The Performance of Microinsurance Programs: A Frontier Efficiency Analysis

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Abstract: This paper employs frontier efficiency analysis to measure the performance of microinsurance programs. Frontier efficiency analysis provides measurement techniques that exactly address the limitations of the performance indicators currently used in the microinsurance industry. Moreover, these techniques encompass the important social function that microinsurers fulfill and provide powerful managerial implications. We illustrate the capabilities of frontier efficiency analysis using a data sample of 21 microinsurance programs provided by the *Microinsurance Network* and recent innovations from efficiency literature, such as bootstrapping of efficiency scores. Our empirical results indicate significant diversity and potential for improvement in the microinsurance industry. The findings also highlight differences between "classic" efficiency and "social" efficiency, which we determine by adding a social output indicator.

Keywords: Efficiency, Data Envelopment Analysis, Stochastic Frontier Analysis, Conditional Mean Analysis, Bootstrapping, Social Output Indicator

1. Introduction

The microinsurance industry today is highly dependent on donor or government subsidies, which, for the most part, are available only temporarily. Without subsidies, all these programs are subject to the same economic forces as commercial insurers, and this requires them to be managed professionally. Management goals, however, cannot be realized without a transparent performance measurement (see Wipf and Garand, 2008). Performance measurement and benchmarking is thus an important issue for the microinsurance industry.

In this paper, we use frontier efficiency analysis to evaluate the performance of microinsurance programs. Frontier efficiency techniques measure firm performance relative to the "best practices" of leading firms in an industry. Typical examples of these techniques are *data envelopment analysis* (DEA; see Cooper, Seiford, and Tone, 2007) and *stochastic frontier analysis*

(SFA; see Kumbhakar and Lovell, 2000). Both have been applied in numerous insurance markets (see Eling and Luhnen, 2009b, for an overview), but we are not aware of any research that evaluates the efficiency of microinsurance programs.

Indeed, research on the performance of microinsurance programs is still in its infancy. Industry practitioners organized in the *Microinsurance Network* have set up a *Performance Indicators Working Group* and initiated the development of 10 performance ratios, which are summarized in a performance indicators handbook (see Wipf and Garand, 2008). Empirical tests show that the performance indicators can enhance comparisons of different schemes and improve transparency, but they cannot capture the large diversity of different microinsurance providers. For example, some projects are still in the start-up phase, while others are large, established programs. It is not 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 could be an ideal tool for assessing the performance of microinsurance programs and a valuable addition to traditional financial ratio analysis since they summarize performance in a single statistic that controls for differences among firms using a multidimensional framework (see Cummins and Weiss, 2000). The techniques are particularly suitable for microinsurers: frontier efficiency methods were originally developed for benchmarking of non-profit organizations such as schools, because, unlike many industries, the production function for these institutions is unknown, which 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 reveal the important social function of microinsurance programs.[1] Gutiérrez-Nieto, Serrano-Cinca,

[1] In our discussions with microinsurance practitioners from the *Performance Indicators Working Group*, the members recognized that frontier efficiency techniques are an interesting approach that can be complementary to the existing 10 performance ratios, but they argued that a single indicator is not that practical when trying to analyze different areas of performance within a program for the purpose of the operational management. In general, we agree that different indicators should be considered, but we believe, however, that the techniques described in this paper can 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 ob-

and Mar Molinero (2009) follow this line of argumentation in a frontier efficiency analysis for the microfinance industry; their results reveal the importance of assessing social efficiency.

This paper uses new data and an innovative methodology. Our data are 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, which contains detailed information on 21 microinsurance programs. We use recent innovations from bootstrapping literature to account for the fact that the standard DEA efficiency scores are sensitive to measurement errors, especially with smaller data samples. For the first-stage determination of DEA efficiency scores, we use the bootstrapping procedure presented in Simar and Wilson (1998). Another important feature of our analysis is that we cross-check our findings using SFA. Most studies use either DEA or SFA; we combine the advantages of both 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, one of our contributions is that we extend the existing key performance indicators with a new, powerful benchmarking tool that addresses the limitations of the 10 indicators currently used in the microinsurance industry. Furthermore, we enhance the comparability of microinsurance programs using a single and simple to interpret performance number. Another contribution of this paper is to transfer frontier efficiency methodologies to the microinsurance industry; our hope is also to encourage further research and discussion on benchmarking and performance measurement in microinsurance from both the academic and practitioner 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,

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tain from DEA. Furthermore, we can calculate slack variables to identify target points on the efficient frontier. DEA thus not only measures efficiency, but can also provide guidance on how to improve the performance of inefficient microinsurers. One aim of this paper is thus to illustrate the capabilities of frontier efficiency techniques for the operational management of microinsurance programs.

as well as the data we use in the empirical analysis. Section 4 presents the empirical results. Section 5 concludes.

