia is an interesting exception in terms of relative changes in efficiency. Here we find average efficiency values decreasing when implementing social performance in the SFA and slightly increasing values in the case of DEA. The inconsistency of these results may originate from large variations in coverage ratios over time and within the sample microinsurers that is particularly prominent in Asia. Since SFA better differentiates variation in the variables the resulting effect is likely to be different compared to DEA. In Africa and Latin America we find an upward shift for all but three microinsurers applying SFA and all but two microinsurers using DEA. As a first result we can conclude that the social performance of microinsurance programs differentiates the respective performance estimates but changes in general propositions are not being found in this case. Further research is needed to investigate the effect of a social performance indicator on efficiency in relation to outputs representing financial performance.

A question that arises when comparing the two models with and without a social output indicator is whether the performance of the non-profit microinsurers is better when the social output indicator is included in the analysis. In our panel, we find significantly higher values for technical and cost efficiency for microinsurers with profit orientation (#1, #10, #14, #15, #17, #21) both in the models with and without social output indicator. Non-profit microinsurers, however, show improvement in efficiency after the implementation of the social output indicator, e.g., in the SFA analysis moving from a technical efficiency estimate of 0.63 to 0.65 on the aggregate level. For-profit microinsurers exhibit decreasing technical efficiency with a value on average declining from 0.82 to 0.78. The DEA results show an improvement for both the non-profit and the for-profit insurers when the social output indicator is analyzed; the improvement, however, is higher for the non-profit insurers. To further investigate the effects of firm specific and environmental variables on efficiency, we extend our analysis in the following part applying a conditional mean approach.

Conditional mean approach

To verify the results displayed in Tables 3 and 4, which show combined efficiency effects, we implemented an analysis that is able to isolate the impact of different time, firm and country-specific effects on efficiency. A one-stage approach is implemented that models the mean of the inefficiency term from the stochastic frontier analysis dependent on a vector of firm and country-specific variables (so called "conditional mean approach;" see Battese/Coelli, 1995, and Greene/Segal, 2004, for an application to the insurance industry).[5]

The following explanatory variables are used in our regression model: (1) Organization: 1 if the insurer is a non-profit organisation; 0 otherwise. (2) A solvency variable: 1 if the company's ratio of equity capital to total assets is above the median; 0 if not. (3) Company size: Dummy variables are included according to the three size classes "small," "medium," and "large." The size category "large" is excluded to avoid singularity. It serves as the reference category for the other two categories. (4) Time: Dummy variables for each year 2005 to 2008 are chosen to capture time effects; 2004 is excluded. (5) Region: Regional dummies are included to take country effects into consideration. Latin America is chosen as the reference category and is omitted from the regression.

Table 4: Results of the conditional mean analysis

	Technical efficiency (without social output indicator)			Technical efficiency (with social output indicator)			Cost efficiency		
	coefficient	t-statistic		coefficient	t-statistic		coefficient	t-statistic	
Intercept	-1.11	-1.42	*	-1.08	-1.61	**	-2.08	-2.46	***
Organization	3.35	5.99	***	4.57	6.63	***	4.21	4.14	***
Solvency	0.48	1.10		-0.24	-0.49		-1.96	-2.26	**
Small	-4.39	-9.75	***	-3.56	-4.59	***	-3.06	-3.51	***
Medium	-2.28	-5.16	***	-3.95	-5.99	***	2.75	3.44	***
Africa	-0.61	-1.47	*	-1.58	-3.01	***	0.33	0.35	
Asia	-2.11	-3.38	***	-1.56	-2.54	***	-1.49	-1.62	*
2005	0.50	0.86		0.85	1.04		-2.33	-2.24	**
2006	0.31	0.51		-0.94	-1.13		-1.89	-1.86	**
2007	0.51	0.87		-0.99	-1.34	*	-1.60	-1.63	*
2008	0.11	0.15		0.49	0.61		0.39	0.42	

Note: * (**, ***) indicates significance level of 10% (5%, 1%).

[5] One assumption of the conditional mean approach is the homoscedasticity of the random error and inefficiency terms, an assumption that simplifies computation and in standard regression problems usually provides adequate estimation results even if the assumption is not true (see Verbeek, 2008). However, in our context, the assumption could be implausible and result in inconsistent estimates, especially because the variability of incurred benefits and costs depends on the size of the insurer and these scale differences might bias the efficiency scores (for more details, see Fenn et al., 2008). There are some approaches that model the variance of the random error and inefficiency term to address potential violations of homoscedasticity (see Kumbhakar/Lovell, 2000; Fenn et al., 2008), but we follow the widely used standard conditional mean approach.

