THE PERFORMANCE OF MICROINSURANCE PROGRAMS:

A FRONTIER EFFICIENCY ANALYSIS

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The Performance of Microinsurance Programs: A Frontier Efficiency Analysis

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., 2007) 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 Indicators Working Group* and initiated the development of ten performance ratios that are summarized in a performance indicators handbook (see Wipf/Garand, 2008). 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, profit-orientation, location, size, and age of the program.

Frontier efficiency techniques might be an ideal tool to assess the performance of microinsurance programs and provide an interesting alternative 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 (see Gutiérrez-Nieto et al., 2009).[1]

This paper uses new data and an innovative methodology. We consider data provided by the *Performance Indicators 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

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[1] In our discussions with microinsurance practitioners from the *Performance Indicators Working Group*, these recognized that frontier efficiency techniques are an interesting approach that can be complementary to what is done with their ten performance ratios. But they argued that a single indicator is not really that practical when one tries to analyze different performance areas within a program for purpose of operational managements. The efficiency measure thus cannot substitute the key performance indicators. While we in general agree that different indicators should be considered for operational management, we believe, however, that the techniques described in this paper can also be a valuable addition in the operational management of microinsurers. For example, we can quantify opportunity costs using the optimization weights (shadow prices) that we obtain from DEA. Furthermore, we may calculate slack variables to identify target points on the efficient frontier. DEA thus not only measures efficiency, but can also provide guidance as to how to improve inefficient microinsurers. One aim of this paper is thus to illustrate the capabilities of frontier efficiency techniques for the operational management of microinsurance programs.

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 cover different dimensions of performance and to ensure the methodological robustness of our findings.

This is the first paper to analyze the efficiency of microinsurance programs. 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 perspective.

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

Microinsurance programs provide insurance for low-income people and businesses in developing countries. The provided insurance coverage can basically be 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. By providing insurance coverage microinsurers also facilitate other businesses. People and businesses that can manage the risk of losses are more capable of making long-term investments and receiving loans from banks (see UNDP, 2008). The argumentation above reveals the close tie between the stage of development of insurance markets and the ability for economic growth, mitigation of poverty, inequality and vulnerability. The common types of risks covered are life, pension, health, disability, and property (especially agricultural 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). Large multinational companies such as Allianz or Munich Re are also getting involved in the marketplace more intense. The most important microinsurance markets are in Asia (China, India, among others), Africa (e.g., Senegal, Uganda) and South America (e.g., Paraguay, Peru; see Roth et al., 2007). Although the idea of insurance schemes organized as mutuals or community based schemes 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 Levin/Rheinhard, 2007) are inherent in microinsurance markets, making the environment challenging from an economic perspective.[2]

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. Practitioners as well as academics recent discussions reinforce the fact that microinsurance programs need to become sustainable. Most microinsurers depend on subsidies that are temporarily available for 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 trans-

[2] The situation faced by microinsurers today is thus similar to challenges of the microfinance industry with problems such as high transactions costs, moral hazard, adverse selection, limited cash flows, low education levels of clients, and weak enforcement mechanisms (see Morduch, 2006).

parent performance measurement process, the *Microinsurance Network* (former *CGAP Working Group on Microinsurance*) has set up a *Performance Indicators Working Group*. They initiated the development of ten performance ratios during two workshops in 2006 and 2007 and summarized the results 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 settlement 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 strength and enhance the comparability and transparency of different schemes. Nevertheless, standard financial ratio analysis cannot capture the large diversity and 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 schemes and social organizations as well as governments finance a lot of their activities, their objectives cannot exclusively 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 Working Group* discussed four potential indicators to reflect the social function that many microinsurers have (see Wipf/Garand, 2008): 1) The social investment ratio defined as total expenditure on information, education, and communication divided by total expenditure of the program. 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

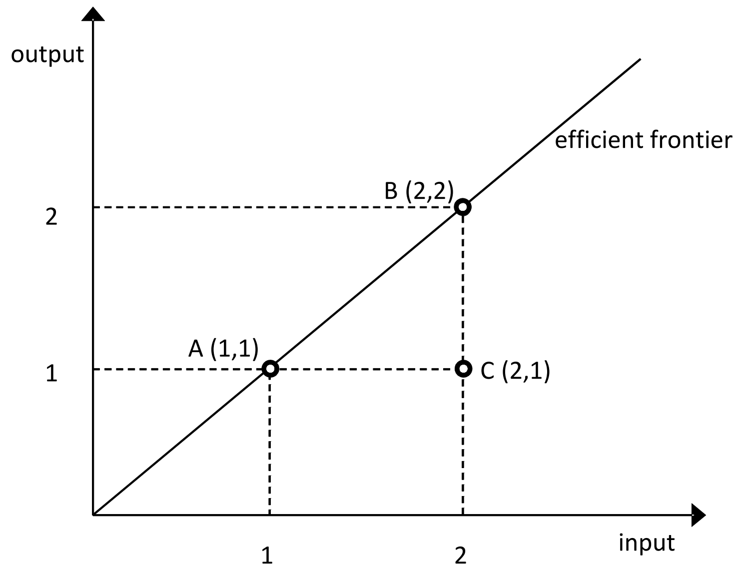
In this Section, we introduce the efficiency methodology and show how to adjust the standard set of inputs and outputs used in efficiency measurement of commercial insurance companies to accommodate the social function that insurance providers have. Furthermore, we present the dataset provided by the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

3.1 Methodology

Modern frontier efficiency methodologies, similar to more traditional techniques such as financial ratio analysis, aim at benchmarking firms of an industry against each other. Using frontier efficiency techniques the performance of a company is measured relative to a "best practice" frontier that consists of the most efficient companies within the industry. In the academic literature on efficiency measurement these methods are considered as an interesting alternative compared 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). Besides the calculation of efficiency statistics the model variables allow the deduction of a lot more managerial information (such as shadow prices and slack variables) as we will describe later. Efficiency estimates are standardized between 0 and 1, with the value 1 (0) assigned to the most (least) efficient firm. The improvement potential of a firm in terms of efficiency can be derived from the difference between a company's assigned value to the maximum possible efficiency score of 1 (see, e.g., Cooper et al., 2007). The frontier efficiency methodology allows for the estimation of various frontiers such as production frontiers, cost frontiers, revenue frontiers, and profit frontiers that are commonly discussed in academic literature.

In the simplest case, a production frontier is estimated, assuming that companies minimize inputs conditional on given output levels (input-orientation) or maximize outputs conditional on given input levels (output-orientation). Figure 1 illustrates the basic case for input orientation.