2. Performance of Microinsurance Programs

Microinsurance programs provide insurance services to the low-income population and small businesses in developing countries. Microinsurance is typically characterized 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 (see Churchill, 2007). As this brief definition implies, microinsurance serves the low-income population based on the same fundamentals as regular insurance. A wide range of risks is covered and products comparable to those in regular insurance markets are provided.[2] Common types of risks covered are life, health, disability, and property (especially agricultural insurance). Microinsurance is delivered through a variety of channels, including commercial insurers, government-owned insurers, nongovernmental organizations (NGOs), mutuals and cooperatives, as well as small community-based schemes (see Roth, McCord, and Liber, 2007; Churchill, 2007). Large multinational companies such as Allianz or Munich Re are also increasingly involved in the microinsurance market. The most important microinsurance markets are (1) Asia, e.g., China and India, (2) Africa, e.g., Senegal and Uganda, and (3) South America, e.g., Paraguay and Peru (see Roth, McCord, and Liber, 2007). Although the idea of insurance schemes organized as mutuals or community-based schemes is nothing new in developing countries, the term *microinsurance* was not used until the mid-1990s and was established along with the development of microfinance. An increasing number of microinsurance programs have been established as either pilot or as ongoing structures in recent years.[3] Numerous classic insurance problems, including moral hazard, adverse selection, correlated risks,

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[2] However, insurance product specifics and relevance for customers significantly deviate from regular insurance markets due to different requirements of the low-income market (see Churchill, 2007; McCord, 2009).

[3] Churchill (2006) and Roth, McCord, and Liber (2007) provide the most comprehensive overview of the market.

high administration costs, and lack of data (see Levin and Rheinhard, 2007), are inherent in microinsurance markets, making the environment challenging from an economic perspective.[4] Despite the growing policy interest in microinsurance, little academic attention has been paid to this market; indeed, management of such organizations has not yet been discussed in the literature. Recent discussion by practitioners as well as by academics emphasizes that microinsurance programs need to become viable. Most microinsurers depend on short-term subsidies. Without subsidies, all these programs are subject to the same economic forces as commercial insurers, and this requires them to be managed professionally. Professional management, however, requires transparent performance measurement. As a first step toward developing transparent performance measurement processes, the *Microinsurance Network* (former *CGAP Working Group on Microinsurance*) set up a *Performance Indicators Working Group*, which initiated the development of 10 performance indicators during two workshops in 2006 and 2007 and summarized the results in a performance indicators handbook. The 10 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 and Garand, 2008, for a definition of the indicators).

All these ratios are important indicators of financial strength and underwriting success and enhance the comparability and transparency of different schemes. Nevertheless, standard financial ratio analysis cannot capture the vast diversity and various characteristics of microinsurance providers. It is very challenging to choose a specific set of financial ratios that will accurately indicate poor, average and excellent performance in this sector of the insurance industry and any choice made implies a tradeoff between the importance of specific goals.

As many microinsurance programs are set up as non-profit schemes and social organizations, not to mention that many are to a large extent financed by governments, often their objectives

[4] The situation faced by microinsurers today is similar to challenges of the microfinance industry, including 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). See also Brau, Merrill, and Staking (2009) for an analysis of challenges facing microinsurance markets.

are not limited to financial performance. Like many microfinance institutions, microinsurers have both financial and social objectives (see Gutiérrez-Nieto, Serrano-Cinca, and Mar Molinero, 2009). The social function of microinsurers, i.e., providing protection against specific perils and thus facilitating economic growth, as well as mitigating poverty, inequality, and vulnerability, is a crucial aspect in evaluating their performance. The *Performance Indicators Working Group* discussed four potential social indicators for reflecting the social function that many microinsurers have a mandate to fulfill (see Wipf and 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 the total number of insured in the scheme, (3) value of incurred claims in comparison to client annual income, and (4) cost of benefits provided in comparison to the cost of annual premium.

In practice, using such measures requires a clear definition of the poverty line and guidelines as to what should be counted as annual income since many insured receive benefits in kind and services instead of cash income. Furthermore, we believe that the existing 10 performance indicators can also illustrate social performance. For example, the higher the coverage ratio, the higher the protection of the target audience and, consequently, the higher the social benefit. Moreover, Social Indicator (4) is very similar to Performance Indicator (3), the incurred claims ratio. However, the performance indicators can only partly 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 be incorporated in the efficiency analysis.[5]

[5] We opt to use the coverage ratio to reflect social performance in our efficiency analysis. However, it would also be feasible to implement any other indicator that reflects social performance whenever such data are available.