For the impact of the organizational form on efficiency ("Organization"), we find significant and positive coefficients for all technical and cost efficiency scores, indicating that non-profit organizations on average operate at lower efficiency. A somewhat surprising result is observed in the equity to total assets ratio ("Solvency") that shows a negative and significant value for cost efficiency. This result indicates that a high equity to assets ratio is in line with higher cost efficiency. Considering the assumption of higher costs of equity capital compared to debt capital this result is not easily found reasonable. We may relate this effect to the complex and somewhat opaque financing structure of microinsurers that in many cases rely on donors- and government credit schemes. The negative coefficients of the size variables ("Small" and "Medium") with technical efficiency show that small- and medium-sized insurers are more efficient than large insurers, which are the reference category. This is an interesting result revealing the very distinct features of microinsurance compared to developed insurance markets since most studies on efficiency in the insurance industry find higher efficiency values for larger firms (see Eling/Luhnen, 2009a). With cost efficiency we can observe positive effects on efficiency only with small microinsurers. The region variables ("Africa", "Asia") reveal an interesting image with the region variables Africa and Asia having a positive effect on technical efficiency. This is in line with the observations made in the SFA and DEA that on average attributed lower efficiency scores to microinsurers from Latin America. However not all of the regional variables are significant in our model. With the time variables ("2005", "2006", "2007", "2008") we find almost no significant impact on efficiency scores for microinsurers.

5. Conclusions

This is the first paper to use frontier efficiency analysis for measuring performance of microinsurance programs. While research on performance in microinsurance has focused on traditional financial ratio analysis in the past, we believe that frontier efficiency might provide a new, powerful performance measurement technique and a valuable addition to the existing performance measures in the field. Efficiency techniques might be helpful to overcome the ambiguities of traditional financial ratios, as it summarizes different characteristics of the firm in a single and easy to interpret performance indicator. Furthermore, the technique can accommodate the important social function that microinsurers have.

In our empirical part we illustrated efficiency values for 21 microinsurance programs from Asia, Africa, and Latin America for the years 2004 to 2008 based on data provided by the *Microinsurance Network*. The empirical findings illustrate significant improvement potential with regard to productivity and efficiency for many programs. The results also illustrate the diversity of different microinsurance providers and emphasizes the relevance of benchmarking in order to identify best practices across different microinsurance providers, countries and organizational forms.

Several limitations have to be kept in mind when interpreting the empirical findings. Although the analyzed dataset is the full dataset used by the *Performance Indicator Working Group* and the only dataset that has been collected on microinsurers so far, it is still relatively small. Furthermore, the analyzed microinsurers are in different parts of the life cycle, i.e., some are still in the start up phase while other schemes are already running for several years. These differences are reflected, e.g., in the low amount of output provided by some schemes and biases their efficiency scores. Nevertheless, we think that the efficiency scores can be useful for benchmarking when keeping these limitations in mind. We thus interpret the empirical part as a first step; a first empirical application of frontier efficiency in microinsurance that might be extended and improved in the coming years.

A natural question for future research would thus be to extend the dataset in order to provide a better basis for the calculation of performance indicators. Once a broader database is set up, the efficiency values might also be used to derive implications for the management of microinsurance schemes. For example, the efficiency values might indicate improvement potential with regard to inputs and outputs. In principle, such an analysis would already be feasible with regard to the dataset considered in this paper, but given the relatively small sample we retain doing so and leave that for future research. In this context an option might be to complement the dataset used here with datasets from commercial data providers such as AM Best. For example, Eling/Luhnen (2009b) conduct a broad efficiency comparison of 6,462 insurers from 36 countries, 657 of which are from emerging markets. These 657 companies might be compared to the microinsurance schemes analyzed in this paper.

Another promising avenue for future research might be to refine the methodology, e.g., to reflect different social output indicators. In this context discussions with academics as well as with practitioners from the microinsurance industries are necessary to develop a theoretical sound and accepted set of input and output indicators.

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Appendix: Methodology

Stochastic Frontier Analysis

For the calculation of *technical efficiency*, we specify a translog stochastic input distance function. The distance function formulation was chosen so as to accommodate multiple outputs and multiple inputs (see, e.g., Coelli/Perelman, 1996; Coelli, 2005). The translog functional form was selected due to its broad acceptance in stochastic frontier analysis in insurance (see, e.g., Cummins/Weiss, 2000). The technical efficiency SFA model is as follows:

$$\begin{aligned} -\ln(x_{Kit}) = {} & \alpha_0 + \sum_{m=1}^{M} \alpha_{mi} \ln(y_{mit}) + 0.5 \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_{mn} \ln(y_{mit}) \ln(y_{nit}) \\ & + \sum_{k=1}^{K-1} \beta_k \ln(x^*_{kit}) + 0.5 \sum_{k=1}^{K-1} \sum_{l=1}^{L-1} \beta_{kl} \ln(x^*_{kit}) \ln(x^*_{lit}) \\ & + \sum_{k=1}^{K-1} \sum_{m=1}^{M} \phi_{km} \ln(x^*_{kit}) \ln(y_{mit}) + \varphi_1 t + 0.5 \phi_{11} t^2 \\ & + \sum_{m=1}^{M} \gamma_{1m} t \ln(y_{mit}) + \sum_{k=1}^{K-1} \kappa_{1k} t \ln(x^*_{kit}) + v_{it} - u_{it}, \end{aligned} \tag{A1}$$