Figure 1: Efficient frontier example for one input, one output and constant returns to scale



In this simple example the efficient frontier is composed of firms A and B. Since firms A and B only consume 1 unit of input to produce 1 unit of output they dominate firm C that requires

2 units of input to produce the same level of output. Its absolute efficiency level is determined by the ratio of the optimally needed amount of inputs to produce 1 output (1) and the actual level of inputs consumed (2). With a resulting efficiency score of 0.5 firm C is half as efficient as firms A and B that receive an efficiency score of 1. The level of efficiency as such reflects the ability of a firm to employ the optimal production technology. The closer the firm is located to the efficient frontier the higher is the efficiency score. The strategy for an inefficient firm C thus is to move in the direction of the efficient frontier, i.e. reducing the amount of input by upgrading its technology to state of the art.

There exist two methodologies in efficient frontier analysis, originating from very different theoretical foundations: the mathematical programming approach based on optimization and the econometric approach based on regression. We shortly introduce the fundamentals of the two approaches and discuss their relevance for the insurance field.[3]

Mathematical programming approach

Linear programming is being used to measure the efficiency of a firm using the relationship of outputs to assigned resources (inputs) within mathematical programming approaches. Since efficiency estimates are the result of an optimization problem, it is not required to formulate assumptions on the specification of the efficient frontier. Furthermore there is no necessity to make assumptions about stochastic elements in the model which is required for the concurrent approach. The most commonly used approach is *data envelopment analysis* (DEA) which goes back to ideas from Farrell (1957) and received wider attention since Charnes, Cooper and Rhodes (1978) first introduced a linear optimization solution to the problem posed by Farrell (1957). There has been a large number of papers with empirical applications and improvements of the methodology since then. DEA model specifications are available for the assumption of constant (CRS) or variable (VRS) returns to scale that can be used to compute

[3] Due to space constraints we restrict ourselves to a basic description of the methodologies and focus on the capabilities and advantages of the method with regard to microinsurance. An extended version of this paper that contains more details on the different methodologies is available upon request.

various efficiency scores, i.e. cost, technical, pure technical, allocative, and scale efficiency (see Cooper et al., 2007).

Econometric approach

The econometric approaches ex ante make assumptions about the shape of specific frontiers, i.e. production, cost, revenue, or profit frontiers respectively. A production frontier for instance represents the maximum amount of output that can be achieved for a given level of input. Deviations from the maximum possible output level that would generally be considered as inefficiency are further differentiated into two stochastic elements: an inefficiency term and an error term that accounts for measurement error. Explicit assumptions about the distributions of the inefficiency and error term are integrated into the model. The most commonly used econometric approach that has achieved broad acceptance in the insurance literature on efficiency since the seminal work of Aigner et al. (1977) and Meeusen and van den Broeck (1977) is *stochastic frontier analysis* (SFA). SFA usually follows a two-step procedure: Based on the assumptions made about the shape of the frontier and the distribution of the parameters, the production, cost, revenue, or profit frontier is first being estimated. The second step estimates deviations from the efficient frontier for individual firms which are decomposed into its two components inefficiency and random deviation (see Cummins/Weiss, 2000).

Two configuration decisions must be made when employing SFA: (1) The choice of the functional form that best approximates 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 is a wide range of other options, including the Cobb-Douglas, Fuss normalized quadratic (see Morrison/Berndt, 1982), and generalized translog (see Caves et al., 1980) that are applied in efficiency studies. 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 (see, e.g. Aigner et al., 1977), truncated normal, exponential (see, e.g. Meeusen/van den Broeck, 1977), or gamma (see, e.g., Berger/Humphrey, 1997).

Managerial capabilities of frontier efficiency analysis

In addition to the descriptive comparison of efficiency statistics to determine the relative performance of a firm to the market, frontier efficiency methodologies provide capabilities to extract further information for the management of a firm. The methodology can be applied on the corporate or aggregate level to depict the performance of business units, firms and markets and might as such be used to support management decisions. The regression options that are used in a two-stage approach with DEA via Tobit analysis (see e.g., Aly et al., 1990, or Stanton, 2002) and which are implemented in the SFA via conditional mean approach (see e.g., Battese/Coelli, 1995, or Greene/Segal, 2004) are a powerful tool to derive internal and external key drivers of firm performance that provide valuable information for the management of a firm. The DEA provides information on the peers and targets on the efficient frontier for each inefficient firm in the panel through inherent variables (see Coelli, 1998). Peer firms operate on the efficient frontier and have similar input-output combinations to the considered inefficient firm. The slack variables that are generated in the DEA give insight into the sources and amounts of inefficiency and as such provide a mean to identify relevant target points on the efficient frontier. This information enables the inefficient firm to identify the in- and output quantity combination that leads to an efficient production. The weighting factors of the in- and outputs obtained from the DEA are referred to as shadow prices of the optimization. Ratios of shadow prices provide powerful economic insights as they represent (1) the marginal rate of substitution (given by the ratio of the shadow prices of two inputs) that reveal the necessary increase in input 1 if we decrease input 2 and maintain the output level constant, (2) the marginal productivity (given by the ratio of the shadow prices of one input and one output) that specifies the increase in the output conditional on the increase of the input by 1 unit, and (3) the marginal rate of transformation (given by the ratio of the shadow prices of two outputs; also referred to as opportunity costs) that indicates the amount of output 1 we have to give up by increasing output 2 by 1 unit.

Advantages of frontier efficiency for microinsurance

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.

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 an interesting alternative 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 profit-orientation, company sizes, solvency, time and many other factors on efficiency, all of which might be important determinants of performance in microinsurance, e.g., using the conditional mean approach (see 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. The financial statements data provide 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 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 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.[4] 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 Indicators 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 addi-

4 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. A pre-specified cost variable is not required in DEA.

tional social indicators. We believe, however, that the coverage ratio can be interpreted as a social output indicator well reflecting the service function of non-profit insurance companies. For the efficiency analysis, however, it would also be feasible to implement one of the four social indicators discusses by the *Performance Indicators Working Group* or any other indicator which reflects the social performance of microinsurance providers.[5]

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. More descriptive statistics on the microinsurance schemes can be found in Appendix 1. In order to keep the anonymity of the analyzed microinsurers, we only present aggregated statistics on an industry level and no individual company data.

5 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; Cummins/Weiss, 2000 for more details on both 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.