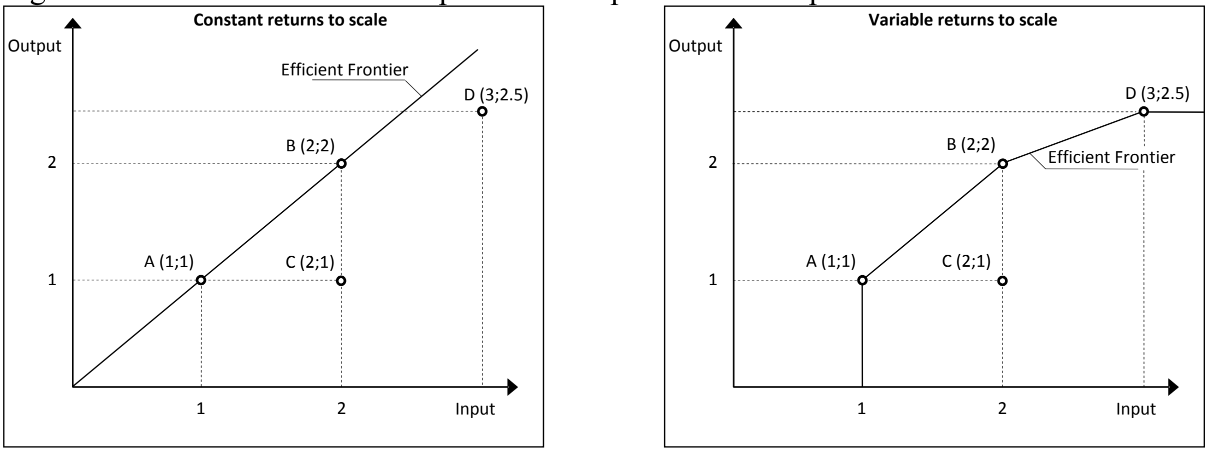
3. Methodology and Data

3.1 Methodology

Modern frontier efficiency methodologies, like more traditional techniques such as financial ratio analysis, aim at benchmarking firms of an industry against each other. Frontier efficiency techniques measure a company's performance relative to the "best practices" of the most efficient companies in the same industry. In the academic literature on efficiency measurement, these methods are viewed as a useful alternative 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 and Weiss, 2000). In addition to calculating efficiency statistics, the model variables can reveal a great deal of managerial-type information (such as key drivers of performance, shadow prices, and slack variables), as we will describe later in this paper. Efficiency estimates are standardized between 0 and 1, with the value 1 (0) assigned to the most (least) efficient firm. A firm's potential for improvement in terms of efficiency can be derived from the difference between a company's assigned value and the maximum possible efficiency score of 1 (see, e.g., Cooper, Seiford, and Tone, 2007). The frontier efficiency methodology permits estimating various frontiers, such as production frontiers, cost frontiers, revenue frontiers, and profit frontiers, all of which are frequently discussed in academic literature.

Using a production frontier to compute technical efficiency is the simplest and most widespread approach in the frontier efficiency literature, generally by means of one of two fundamental orientations. The input orientation aims at minimizing inputs conditional on given output levels. The output orientation, on the other hand, maximizes output levels conditional on a given input consumption. Figure 1 illustrates input orientation with constant (CRS) and variable returns to scale (VRS).

Figure 1: Efficient frontier - example for one input and one output



In this simple example of CRS, the efficient frontier is composed of firms A and B. Since these firms consume only 1 unit of input to produce 1 unit of output, they dominate firms C and D, which require 2 input units (for 1 output unit) and 3 input units (for 2.5 output units), respectively. The efficiency level is determined by the ratio of the optimal amount of input to produce 1 unit of output and the actual level of input consumed. The resulting efficiency score for C is 0.5 and 0.83 for D. Firms A and B have an efficiency score of 1 and lie on the efficient frontier. If we opt for VRS, the shape of the efficient frontier is altered and firm D is now located on it. In contrast to the CRS frontier, representing scale efficient production, the VRS frontier is used to estimate pure technical efficiency, which indicates potential input reduction by utilizing state-of-the-art technology. The level of efficiency assuming VRS thus reflects the firm's ability to employ optimal production technology. The closer the firm is to the efficient frontier, the higher is its efficiency score. The strategy for an inefficient firm C thus is to move in the direction of the efficient frontier, i.e., reduce the amount of input by upgrading to state-of-the-art technology.

There are two fundamental methodologies in frontier efficiency analysis, each originating from a different theoretical foundation: the mathematical programming approach, based on optimization, and the econometric approach, based on regression. Below, we briefly address the fundamentals of the two approaches and discuss their relevance for the insurance field.[6]

Mathematical programming approach

Mathematical programming approaches are used to measure the efficiency of a firm based on the weighted relationship of outputs to assigned resources (inputs). Since efficiency estimates are the result of an optimization problem, it is not necessary to specify the shape of the efficient frontier. Furthermore, there is no need to formulate hypothesis about stochastic elements in the model, as is required for the econometric methodology. The most commonly used approach of this type is *data envelopment analysis* (DEA), which dates back to Farrell (1957) and has received more attention ever since Charnes, Cooper, and Rhodes (1978) introduced a linear optimization solution to the problem posed by Farrell (1957). There have been many empirical applications and improvements of the methodology since then. DEA model specifications are available for the assumption of CRS or VRS, which can be used to compute various efficiency scores, i.e., cost, technical, pure technical, allocative, and scale efficiency (see Cooper, Seiford, and Tone, 2007).

Econometric approach

The econometric approaches make ex ante assumptions about the shape of specific frontiers, e.g., production, cost, revenue, or profit frontiers. 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 errors. Explicit assumptions about the distributions of the inefficiency and error term are integrated in the model. Since the seminal work of Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), the most com-

[6] 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 containing more detail on the different methodologies is available upon request.

monly used econometric approach is *stochastic frontier analysis* (SFA). SFA usually follows a two-step procedure. Based on assumptions made about the shape and the distribution of the parameters, the efficient frontier is estimated first. In a second step, deviations from the efficient frontier for individual firms are estimated and further decomposed into its two components: inefficiency and random deviation (see Cummins and Weiss, 2000).

Two configuration decisions must be made when employing SFA: (1) the choice of the functional form that best approximates the real underlying efficient frontier, and (2) the distributional assumption for the inefficiency term. The translog (see Christensen, Jorgenson, and Lau, 1973) 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 and Berndt, 1982), and generalized translog (see Caves, Christensen, and Tretheway, 1980). The composite cost (see Pulley and 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 Aigner, Lovell, and Schmidt, 1977), truncated normal, exponential (see Meeusen and van den Broeck, 1977), or gamma (see Berger and Humphrey, 1997).