where x_{kit} are the k inputs of insurer i at time t and y_{mit} are the m outputs of insurer i at time t. To ensure linear homogeneity of degree 1 in inputs, we randomly choose one input (such as x_{Ki} in our case) and divide all other inputs by this input. Thus $x^*_{ki} = x_{ki} / x_{Ki}$. This is also why all summations in Equation (A1) involving x^*_{ki} are over M-1 and not M. To account for technological change over time, a time factor t is included as a regressor in the model. The random error is included in Equation (A1) by v_{it}, which is assumed to be distributed normally. Inefficiencies are modeled by the term u_{it}, which is assumed to follow a truncated normal distribution. Using a one-stage approach, the mean m_{it} of u_{it} is assumed to vary depending on a vector of firm-specific variables ("conditional mean approach"; see Battese/Coelli, 1995, or Greene/Segal, 2004, following an approach similar to Huang/Liu, 1994):

$$m_{it} = \delta_0 + \delta_1 a_{it} + \delta_2 b_{it} + \delta_3 c_{it} + \delta_4 d_{it} + \delta_\theta f_{i\theta} + \delta_\gamma g_{i\gamma}, \tag{A2}$$

where a_{it} is a dummy variable reflecting profit profile (1 for non-profit and 0 for profit). b_{it} is the solvency variable (1 if the company's ratio of equity capital to total assets is above the median in the respective region (Africa, Asia, Latin America); 0 otherwise). c_{it} and d_{it} reflect firm size: c_{it} is equal to 1 if the company is in the "small" size class (0 otherwise); d_{it} is equal to 1 if the company is "medium" size (0 otherwise). The size category "large" is excluded to avoid singularity and serves as the reference category. $f_{i\theta}$ are region dummy variables with θ =1, 2 representing Africa and Asia. $g_{i\gamma}$ are five time dummy variables with γ=2005,…, 2008, 2004 is excluded.

For the calculation of cost efficiency, we specify a translog stochastic cost function:

$$\begin{aligned}\ln(\frac{C_{it}}{p_{Kit}}) &= \alpha_0 + \sum_{m=1}^{M}\alpha_{mi}\ln(y_{mit}) + 0.5\sum_{m=1}^{M}\sum_{n=1}^{N}\alpha_{mn}\ln(y_{mit})\ln(y_{nit}) \\ &+ \sum_{k=1}^{K-1}\beta_k \ln(p^*_{kit}) + 0.5\sum_{k=1}^{K-1}\sum_{l=1}^{L-1}\beta_{kl}\ln(p^*_{kit})\ln(p^*_{lit}) \\ &+ \sum_{k=1}^{K-1}\sum_{m=1}^{M}\phi_{km}\ln(p^*_{kit})\ln(y_{mit}) + \varphi_1 t + 0.5\phi_{11}t^2 \\ &+ \sum_{m=1}^{M}\gamma_{1m}t\ln(y_{mit}) + \sum_{k=1}^{K-1}\kappa_{1k}t\ln(p^*_{kit}) + v_{it} + u_{it},\end{aligned} \qquad \text{(A3)}$$

where C_{it} are total cost of insurer i at time t. p_{kit} are the k input prices of insurer i at time t and y_{mit} are the m outputs of insurer i at time t. To ensure linear homogeneity of degree 1 in input prices, we randomly choose one input price (such as p_{Ki} in our case) and divide the dependent variable (C_{it}) and all other input prices by this input price. The rest of the model specification, including the distributional assumptions of the random error v_{it} and the inefficiency term u_{it}, are analogous to the technical efficiency SFA model.

Data Envelopment Analysis

To illustrate DEA, we discuss a basic model for measuring technical efficiency assuming CRS (see, e.g., Cooper et al., 2006; Cummins/Nini, 2002; Worthington and Hurley, 2002). Efficiency e of an insurer i is measured by the ratio:

$$e_i = s_i^T y_i / r_i^T x_i, \tag{A4}$$

where y_i is a vector with outputs , j $y_{j,i}$ = 1,…, z, of firm i. x_i is a vector with inputs $x_{k,i}$, k = 1,…, w. s_i^T is the transposed vector of output weights and r_i^T the transposed vector of input weights. Input and output data are assumed to be positive. For each insurer i, the following optimization problem must be solved in order to obtain optimal input and output weights for the maximization of efficiency:

$$\begin{aligned}&\max_{s,r} e_i = s_i^T y_i / r_i^T x_i, \text{ subject to:}\\ &s_i^T y_i / r_i^T x_i \le 1\\ &s_{j,i}, r_{k,i} \ge 0, \ \forall\, j = 1,...,z\ , k = 1,...,w\end{aligned} \tag{A5}$$

The first condition of Equation (5) limits the ratio e_i of weighted outputs to weighted inputs to a maximum of 1. Since the fractional program (Equation (5)) has an infinite number of solutions, it must be transformed into a linear program by imposing the constraint $r_i^T x_i = 1$, implying that the weighted sum of inputs is standardized to 1:

$$\begin{aligned}&\max_{s,r} e_i = s_i^T y_i, \text{ subject to:}\\ &r_i^T x_i = 1\\ &s_i^T y_i - r_i^T x_i \le 0\\ &s_{j,i}, r_{k,i} \ge 0, \ \forall\, j = 1,...,z\ , k = 1,...,w\end{aligned} \tag{A6}$$