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	122.44	199.84	0.77	759.19
Debt capital	US $	10,384,524.31	37,155,668.84	38.52	203,929,777.20
Equity capital	US $	2,638,413.29	4,755,817.33	0.00	21,978,035.22
Price of labor	US $	7,924.87	1,281.02	5,822.30	10,201.73
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 $	155,132.77	380,970.47	0.00	1,835,886.79
Investments	US $	9,949,123.58	32,468,481.49	0.00	183,012,185.86
IMF consumer price index	%	13.76	15.76	0.00	89.22
Social output indicator	%	0.45	0.43	0.01	1.00

Considering the characteristics of the programs in our panel most of the microinsurers are small programs in terms of total assets compared to developed insurance markets. Eling/Luhnen (2009b) found an average value of debt capital (equity capital) of US $ 1.5 Billion (US $ 369 Million) and a maximum of US $ 393 Billion (US $ 82 Billion) in their efficiency study on 6,462 insurers from 36 countries. In our study of microinsurers the respective debt capital (equity capital) numbers are US $ 10.38 Million (US $ 2.64 Million) for the mean and US $ 203.93 Million (US $ 21.98 Million) for the maximum. All other company specific balance sheet or profit and loss statement items on average display extreme lower values. As expected, the price of labor is much lower (73%), while the price of debt (3.2%) and equity (3.6%) is higher. This is an economically meaningful finding, since equity- and debt holders in emerging markets might require a risk premium compared to investors in developed markets. Inflation reflected by the consumer price index (10%) also exhibits a higher value than in Eling/Luhnen (2009b).

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 forms of profit-orientation (non-profit, for-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 US $ 7,737,681), medium, and small (total assets smaller than US $ 37,655) 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

4.1. Measurement of efficiency

Data envelopment analysis (model without social output indicator)

In a first step we analyze DEA efficiency values not considering social performance. The implementation of a social output indicator will be discussed later. Our model specification allows us to compute Shephard input distance functions (see Shephard, 1970) which are the reciprocals of the Farrell (1957) input efficiency measures assuming VRS. Since sensitivity to measurement error is an intrinsic problem of standard DEA, we apply the bootstrapping procedure presented in Simar/Wilson (1998) on the distance measures obtained. For more details on the DEA specification, the reader is referred to Appendix 2. Table 2 displays the bias-corrected DEA Farrell efficiency values for technical and cost efficiency.[6] 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 last column following the annual estimates. We also show mean technical and cost efficiency estimates for each of the regions in the panel.

[6] The DEA results in Table 2 are based on a one-world frontier and estimated separately for all years, while we analyze SFA based on an unbalanced panel (Table 3).

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	0.89	0.86	0.53	0.76	n/a	n/a	1.00	1.00	1.00	1.00
	2	0.85	0.95	0.97	0.94	n/a	0.93	0.03	0.08	0.04	0.06	n/a	0.05
	3	n/a	n/a	0.88	0.86	n/a	0.87	n/a	n/a	1.00	1.00	n/a	1.00
	4	n/a	0.87	0.90	0.89	0.53	0.80	n/a	1.00	1.00	0.85	1.00	0.96
	5	0.77	0.87	0.90	0.88	0.53	0.79	1.00	1.00	0.90	0.90	1.00	0.96
	6	n/a	n/a	n/a	0.86	0.53	0.69	n/a	n/a	n/a	0.25	1.00	0.62
	7	0.81	0.91	0.94	0.77	n/a	0.86	1.00	0.98	0.87	0.74	n/a	0.90
	Mean	0.81	0.90	0.91	0.87	0.53	**0.81**	0.68	0.76	0.80	0.68	1.00	**0.79**
Asia	8	0.77	0.86	0.88	0.86	n/a	0.85	0.45	0.46	0.39	0.39	n/a	0.42
	9	0.77	0.77	0.76	0.90	n/a	0.80	1.00	0.45	0.47	0.64	n/a	0.64
	10	n/a	n/a	0.88	0.86	0.53	0.76	n/a	n/a	1.00	1.00	0.68	0.89
	11	n/a	n/a	0.89	0.87	0.53	0.76	n/a	n/a	1.00	0.63	0.75	0.79
	12	n/a	0.87	0.92	0.86	0.52	0.79	n/a	0.80	0.61	0.15	0.23	0.44
	13	0.78	0.86	0.88	0.91	0.53	0.79	1.00	1.00	0.42	0.30	0.35	0.61
	14	n/a	n/a	n/a	0.89	0.51	0.70	n/a	n/a	n/a	0.28	0.26	0.27
	Mean	0.77	0.84	0.87	0.88	0.52	**0.78**	0.82	0.68	0.65	0.48	0.45	**0.58**
Latin America	15	0.85	0.89	0.89	0.76	0.53	0.78	0.70	0.81	0.74	0.62	1.00	0.77
	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	0.77	0.87	0.88	0.86	n/a	0.85	1.00	1.00	1.00	1.00	n/a	1.00
	18	0.82	0.88	0.63	0.53	0.53	0.68	0.64	0.72	0.47	0.45	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	0.83	0.88	0.91	0.88	0.00	0.70	0.81	0.98	0.98	0.87	0.00	0.73
	21	0.77	0.87	0.88	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	0.35	**0.70**	0.70	0.78	0.73	0.71	0.67	**0.74**
Mean		0.74	0.83	0.84	0.81	0.48	**0.76**	0.73	0.75	0.73	0.63	0.69	**0.70**

Overall, the DEA efficiency estimates are relatively high compared to those found in other studies with Africa (0.81) and Asia (0.78) being the most technical efficient regions. Note, however, that frontier efficiency always conducts a relative comparison with the most efficient companies in the markets, i.e. the peer group are the other microinsurers. Furthermore, 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/Bartles (1998) into consideration.[7]

The African microinsurers also show high cost efficiency values (0.79) followed by Latin America (0.74) and Asia (0.58) as least cost efficient market. Observing aggregated results over time we find increasing efficiency estimates from 2004 on with a peak in 2006 and decreasing subsequent values reaching the bottom line in 2008 which is consistent with the results found in the SFA. The results are especially interesting on the macro-level since microinsurance markets in Africa are usually being considered as the least covered in the world.

[7] We address the problem of upward biased efficiency estimates due to small sample size in the DEA with the bootstrapping procedure presented in Simar/Wilson (1998).