Managerial capabilities of frontier efficiency analysis

In addition to providing efficiency statistics to determine the relative performance of a firm in a market, frontier efficiency methodologies can extract other information relevant to the management of a firm. The methodology can be applied at various levels of aggregation: (1) at the business-unit level to show the performance of different business units, (2) at the corporate level to assess the performance of the firm, and (3) at the macroeconomic level to evaluate the performance of different markets. Thus, the methodology offers a wide range of competitive and governance information to support management decisions. The regression options that are used in a two-stage approach with DEA via Tobit analysis (see Aly et al., 1990; Stanton,

2002) and that are implemented in the SFA via conditional mean approach (see Battese and Coelli, 1995; Greene and Segal, 2004) are powerful tools for deriving internal and external key drivers of firm performance. 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). The slack variables that are generated in DEA give insight into the sources and amounts of inefficiency and can thus reveal relevant target points on the efficient frontier, information that will allow the inefficient firm to identify the input- combination that will lead to efficient production. The weighting factors of the inputs and outputs obtained from 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), which reveal the increase in input 1 necessary to maintain constant output if input 2 is decreased, (2) the marginal productivity (given by the ratio of the shadow prices of one input and one output), which 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), which indicates the amount of output 1 we will forfeit by increasing output 2 by 1 unit.

Advantages of frontier efficiency for microinsurance

Frontier efficiency techniques have 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. For example, Eling and Luhnen (2009a) surveyed 95 studies on efficiency measurement in the insurance industry. Recent work in the field addresses methodological aspects as well as new areas of application (thematic and geographic scope), including emerging markets such as China and Taiwan. However, 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 (not a microinsurance), context is Gutiérrez-Nieto, Serrano-Cinca, and Mar Molinero (2009). They rely on the *Microfinance Information eXchange* database and show the advantages of DEA for measuring efficiency in banking.

Frontier efficiency techniques could be an ideal tool for assessing the performance of microinsurance programs for the following reasons.

(1) Frontier efficiency methods have found wide acceptance for benchmarking non-profit organizations, such as public institutions, because, unlike many industries, the production function for these institutions is unknown, which is exactly the situation faced by microinsurance providers.

(2) The methods are a valuable addition 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 and Weiss, 2000). Instead of 10 different indicators, we have one easy to use and easy to interpret performance indicator.

(3) Inputs and outputs used in efficiency measurement include financial indicators, but the methods can also accommodate social output indicators and thus reveal the important social function of microinsurance providers.

(4) The techniques measure efficiency and identify areas in which a program is strong 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 allocated so as to improve efficiency.

(5) From an economic point of view, several useful parameters (which 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 performance.

(6) With SFA we can isolate and directly model the effects on efficiency of profit orientation, company size, solvency, time, and many other factors, all of which might be important deter-

minants of performance in microinsurance, e.g., using the conditional mean approach (see Greene and Segal, 2004).

(7) The data requirements are not too taxing, which is extremely relevant given the limited availability and quality of data in this emerging field of research. Only a fraction of the data needed to calculate key performance indicators is needed to compute efficiency scores. Also, different methodologies can be used for data of varying quality. For example, when data are known to be noisy, SFA might be appropriate because it distinguishes between random deviations from the efficient frontier and deviations due to inefficiency.

We thus believe that frontier efficiency analysis is a powerful performance measurement technique for microinsurers and a valuable addition to the existing performance measures in the field.

3.2 Data and Configuration of Efficiency Analysis

We received data from the *Microinsurance Network* on 21 microinsurance schemes that provide life and health insurance. The data contain balance sheet and statement of income information from 2004 to 2008. We do not have data for all years for all companies and thus consider unbalanced panel data. In total, 78 firm-years are available for analysis. The financial statements data provide an ideal basis for efficiency analysis as most of the inputs and outputs used in efficiency analysis rely on data provided in the balance sheet and the statement of income. We have seven companies each from Africa, Asia, and Latin America.

As is common in the literature, we use labor, business services and material, debt capital, and equity capital as inputs (see Cummins, Rubio-Misas, and Zi, 2004). Labor and business services were merged into operating expenses (including commissions) as a single variable, a frequent practice in international efficiency studies due, as is the case here, to limited data availability (see Diacon, Starkey, and O'Brien, 2002; Fenn et al., 2008; Eling and Luhnen, 2009b). This approach also reduces the number of parameters to be estimated, which is, given that we have only 21 microinsurers, another argument for this simplification (see Ennsfellner, Lewis, and Anderson, 2004). We thus use operating expenses to proxy both labor and business services and handle these as a single input.

To determine the price of operating expenses, we utilize the results of an analysis of operating expenses in the U.S. insurance industry covering life and non-life insurance companies. In that study, Cummins and Weiss (2000) show that these are mostly labor related, i.e., the largest expenses are employee salaries and commissions. The price of labor, determined by the ILO Main Statistics and October Inquiry, is thus used to proxy the price of operating expenses. ILO statistics are based on international surveys of wages published by the *International Labour Organization* (ILO) and are often used in efficiency studies (see, e.g., Fenn et al., 2008; Eling and Luhnen, 2009b). Since in our case data are not available for all countries (such as Burkina Faso or Cambodia), we needed to proxy the price of labor using regional averages for Africa, Asia, and Latin America. The price of debt capital is determined by region-specific bond indices for each year of the sample period. The price of equity capital is proxied using rolling window five-year averages of the yearly rates of total return of regional MSCI Emerging Markets Indices (all data were obtained from the Thomson Datastream database). To ensure the comparability of all monetary values, we deflate all inputs by the consumer price index to the base year 2004 (see, e.g., Cummins and Zi, 1998). Annual country-specific consumer price indices were obtained from the *International Monetary Fund* (IMF) database.

In specifying the outputs, we use the frequently employed value-added approach (see Grace and Timme, 1992; Berger et al., 2000). Accordingly, we distinguish between the three essential services provided by insurance companies: risk-pooling/-bearing, financial services, and intermediation. To proxy risk-pooling/-bearing and financial services, we follow Yuengert (1993) and use the value of current losses paid plus additions to reserves (real incurred losses). As the microinsurance programs included in the database provide life and health insurance coverage, the present value of net incurred benefits best represents the risk-pooling/-

bearing and financial services output. Losses are highly correlated with the financial services function, which is why we consider real incurred losses as representing risk-pooling/-bearing and financial services both (see Berger et al., 2000). Microinsurers, like regular insurers, receive funds from their customers and invest them until they are required to pay claims or the funds are withdrawn by the policyholder in the case of asset accumulation products (see Cummins and Weiss, 2000). The output variable, which proxies the intermediation function, is thus the real value of total investments. The cost variable necessary to estimate SFA cost efficiency is calculated, following Choi and Weiss (2005), as operating expenses plus cost of capital.[7]

In an additional model, we complement the technical efficiency analysis by implementing a further output variable that represents the microinsurer's social function. For this purpose we selected an indicator that reveals the capacity of microinsurers to reach their target population. Along with the specification of a coverage ratio by the *Performance Indicators Working Group* of the *Microinsurance Network* (see Wipf and Garand, 2008), we defined the additional output as the number of people insured relative to the target population as stated by the respective microinsurer. Note that the coverage ratio is one of the 10 key performance indicators in the performance indicators handbook and not one of the four additional social indicators. We believe, however, that the coverage ratio can be interpreted as a social output indicator, well reflecting the social function of microinsurance companies.[8/9]

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7 Contrary to DEA, SFA cost efficiency estimation requires prespecification of a cost variable reflecting total observed costs of the microinsurer as a dependent variable in the regression. DEA computes a cost minimizing vector of input quantities as an optimization solution from which cost efficiency can be calculated by dividing it by the actual consumed quantities. A prespecified cost variable is thus not required in DEA.

8 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 hypothesis (see Mayers and Smith, 1988 and Cummins and Weiss, 2000 for more details on both hypotheses). While the stock insurer's primary goal is to ensure high profits with a given solvency level set by regulators or rating agencies, the primary goal of a mutual insurer is fulfilling owner demand and a high-quality service. The fulfillment of owner demand 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.

9 Feedback at the microinsurance conference clearly confirmed the importance of adding social indicators to the "classic" efficiency measurement framework, since an analysis neglecting social aspects might not be accepted by a large fraction of the microinsurance community. As mentioned, an important advantage of the

Table 1 presents an overview of the inputs, input prices, and outputs used in this analysis (Panel A), as well as summary statistics on the variables employed (Panel B). All numbers were deflated to 2004 using the IMF consumer price indices and converted into U.S. dollars using the exchange rates available from the Thomson Datastream database. More descriptive statistics on the microinsurance schemes can be found in Appendix 1. To protect the anonymity of the analyzed microinsurers, we present aggregate statistics at the industry level only, and no individual company data.[10]

Most of the microinsurers in our sample are small in terms of total assets compared to regular insurance markets. Eling and Luhnen (2009b) found an average value of debt capital (equity capital) of \$1.5 billion (\$369 million) and a maximum of \$393 billion (\$82 billion) in their efficiency study of 6,462 insurers from 36 countries. In our study of microinsurers, the debt capital (equity capital) numbers are \$10.38 million (\$2.64 million) for the mean and \$203.93 million (\$21.98 million) for the maximum. All other company-specific balance sheet, as well as profit and loss statement items, on average display significantly lower values than those observed in developed markets. As expected, the price of labor is much lower (73%), while the price of debt (3.2%) and equity (3.6%) is higher compared to figures found by Eling and Luhnen (2009b). This is an economically meaningful finding since equity- and debtholders in emerging markets require a higher risk premium compared to investors in regular markets.

frontier efficiency technique is that it can provide two types of analysis, one that is restricted to financial indicators and another that also considers social indicators. The method can thus accommodate different measurement purposes and be of relevance to different target groups, including managers, regulators, policymakers, and development aid workers. In this context, the choice of social indicators is an open question and one that was critically addressed at the microinsurance conference. From a methodological point of view, however, it does not matter which indicators to consider; more important is the question of data availability and whether an inclusion makes sense from a theoretical point of view. We would thus be interested in an analysis of further social indicators whenever such data are available. In this paper, we tested a second social indicator, the cost of benefits provided in comparison to the cost of annual premium (i.e., Social Indicator 4). The results of these tests are available upon request.

10 A requirement for the efficiency analysis is that all input and output values should be positive. However, given the translation invariance described in Pastor (1996), negative parameter values can be easily transformed by adding a fixed number. Negative values for certain parameters, however, might raise questions as to the financial soundness of the analyzed insurers. More precisely, we found a negative equity capital in five of the 78 firm-years, which raises questions as to the solvency status of these companies. We assume, however, that future donor or government subsidies not reflected in our balance sheet data might be available to ensure the ability of these microinsurers to pay future benefits. We thus did not eliminate these cases from our analysis, but instead transformed the negative values by adding a fixed number as proposed in literature.