Asia on the other hand shows a strong and constant development in recent years which has particularly been supported by government regulation of insurance markets aiming at an increase of product distribution particularly to rural areas, e.g. in India.[8]

A possible explanation for the relatively high DEA estimates on the aggregate level might be that the sample is relatively heterogeneous, consisting of a variety of different insurance schemes with large differences in size, institutional form, profit-orientation, regional focus, product range and client structure. We also face a dataset of varying quality and consistency such that statistical noise is likely to alter the quality of our analysis. It might thus be promising to complement the mathematical programming method (DEA) with an econometric frontier efficiency method (SFA) that is able to distinguish between random departures from efficiency such as noise and departures due to inefficiency.

Stochastic frontier analysis (model without social output indicator)

For the stochastic frontier estimation we specify a production function in the form of a translog stochastic input distance function. We opt for the distance function formulation to incorporate multiple outputs and multiple inputs (see, e.g., Coelli/Perelman, 1996; Coelli, 2005). The *cost efficiency* calculation follows our above specification and thus utilizes a translog stochastic cost function as in the case of technical efficiency. The inefficiency term for technical as well as cost efficiency is assumed to follow a truncated normal distribution. The random error term is specified as normally distributed. For more details on the SFA model (which follows Battese/Coelli, 1995), the reader is referred to Appendix 2. The results displayed in Table 3 are presented in the structure of Table 2.

[8] See Roth et al. (2007) for details on market coverage in developing countries. Eling/Luhnen (2009b) document that the efficiency scores found in emerging markets are typically lower than those in advanced markets, which is the reason why we expect a positive connection between market coverage and efficiency. However, this connection is only partly confirmed in this study. See below for a more detailed discussion.

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	0.92	0.94	0.87	0.91	n/a	n/a	0.70	0.66	0.43	0.60
	2	0.45	0.20	0.31	0.14	n/a	0.28	0.11	0.19	0.68	0.57	n/a	0.39
	3	n/a	n/a	0.71	0.86	n/a	0.79	n/a	n/a	0.83	0.66	n/a	0.75
	4	n/a	0.87	0.87	0.88	0.88	0.88	n/a	0.70	0.85	0.80	0.68	0.75
	5	0.66	0.70	0.54	0.45	0.25	0.52	0.73	0.70	0.80	0.72	0.52	0.69
	6	n/a	n/a	n/a	0.46	0.47	0.46	n/a	n/a	n/a	0.79	0.12	0.46
	7	0.27	0.36	0.24	0.27	n/a	0.29	0.60	0.70	0.67	0.53	n/a	0.63
	Mean	0.46	0.53	0.60	0.57	0.62	**0.59**	0.48	0.57	0.76	0.68	0.44	**0.61**
Asia	8	0.85	0.70	0.88	0.94	n/a	0.84	0.03	0.09	0.28	0.14	n/a	0.14
	9	0.95	0.61	0.75	0.75	n/a	0.77	0.55	0.27	0.65	0.54	n/a	0.50
	10	n/a	n/a	0.87	0.96	0.95	0.93	n/a	n/a	0.83	0.89	0.89	0.87
	11	n/a	n/a	0.96	0.91	0.90	0.93	n/a	n/a	0.87	0.78	0.65	0.77
	12	n/a	0.88	0.93	0.16	0.17	0.54	n/a	0.82	0.88	0.09	0.03	0.46
	13	0.88	0.84	0.77	0.71	0.46	0.73	0.74	0.67	0.72	0.61	0.52	0.65
	14	n/a	n/a	n/a	0.94	0.86	0.90	n/a	n/a	n/a	0.52	0.26	0.39
	Mean	0.89	0.76	0.86	0.77	0.67	**0.80**	0.44	0.46	0.71	0.51	0.47	**0.54**
Latin America	15	0.21	0.23	0.22	0.21	0.39	0.25	0.16	0.59	0.60	0.26	0.53	0.43
	16	n/a	n/a	0.56	0.64	n/a	0.60	n/a	n/a	0.62	0.38	n/a	0.50
	17	0.92	0.84	0.64	0.70	n/a	0.77	0.72	0.85	0.82	0.61	n/a	0.75
	18	0.30	0.30	0.26	0.35	0.49	0.34	0.18	0.49	0.56	0.43	0.58	0.45
	19	0.04	0.03	0.04	0.04	n/a	0.04	0.01	0.03	0.06	0.04	n/a	0.04
	20	0.24	0.23	0.24	0.25	0.00	0.19	0.23	0.67	0.77	0.55	0.03	0.45
	21	0.59	0.51	0.43	0.44	n/a	0.49	0.37	0.62	0.78	0.48	n/a	0.56
	Mean	0.38	0.36	0.34	0.38	0.29	**0.38**	0.28	0.54	0.60	0.39	0.38	**0.45**
Mean		0.53	0.52	0.59	0.57	0.56	**0.59**	0.37	0.53	0.68	0.53	0.44	**0.53**

As expected, we find considerably lower efficiency values with the SFA compared to the DEA. With SFA, the efficiency results also reflect our expectations on the ranking of the three geographic areas on the aggregate level. Asia displays the highest average technical efficiency with 0.80. Nevertheless we find that Asia (0.54) is less cost efficient compared to Africa (0.61), but superior to Latin America (0.45). In terms of technical efficiency Asia (0.80) is followed by Africa (0.59) and Latin America (0.38).

Considering the consistency of the results received by DEA and SFA, Spearman's rank correlation of the technical efficiency scores for both methodologies is relatively low (14%) compared to other studies. Rank correlation between DEA and SFA cost efficiency on the other hand receives a value of 52% which is consistent with results from other studies (Cummins/Zi (1998), e.g., find a rank correlation of 0.58.).[9] One possible explanation for the low rank cor-

[9] We computed Spearman's rank correlation statistic ρ. In the case of technical efficiency (cost efficiency) we could reject the null hypothesis of $\rho=0$ to the 10% (1%) level.

relation found with technical efficiency might be statistical noise in the data, the size of the panel, and heterogeneity that differentiates the results of the SFA from those obtained by the DEA. As shown in simulation studies by Gong/Sickles (1992), SFA methodology outperforms DEA in the presence of statistical noise and small panel size which is the situation we face here. We also face a heterogeneous set of data, covering microinsurers with large variation in terms of company size from three continents. As it has been shown in several works on DEA sensitivity to statistical noise, nonparametric methods tend to be very sensitive to outliers (see, e.g. Wilson, 1995) whereas SFA models are found to be substantially less sensitive to these problems. Thus SFA most probably better reflects the efficiency of the microinsurance schemes in our analysis.

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. As with DEA we find a peak in 2006 with declining subsequent values for technical and cost efficiency and especially poor results for 2008. Time effects will also be discussed in an additional conditional mean analysis below that confirms the negative results for 2008.

DEA and SFA model with social output indicator

To capture the financial and social performance of microinsurers at the same time 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). The selection of coverage ratio as an additional output variable is based on the perception that a primary social goal of the microinsurance company is the fulfillment of demand for the target population and a high service quality. The fulfillment of demand is comparable to the coverage ratio. Since microinsurers considered in this analysis mostly have a non-profit-orientation we think that coverage ratio suits best our purpose to integrate an additional indicator reflecting social performance.

Nevertheless the expansion of the set of output variables might as well reveal interesting differences between non-profit and for-profit insurers and provide valuable insights into how social and financial performance can be aligned to build the foundation for sustainable development. Table 4 displays the technical efficiency estimates of microinsurers after the incorporation of the social performance variable.

Table 4: Technical efficiency incorporating social performance

		DEA technical efficiency						SFA technical efficiency					
	Microinsurer	2004	2005	2006	2007	2008	Mean	2004	2005	2006	2007	2008	Mean
Africa	1	n/a	n/a	0.96	0.95	0.52	0.81	n/a	n/a	0.91	0.83	0.55	0.76
	2	0.80	0.87	0.97	0.96	n/a	0.90	0.48	0.29	0.72	0.32	n/a	0.45
	3	n/a	n/a	0.96	0.95	n/a	0.95	n/a	n/a	0.78	0.93	n/a	0.85
	4	n/a	0.87	0.96	0.95	0.52	0.83	n/a	0.93	0.93	0.87	0.75	0.87
	5	0.77	0.88	0.96	0.95	0.52	0.82	0.67	0.81	0.61	0.49	0.22	0.56
	6	n/a	n/a	n/a	0.95	0.52	0.73	n/a	n/a	n/a	0.87	0.39	0.63
	7	0.81	0.91	0.97	0.81	n/a	0.88	0.75	0.87	0.29	0.24	n/a	0.54
	Mean	0.80	0.88	0.96	0.93	0.52	**0.84**	0.63	0.72	0.71	0.65	0.48	**0.67**
Asia	8	0.77	0.87	0.96	0.95	n/a	0.89	0.89	0.68	0.80	0.76	n/a	0.78
	9	0.77	0.87	0.96	0.95	n/a	0.89	0.95	0.68	0.79	0.90	n/a	0.83
	10	n/a	n/a	0.96	0.95	0.53	0.81	n/a	n/a	0.91	0.95	0.86	0.90
	11	n/a	n/a	0.96	0.95	0.52	0.81	n/a	n/a	0.97	0.92	0.94	0.94
	12	n/a	0.87	0.97	0.95	0.52	0.83	n/a	0.73	0.78	0.13	0.15	0.44
	13	0.77	0.88	0.96	0.96	0.53	0.82	0.93	0.93	0.87	0.75	0.48	0.79
	14	n/a	n/a	n/a	0.95	0.53	0.74	n/a	n/a	n/a	0.96	0.92	0.94
	Mean	0.77	0.87	0.96	0.95	0.53	**0.83**	0.92	0.75	0.85	0.77	0.67	**0.81**
Latin America	15	0.81	0.89	0.97	0.94	0.52	0.83	0.17	0.16	0.12	0.09	0.14	0.14
	16	n/a	n/a	0.96	0.95	n/a	0.95	n/a	n/a	0.44	0.51	n/a	0.47
	17	0.78	0.87	0.96	0.95	n/a	0.89	0.92	0.67	0.37	0.32	n/a	0.57
	18	0.77	0.87	0.96	0.95	0.52	0.81	0.44	0.52	0.45	0.53	0.21	0.43
	19	0.11	0.28	0.60	0.67	n/a	0.41	0.07	0.05	0.03	0.02	n/a	0.04
	20	0.83	0.89	0.97	0.95	0.00	0.73	0.50	0.36	0.25	0.17	0.00	0.25
	21	0.77	0.88	0.96	0.95	n/a	0.89	0.49	0.36	0.22	0.14	n/a	0.30
	Mean	0.68	0.78	0.91	0.91	0.35	**0.79**	0.43	0.35	0.27	0.25	0.12	**0.32**
Mean		0.73	0.84	0.94	0.93	0.48	**0.82**	0.60	0.57	0.59	0.56	0.47	**0.60**

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. This result is expected since the integration of an additional variable into the regression model ceteris paribus leads to higher efficiency values. The estimates for technical efficiency are in general consistent with results obtained by the previous analysis without the social output indicator (the rank correlation for both approaches is 0.93 with DEA and 0.89 with SFA). An interesting aspect, however, is the variation of average efficiency for the two distinct classes of microinsurers in the panel, i.e. non-profit and for-profit microinsurers. When not considering social performance (Table 2 and 3), we find higher technical and cost efficiency for microinsurers with profit-orientation compared to non-profit microinsurers. Non-profit microinsurers, however, show a significant upward shift in average efficiency after the implementation of the social output indicator into the model (e.g., from 0.52 to 0.57 with technical efficiency in the SFA). For-profit microinsurers exhibit decreasing technical efficiency with a value on average declining from 0.64 to 0.52. As we found a significant difference in mean efficiency values for non-profit and for-profit microinsurers in the original model, the difference is no longer significant if we implement the social output indicator.[10] Hence we can conclude that non-profit microinsurers were able to catch up to for-profit microinsurers in terms of technical efficiency.

Consistent with general expectation is that microinsurers with low coverage ratios on average exhibit the largest decreases in technical efficiency. The results for the DEA are less clear in terms of significance but reveal the same tendencies as the SFA. As a first result we can conclude that the social performance of microinsurance programs differentiates the respective performance estimates but large changes in general propositions are not being found in this case (see rank correlation of DEA and SFA results).

Further research is needed to investigate the effect of a social performance indicator on efficiency in relation to outputs representing financial performance. To further investigate the effects of firm specific and environmental variables on efficiency, we extend our analysis in the following part applying the conditional mean approach (see Battese/Coelli, 1995, and Greene/Segal, 2004).

4.2. Managerial implications of frontier efficiency analysis

Conditional mean approach

To verify the results displayed in Tables 3 and 4 and to extend our analysis to the detection of important drivers of firm performance we implemented an analysis that is able to isolate the

[10] We conducted a Welch two-sample t-test (see Welch, 1947) to test the null hypothesis of a true difference in means of 0 as well as Wilcoxon rank-sum test (Wilcoxon, 1945) for the null hypothesis of a true location shift of 0 for non-profit and for-profit microinsurers (at significance level of 5%).