Inflation, reflected by the consumer price index (10%), also exhibits a higher value than that found by Eling and Luhnen (2009b).

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	$	10,384,524.31	37,155,668.84	38.52	203,929,777.20
Equity capital	$	2,638,413.29	4,755,817.33	0.00	21,978,035.22
Price of labor	$	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	$	155,132.77	380,970.47	0.00	1,835,886.79
Investments	$	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	%	44.59	42.59	0.53	100.00

In the next section, we consider 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) in an analysis of technical and cost efficiency. The companies are sorted into size categories by their total assets, large companies have total assets more than $7,737,681, small companies have total assets less than $37,655, and the remainder are considered to be medium size (see Cummins and Zi, 1998; Diacon, Starkey, and O'Brien, 2002; Eling and Luhnen, 2009b). The classification of a microinsurer as for-profit or non-profit is based on information in the data files of the *Microinsurance Network*.

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 without considering social performance. 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 introduced by Simar and Wilson (1998) to 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.[11] For comparison purposes, the average annual values are presented in the last line of the table and the average values for the respective microinsurer in the last column following the annual estimates. We also show mean technical and cost efficiency estimates for each of the regions in the panel. The "n/a" in the table indicate that no data were available for the particular microinsurer in the respective year.

Overall, the DEA efficiency estimates are relatively high compared to those found in other studies (see, e.g., Eling and Luhnen, 2009b). Africa (0.81) and Asia (0.78) are the most technically efficient regions. Note, however, that a frontier efficiency analysis is a comparison between companies in the same market, that is, the peer group consists of the other microinsurers.

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

[11] DEA efficiencies in Table 2 are estimated separately for all years and based on a one-world frontier, whereas we analyze SFA based on the unbalanced panel (Table 3).

ance markets in Africa are usually considered the least covered in the world. Asia, on the other hand, shows strong and constant development in recent years, a situation due at least in part to government regulation of insurance markets aimed at increasing product distribution, especially in rural areas, e.g., in India.[12]

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

		Technical efficiency						Cost efficiency					
	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**

A possible explanation for the relatively high DEA estimates at the aggregate level might be that the sample is relatively heterogeneous, consisting of a variety of different insurance schemes of different sizes, institutional forms, profit orientations, regional focus, product ranges, and client structures. We also have a dataset of varying quality and consistency such that statistical noise is likely to affect the quality of our analysis. Furthermore, the sample is relatively small and as such may be biased upward, taking the effect of sample size on average efficiency scores, as discussed by Zhang and Bartles (1998), into consideration.[13] It thus

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

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

might be useful 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 those due to noise, and true 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 so as to incorporate multiple inputs and multiple outputs (see, e.g., Coelli and 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 Eling and Luhnen, 2009b), the reader is referred to Appendix 2. The results are set out in Table 3.

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

		Technical efficiency						**Cost efficiency**					
	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 those found with DEA. The SFA efficiency results are more in line with expectations as to ranking of the three geographic areas at the aggregate level. Asia displays the highest average technical efficiency with 0.80. Nevertheless, we find that Asia (0.54) is less cost efficient than Africa (0.61), but more so than Latin America (0.45). In terms of technical efficiency, Asia (0.80) is first, followed by Africa (0.59) and then Latin America (0.38).

As to the consistency of the results from the 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, is 52%, which is consistent with results from other studies (e.g., Cummins and Zi (1998) find a rank correlation of 0.58). Consistent results from the two approaches are, however, not necessarily expected, since the origin of each is quite different. Hjalmarsson, Kumbhakar, and Heshmati (1996) show this inconsistency in a comparison of DEA and SFA models and find significantly different results depending on the model setup. Besides the methodological differences, other possible explanations for the low rank correlation found for technical efficiency could relate to statistical noise in the data, the size of the panel, and heterogeneity. As shown in simulation studies by Gong and 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 have a heterogeneous set of data, covering a sample of microinsurers, of very different sizes, from three continents. As shown in several works on DEA sensitivity to statistical noise, nonparametric methods tend to be sensitive to outliers (see Wilson, 1995), whereas SFA models are less sensitive to these problems. Thus SFA is probably the better approach for measuring the efficiency of the microinsurance schemes in our analysis.

As to the issue of time as a factor in the efficiency of insurance markets, we observe no clear trend indicating improvements over time for either technical or cost efficiency at the aggregate level. As with DEA, we find a peak in 2006 with subsequently declining values for technical and cost efficiency and especially poor results for 2008. Time effects will be discussed again below in an additional conditional mean analysis that confirms the negative results for 2008.

DEA and SFA model with social output indicator

To capture the financial and social performance of microinsurers simultaneously, we incorporate a supplementary output variable in our analysis. For this purpose, we rely 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 a coverage ratio as an additional output variable is based on the perception that a primary social goal of the microinsurance company is to meet the demand of the target population and provide high-quality service. Meeting demand is comparable to the coverage ratio. Since the microinsurers considered in this analysis mostly have a non-profit orientation, we think that coverage ratio best suits our purpose of integrating an additional indicator that will reflect social performance. Additionally, expanding the set of output variables could very well reveal interesting differences between non-profit and for-profit microinsurers[14] and provide valuable insights into how social and financial performance can be aligned. Table 4 sets out the technical efficiency estimates of microinsurers after incorporation of the social performance variable. We restrict ourselves to analyzing technical efficiency in showing the effects of an additional social output indicator.