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).[11] The following explanatory variables are used in our regression model: (1) Profit-orientation: 1 if the insurer has a non-profit-orientation; 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) "Age" of the program: 1 if the age of the program is higher than the median of the sample; 0 otherwise. (5) Products: Dummy variables for each category of products "Life", "Health", Credit-life" and "Multi-product". "Multi-product" was chosen as reference category. (6) The term "Group" refers to the contract design: 1 if policies are sold as group-policies; 0 if individual policies are provided. (7) 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. (8) Time: Dummy variables for each year 2005 to 2008 are chosen to capture time effects; 2004 is excluded. Table 5 shows the results for the conditional mean analysis. Note that we explain the inefficiency term, thus a positive regression coefficient has to be interpreted as increasing inefficiency and hence decreasing efficiency and vice versa.

[11] 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.

Table 5: Results of the conditional mean analysis

	Technical efficiency			Technical efficiency			Cost efficiency		
	coefficient	t-statistic		coefficient	t-statistic		coefficient	t-statistic	
Intercept	-0.19	-0.24		0.69	0.64		-0.17	-0.15	
Profit-orientation	2.82	3.54	***	0.83	0.92		0.95	1.10	
Solvency	-0.58	-0.79		-0.48	-0.75		1.40	1.78	**
Small	-1.44	-1.73	*	-1.26	-1.46	*	-2.89	-3.16	**
Medium	-0.27	-0.28		0.37	0.50		1.72	2.15	**
Age	1.56	2.14	*	0.88	1.41	*	-0.88	-0.96	
Life	0.31	0.33		-0.96	-1.07		-1.20	-1.46	*
Health	-1.30	-1.61	*	-0.76	-0.90		-0.92	-0.96	
Credit-Life	-1.63	-1.60	*	-3.02	-3.35	***	-2.59	-2.88	**
Group	-1.36	-1.67	*	0.54	0.81		-0.77	-0.88	
Africa	-1.47	-1.86	*	-1.59	-1.73	**	0.97	1.01	
Asia	-4.32	-4.63	***	-4.10	-5.96	***	0.31	0.40	
2005	0.36	0.38		0.36	0.45		-2.01	-1.74	**
2006	0.08	0.08		0.60	0.70		-0.55	-0.61	
2007	-0.51	-0.58		0.79	1.12		-2.96	-3.52	**
2008	1.32	1.40	*	2.42	2.40	***	-0.32	-0.37	

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

For the impact of profit-orientation on efficiency, we find significant and positive coefficients for technical efficiency in the model not considering social performance, indicating that non-profit microinsurers on average operate at lower efficiency. This result approves our observations from the efficiency analysis where we found significantly higher values with for-profit microinsurers. It also supports the observation that the gap between non-profit and for-profit microinsurers becomes smaller when we allow for social performance in our model setup. This is reflected by a non-significant regression coefficient for the non-profit variable with the social performance indicator model. Regarding the "Solvency" variable we do not find a significant effect on performance for technical efficiency. However cost efficiency is negatively affected by the solvency level. Considering the assumption of higher costs of equity capital compared to debt capital, the cost efficiency results reflect the more cost efficient use of capital for microinsurers with a lower ratio of equity capital to debt capital. The negative coefficients of the size variable "Small" with technical efficiency shows that small microinsurers are more efficient in terms of the employment of production technology as well as costs than medium and 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, e.g., Eling/Luhnen, 2009a). The age of the microinsurance program has a negative impact on technical efficiency. Especially for the younger programs in our panel we find a strong start up performance and decreasing subsequent performance. However our analysis does not support this finding in the case of cost efficiency. The reason for the age effects found with technical efficiency might be significant donors or government subsidies provided in the start-up phase of a program. However, our analysis can only provide a very preliminary indication of these efficiency effects. A lager dataset with a substantially higher amount of young and experienced microinsurance schemes might be necessary to analyze the efficiency of microinsurers in different development stages in more detail. We also considered the range of products supplied by different microinsurers in our analysis. We can conclude from the regression analysis that credit-life products are being provided most efficient in terms of technology and costs. This is not surprising since these simple products are mostly sold by microfinance institutions as compulsory supplement to the credit granted and as such are tied to an existing distribution channel. Hence we find limited benefits, low administrative costs and a reasonable risk spread for the microinsurer (see Churchill, 2006). Another aspect we were interested in is the influence of different means to distribute insurance policies (group policies and individual policies) on performance. Here we find a positive impact of the supply of group policies on technical efficiency which is in line with first studies on microinsurance products that indicate lower underwriting and screening costs with group-based contracts as well as reduced information asymmetries (see Roth et al., 2007 and Churchill, 2006). The region variables ("Africa", "Asia") reveal an interesting image with 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. With the time variables ("2005", "2006", "2007", "2008") we find a mixed picture and mostly positive but not in every case significant values for technical efficiency and negative values for cost efficiency. The year 2008 is an exception with a negative and significant impact on efficiency.

Analysis of shadow prices and slack variables within DEA

Another feature of DEA is that it provides managerial information on shadow prices and slack variables. To illustrate the potential use of the shadow prices and slack variables for managerial decision making, Table 6 displays detailed results for two microinsurance schemes.[12]

Table 6: DEA optimization weights and slack variables

MI	Year	DEA	Weights					Slacks				
			r1	*r2*	*r3*	*s1*	*s2*	*IS1*	*IS2*	*IS3*	*OS1*	*OS2*
19	2004	0.11	0.00E+00	5.60E-07	1.20E-07	3.54E-06	2.30E-06	25	0	0	0	0
19	2005	0.28	0.00E+00	4.50E-07	1.40E-07	7.73E-06	0.00E+00	78	0	0	0	58,1165
19	2006	0.06	0.00E+00	3.90E-07	6.00E-08	5.90E-06	6.60E-07	6	0	0	0	0
19	2007	0.08	0.00E+00	0.00E+00	4.00E-07	3.43E-06	0.00E+00	9	1	0	0	9,3731
20	2008	0.00	2.20E-03	0.00E+00	0.00E+00	1.77E-03	9.98E-01	0	8	26,758	0	0

MI=Microinsurer, DEA=DEA technical efficiency score, r_i=optimization weight for input *i*, *i*=1,2,3, s_j=optimization weight for output *j*=1,2, IS_i=slack variable for input *i*, OS_j=slack variable for output *j*