Both methodologies, *data envelopment analysis* and *stochastic frontier analysis,* show slight upward variations at the aggregate level compared to the setup not considering social performance. This result is expected since the integration of an additional variable in the regression model, ceteris paribus, leads to higher efficiency values. The estimates for technical efficiency considering social performance are in general consistent with results obtained by the previous analysis that ignored social performance, with high rank correlation values for DEA (0.93) and SFA (0.89). More interesting, however, is the variation of average efficiency for the two

[14] The microinsurers 1, 10, 14, 15, 17, and 21 have a for-profit orientation, while the others have a non-profit orientation.

distinct classes of microinsurers in the panel, i.e., non-profit and for-profit microinsurers. When not considering social performance (Tables 2 and 3), we find higher technical and cost efficiency for microinsurers with a for-profit orientation compared to non-profit microinsurers.

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**

Non-profit microinsurers, however, show a significant upward shift in average efficiency after implementing the social output indicator in 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. We found a significant difference in mean efficiency values for non-profit and for-profit microinsurers in the original model (Tables 2 and 3), but this difference is no longer significant when implementing the social output indicator (Table 4).[15] We thus conclude that non-profit microinsurers are on a par with for-profit micro-

15 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 a Wilcoxon rank-sum test (see Wilcoxon, 1945) for the null hypothesis of a true location shift of 0 for non-profit and for-profit microinsurers (α=5%).

insurers in terms of technical efficiency if one takes their social output into consideration.[16] Consistent with general expectations is the finding 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 not to a great degree (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 next extend our analysis by employing the conditional mean approach.

4.2. Managerial Implications of Frontier Efficiency Analysis

Conditional mean approach

To extend our analysis and discover important drivers of firm performance, we isolate the impact of time-, firm-, and regional-specific effects on efficiency using an integrated one-stage approach. Under the conditional mean approach, the mean of the inefficiency term from the *stochastic frontier analysis* is modeled depending on a vector of firm-specific variables (see, e.g., Battese and Coelli, 1995; Greene and Segal, 2004; Eling and Luhnen, 2009b). The following regressors are used in our 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 in-

[16] An interesting comment from the microinsurance conference was that non-profit and for-profit microinsurers might serve different market segments. While for-profit microinsurers might focus on standardized, established and maybe also more profitable segments such as credit-life, the non-profit microinsurers might focus on more difficult markets and products which might also not be profitable yet. There is a very well known related discussion in commercial insurance markets considering different organizational forms (stock and mutual insurers) and their effects on efficiency. According to the managerial discretion hypothesis stock and mutual insurers use different technologies and mutual companies operate more efficient in lines of business with relatively low managerial discretion (see Mayers and Smith, 1988). Cummins, Weiss and Zi (1999) introduced the cross-frontier analysis to analyze differences in organizational form. Since we only have 21 firm years of for-profit and 57 firm years of non-profit microinsurers, we do not conduct a cross-frontier analysis at this point of time. Future research with more data is needed to analyze differences between profit orientation and efficiency in more detail. We are grateful to Andreas Landmann for highlighting potential differences between for-profit and non-profit microinsurers.

cluded according to the three size classes of small, medium, and large; the large category 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, e.g., life, health, credit-life, and multi-product; multi-product is the 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 the reference category and is omitted from the regression, (8) time: dummy variables for each year from 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 must be interpreted as increasing inefficiency and hence decreasing efficiency and vice versa. For more details on the conditional mean analysis, the reader is referred to Appendix 2.

Table 5: Results of the conditional mean analysis

	Technical efficiency (without social output indicator)			Technical efficiency (with social output indicator)			Cost efficiency (without social output indicator)		
	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 a 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 accords with our observations from the efficiency analysis where we found significantly higher values in the case of for-profit microinsurers. It also supports the observation that the gap between non-profit and for-profit microinsurers becomes smaller when we include the social output indicator in the model. This is reflected by a nonsignificant regression coefficient for the profit orientation variable with the social output 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 having a lower ratio of equity capital to debt capital.

The negative coefficients of the size variable small show that small microinsurers are more efficient in terms of technology as well as costs than are medium and large insurers, which are the reference category. This is an interesting result and reveals how very different microinsurance is from regular insurance markets since most studies on efficiency in the insurance industry find higher efficiency values for larger firms (see Eling and Luhnen, 2009a). The age of the microinsurance program has a negative impact on technical efficiency. Particularly for the younger programs in our panel, we find 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 due to significant donations or government subsidies received during the start-up phase of a program. However, our analysis can provide only a very preliminary indication of these efficiency effects. A larger dataset with a substantially higher number of both young and experienced microinsurance schemes would make it more feasible to study the efficiency of microinsurers at various stages of development.

We also considered the range of products supplied by different microinsurers. We can conclude from the regression analysis that credit-life products are being provided the most efficiently in terms of technology and costs. This is not surprising since these simple products are mostly sold by microfinance institutions as a 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).

Also of interest is the influence of contract design (group policies vs. individual policies) on performance. Here we find that selling group policies has a positive impact on technical efficiency, which is in line with some of the first work on microinsurance products, which finds lower underwriting and screening costs for group-based contracts as well as reduced information asymmetries (see Roth, McCord, and Liber, 2007; Churchill, 2006).