From Table 6 we can derive explicit management goals that will affect the performance of the microinsurance scheme. We first consider the optimization weights obtained from the DEA which are also referred to as shadow prices. Due to the restrictions made in the formulation of the optimization problem (see equation A6 in Appendix 2) we find very small values for the in- and output weights. These weights, however, show which in- and outputs contribute to what extend to the performance of the respective microinsurer. In other words the weights illustrate by how much the efficiency score increases when the respective input (output) is decreased (increased) by one unit. For management purposes it would further be necessary to consider cross-effects caused by altering single in- and outputs. This can be done by calculating the marginal rate of substitution, the marginal productivity, and the marginal rate of transformation. For microinsurer no. 19 in 2004 as an example we find (1) a significant cross-effect between input 2 (debt capital) and input 3 (equity capital) with a marginal rate of subs-

[12] The two schemes are those with the lowest DEA technical efficiency scores for each year of our panel. It is especially worth studying microinsurers with low performance values since they have the highest improvement potential in terms of efficiency and as such provide results useful to highlight the managerial capabilities of shadow prices and slack variables.

titution of 4.67 indicating that decreasing equity capital by one unit ceteris paribus would have to be complemented by an increase of debt capital by 4.67 units. There are no other inherent cross-effects for inputs. (2) Marginal productivity values determine a positive but low effect (<25%) of an increase in debt and equity capital on both outputs, i.e. output 1 (benefits + additions to reserves) and output 2 (investments). (3) The analysis of the marginal rate of substitution concludes that an increase in the level of output 2 (investments) by one unit ceteris paribus goes along with a decreasing level of output 1 (benefits + additions to reserves) of 1.54 units.

The slack variables provide further information on the relative adjustment of the variables. The concept is directly related to technical efficiency. An efficiency score smaller than 1 indicates a simultaneous reduction in inputs equivalent to the spread of the realized efficiency score and the maximum attainable score of 1 without altering the relative proportions of input variables (input mix). If a microinsurer exhibits non-zero slacks, an adjustment of the relative proportions of inputs is necessary to realize an efficient utilization of inputs. The inefficiencies associated with non-zero slacks are thus referred to as "mix inefficiencies" (Cooper et al., 2007). On the input side, none-zero slacks are also being interpreted as input excess, meaning that the last IS_i units of the respective variable i spent for production had no effect on efficiency. On the output side, non-zero slacks are referred to as output shortfall, indicating the minimum amount OS_i of the respective output variable i that is necessary to realize an effect on performance. There is hence a direct relationship between slack variables on the one hand side and shadow prices on the other that is expressed in the complementary slackness theorem, stating that in every optimal solution the pairs (r_i, IS_i), and (s_i, OS_i) are complementary to each other, i.e., at least one element of the respective pair is equal to 0 (see Nering/Tucker, 1993). The management implications for microinsurer no. 19 in 2004 from this is thus to decrease inputs 2 and 3 in equal proportions and input 1 by a further 25 units. Considering the technical efficiency score of 0.11 the reduction in inputs 2 and 3 necessary to become wholly efficient would be 89%.

Comparison of frontier efficiency methodology and key performance indicators

One research area of special interest to microinsurance practitioners is the comparison of the frontier efficiency methodology with the existing key performance indicators. Are the micro-insurers with good key performance indicators also ranked high in frontier efficiency analysis? Table 7 shows the pair wise rank correlation coefficients between the key performance indicators, DEA and SFA.[13]

Table 7: Rank correlation statistics for performance indicators

	NIR	IER	ICR	RR	CRR	GR	CR	SR	LR	DEA	SFA
NIR	1.00	-0.02	0.36	-0.20	-0.26	0.05	0.11	0.08	-0.06	-0.20	0.03
IER		1.00	0.24	-0.32	0.05	0.25	0.13	-0.27	-0.14	0.19	-0.10
ICR			1.00	-0.18	-0.05	0.37	-0.03	0.05	-0.30	0.04	0.36
RR				1.00	-0.38	-0.05	0.12	-0.28	-0.95	-0.10	0.38
CRR					1.00	-0.05	-0.43	-0.33	0.39	0.01	0.14
GR						1.00	0.40	-0.16	-0.37	-0.08	-0.04
CR							1.00	-0.23	-0.04	-0.15	-0.10
SR								1.00	-0.01	0.10	0.23
LR									1.00	-0.30	-0.11
DEA										1.00	0.14
SFA											1.00

NIR= net income ratio, IER=incurred expense ratio, ICR=incurred claims ratio, RR=renewal ratio, CRR=claims rejection ratio, GR=growth ratio, CR=coverage ratio, SR=solvency ratio, LR=liquidity ratio, DEA=DEA technical efficiency score, SFA=SFA technical efficiency score

A within comparison of the key performance indicators shows a very distinct ranking of the microinsurers and no clear pattern that separates excellent from poor performance. These results stress the argument that there are hardly any microinsurers receiving a consistent ranking using the key performance indicators in our panel. This again proves the high level of heterogeneity and raises the issue of goal ambiguity for microinsurers. Most of the programs in our panel are non-profit organizations with a strong customer orientation as we confirmed by the

[13] We computed pair wise Spearman rank correlation statistics. The ranking of the key performance indicators is based on the definition of excellent and poor results for the specific indicators made by Wipf/Garand (2008). We omitted one of the 10 proposed indicators (promptness of claims settlement) since the respective data is not available for many of the microinsurers in our sample.

efficiency analysis.[14] Financial performance usually is not a primary goal for these organizations.[15]

Since key performance indicators have not been surveyed until recently and financial performance is not a primary goal for most microinsurers, a strong awareness of the management implications that should be used to control the indicators is not expected and this is exactly what the key performance indicators confirm. But even in the presence of a constant monitoring, exclusively managing the operations based on key performance indicators is problematic. The choice of a specific set of performance indicators and respective performance levels signifying poor, average and excellent performance is challenging and as such implies a trade-off between the importance of specific corporate goals. As such frontier efficiency techniques are a useful way to support management decisions, identify best practices and provide unambiguous guidance to increase the performance and viability of a microinsurance scheme.

5. Conclusions

This is the first paper to use frontier efficiency analysis for measuring performance of microinsurance programs. While first research on performance measurement in microinsurance has focused on traditional financial ratio analysis, 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.

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14 We find a considerable improvement in the level of technical efficiency for non-profit microinsurers when incorporating the social output indicator that exhibits the ability of a microinsurer to reach the target population (see the related discussion of DEA and SFA results incorporating the social output indicator as well as the results for the conditional mean analysis).

15 The net income ratio is usually used to reflect the profitability. Only 9% of the data points in our panel show acceptable results for this ratio which underlines the low profit-orientation for the microinsurer in our panel.

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.[16] The results also illustrate the diversity of different microinsurance providers and emphasize the relevance of benchmarking in order to identify best practices across different microinsurance providers, countries and institutional 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 Indicators 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. For example, a larger dataset of programs in the start-up phase and experienced programs might be interesting to provide more insights into the efficiency of microinsurers in different stages of their life cycle. Once a broader database is set up, the efficiency values might also be used to derive implications for the management of microinsurance schemes. The efficiency values might indicate improve-

[16] As mentioned Eling/Luhnen (2009b) found in an analysis of commercial insurers that the efficiency scores in emerging markets with limited capacity are typically lower than those in advanced insurance markets with relatively high capacity. Improving the capacity, i.e. both technical and business skills, might thus be helpful to enhance the efficiency of microinsurers.

ment 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 also 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 1: Microinsurance schemes

Table A1: Descriptive statistics of microinsurance schemes

Geographic region	Countries covered	Average age of micro-insurers (years)	Average number of insured per microinsurer in last re-porting year	Profit orientation		Microinsurance products provided			
				Non-profit	For-profit	Life	Health	Credit-life	Multi-product
Africa	Benin (2x), Mali, Togo, Burkina Faso, Congo, Senegal	5.46	38,304	6	1	1	3	3	0
Asia	Bangladesh, Cambodia, India (3x), Indonesia, Vietnam	4.76	48,755	5	2	1	0	2	4
Latin America	Bolivia (3x), Guatemala, Mexico, Peru (2x)	8.59	69,175	4	3	3	1	1	2
	Mean/Total	**6.27**	**52,078**	**15**	**6**	**5**	**4**	**6**	**6**

Appendix 2: Methodology

Stochastic frontier analysis

Technical efficiency is estimated utilizing a translog stochastic input distance function. The model specification based on distance functions was selected to allow for multiple outputs and multiple inputs (see, e.g., Coelli/Perelman, 1996; Coelli, 2005). The broad acceptance of the translog specification of the production technology in *stochastic frontier analysis* in insurance (see, e.g., Cummins/Weiss, 2000) is the rationale to opt for this specific functional form. The SFA model for technical efficiency is as follows:

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

with x_{kit}, the *k* inputs of insurer *i* at time *t* and y_{mit}, the *m* outputs of insurer *i* at time *t*. The condition of linear homogeneity of degree 1 in inputs is satisfied by randomly choosing one input (such as x_{Ki} in our case) and dividing all other inputs by this input. Thus we determine $x^*_{ki} = x_{ki} / x_{Ki}$. Using this notation all summations in Equation (A1) involving x^*_{ki} are consequently over *M-1* and not *M*. A time variable *t* is incorporated as a regression coefficient into our model to account for technological change over time. Random error is included in Equation (A1) by v_{it}, which is assumed to be distributed normally. We account for inefficiency using the term u_{it}, which is assumed to follow a truncated normal distribution. A one-stage approach (conditional mean approach; see Battese/Coelli, 1995, or Greene/Segal, 2004, following an approach similar to Huang/Liu, 1994) is applied to characterize the mean m_{it} of u_{it} that is assumed to vary depending on a vector of firm-specific variables. The model for m_{it} is as follows:

$$m_{it} = \delta_0 + \delta_1 a_{it} + \delta_2 b_{it} + \delta_3 c_{it} + \delta_4 d_{it} + \delta_5 e_{it} + \delta_6 f_{it} + \delta_\theta g_{i\theta} + \delta_\gamma h_{i\gamma} + \delta_\delta k_{i\delta}, \qquad \text{(A2)}$$

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; 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. e_{it} is a dummy variable reflecting the age of the program (1 if the age of the program is higher than the median; 0 otherwise). The variable f_{it} reflects the distribution of insurance policies (1 if group policies are provided; 0 if individual policies are provided). $g_{i\theta}$ are three product dummy variables with θ=1, 2, 3 representing life, health and credit-life; multi-product was excluded to avoid singularity. $h_{i\gamma}$ are region dummy variables with γ =1, 2 representing Africa and Asia where Latin America is referred to as the reference category. $k_{i\delta}$ are five time dummy variables with δ=2005,…, 2008; 2004 is excluded.

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

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

with C_{it}, the total cost of insurer i at time t, p_{kit}, the k input prices of insurer i at time t and y_{mit}, the m outputs of insurer i at time t. The condition of linear homogeneity of degree 1 in input prices is satisfied by randomly choosing one input price (such as p_{Ki} in our case) and dividing the dependent variable (C_{it}) and all other input prices by this input price. The rest of the model, including the distributional assumptions, is specified analogous to the technical efficiency SFA model.

Data envelopment analysis

To illustrate DEA, we discuss the applied model for measuring technical efficiency assuming VRS used throughout the paper (see, e.g., Banker, Charnes, Cooper, 1984; Cooper et al., 2007). Efficiency e of an insurer i is measured by the ratio:

$$e_i = s_j^T y_{j0} - u_0 / r_k^T x_{k0} \ , \qquad \text{(A4)}$$

where y_j is a vector with outputs $j = 1,\ldots,$ z. x_k is a vector with inputs $k = 1,\ldots, w$. s_j^T is the transposed vector of output weights and r_k^T the transposed vector of input weights. u_o accounts for VRS and may be positive, negative or zero. 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:

$$\max e_i = s_j^T y_{j0} - \ u_0 / r_k^T x_{k0}$$

$$\text{subject to} \quad s_j^T y_{ji} - u_0 / r_k^T x_{ki} \leq 1 \ (i = 1, \ldots, n), \qquad \text{(A5)}$$

$$s_j \geq 0, r_k \geq 0 \ \forall \ j = 1, \ldots, z, k = 1, \ldots, w, \ u_0 \ unconstrained \ in \ sign.$$

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 $r_k^T = 1$, implying that the weighted sum of inputs is standardized to 1:

$$\max e_i = s_j^T y_{j0} - u_0$$

$$\text{subject to} \quad r_k^T x_0 = 1 \ , \qquad \text{(A6)}$$

$$s_j^T y_{ji} - r_k^T x_{ki} - u_0 \leq 0 \ ,$$

$$s_j \geq 0, r_k \geq 0 \ \forall \ j = 1, \ldots, z, k = 1, \ldots, w, u_0 \ unconstrained \ in \ sign.$$