The region variables (Africa, Asia) paint an interesting picture, with Africa and Asia having a positive effect on technical efficiency. This is in line with the SFA and DEA, which showed, on average, lower efficiency scores for microinsurers in Latin America. The time variables (2005, 2006, 2007, and 2008) are mostly positive, but not significant, for technical efficiency and mostly negative, but again not always significant, for cost efficiency.

Analysis of shadow prices and slack variables within DEA

DEA provides information on shadow prices and slack variables (slacks). To illustrate their potential use for managerial decision making, Table 6 displays detailed results for the least technically efficient microinsurance scheme in each year of our panel as an example.[17]

Table 6: DEA optimization weights and slack variables

Year	DEA technical efficiency	Weights					Slacks				
		Input 1 (labor)	*Input 2 (debt)*	*Input 3 (equity)*	*Output 1 (benefits)*	*Output 2 (investm.)*	*Input 1 (labor)*	*Input 2 (debt)*	*Input 3 (equity)*	*Output 1 (benefits)*	*Output 2 (investm.)*
2004	0.11	0.0E+00	5.6E-07	1.2E-07	3.5E-06	2.3E-06	25	0	0	0	0
2005	0.28	0.0E+00	4.5E-07	1.4E-07	7.7E-06	0.0E+00	78	0	0	0	581,165
2006	0.06	0.0E+00	3.9E-07	6.0E-08	5.9E-06	6.6E-07	6	0	0	0	0
2007	0.08	0.0E+00	0.0E+00	4.0E-07	3.4E-06	0.0E+00	9	1	0	0	93,731
2008	0.00	2.2E-03	0.0E+00	0.0E+00	1.7E-03	9.9E-01	0	8	26,758	0	0

From Table 6 we can derive explicit management goals that will affect the microinsurer's performance. We first consider the optimization weights obtained from the DEA, which are also referred to as shadow prices. Due to restrictions made in formulating the optimization problem (see A6 in Appendix 2), we find small values for the input and output weights. These

[17] It is especially worth studying microinsurers with low efficiency estimates since they have the highest potential for improvement and as such provide results useful for highlighting the managerial capabilities of shadow prices and slack variables.

weights, however, show the extent to which individual inputs and outputs contribute to the microinsurer's performance. In other words, the weights illustrate by how much the efficiency score increases when the respective input (output) is decreased (increased) by one unit. Considering the microinsurer in 2004 as an example, a decrease of input 2 (debt capital) by one unit would, ceteris paribus, increase the level of efficiency by 5.6E-07, while a decrease in input 3 (equity capital) by one unit would only increase efficiency by 1.2E-07. An increase in output 1 (benefits + additions to reserves) by one unit increases efficiency by 3.5E-06, while the same increase in output 2 (investments) only leads to an increase of 2.3E-06. It might also be relevant for management to know that a decrease in input 1 (labor) will not affect the level of efficiency, since the shadow price is zero. For this microinsurer, then, the best course of action toward increasing efficiency might be to focus on decreasing input 2 and increasing output 2. It is, however, important to emphasize that the shadow prices are valid for only relatively small changes in inputs and outputs and that bigger changes require careful monitoring and calculation of the new slack variables after implementation.

Management may also be very interested in cross-effects caused by altering single inputs and outputs and these can be discovered by calculating (1) the marginal rate of substitution, (2) the marginal productivity, and (3) the marginal rate of transformation. Taking again the microinsurer in 2004 as an example (see Table 6), we find a significant cross-effect between input 2 (debt) and input 3 (equity) with a marginal rate of substitution of 4.67 (5.6E-07/1.2E-07), 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 in order to reach the same level of efficiency. There are no other inherent cross-effects for inputs. Marginal productivity values determine a positive but low effect of an increase in debt and equity capital on both outputs (<25%), i.e., output 1 (benefits + additions to reserves) and output 2 (investments). From analyzing the marginal rate of transformation, we conclude that an increase in the level of output

2 (investments) by one unit, ceteris paribus, is accompanied by a decrease in output 1 (benefits + additions to reserves) of 1.52 units (3.5E-06/2.3E-06).

The slack variables provide further information on the relative adjustment of the inputs and outputs and reveal areas of inefficient resource allocation. The concept is directly related to technical efficiency. The efficiency score of an inefficient firm indicates by what proportion all inputs must be equally reduced to realize an efficiency level of one. If a microinsurer exhibits nonzero slacks, an adjustment of the relative proportions of inputs is necessary to realize an efficient utilization of inputs. The inefficiencies associated with nonzero slacks are thus referred to as "mix inefficiencies" and reveal where resources are spent inefficiently (see Cooper, Seiford, and Tone, 2007). On the input side, nonzero slacks can be interpreted as input excess, meaning that the last unit in the amount of the slack of the respective input spent for production had no effect on efficiency. On the output side, nonzero slacks are referred to as output shortfall, indicating the minimum amount of the respective output variable that is necessary to realize an effect on performance. There is hence a direct relationship between the slack variables and the shadow prices; this is known as the complementary slackness theorem, which states that in every optimal solution the pairs (input weight i, input slack i, with i=1, 2, 3) and (output weight j, output slack j, with j=1, 2) are complementary, i.e., at least one element of the respective pair is equal to 0 (see Nering and Tucker, 1993).

Continuing with our example, the management implication for the microinsurer in 2004 is thus to decrease inputs 2 (debt) and 3 (equity) in equal proportions and input 1 (labor) by a further 25 units. Given this microinsurer's technical efficiency score of 0.11, the reduction in inputs 2 (debt) and 3 (equity) necessary to become wholly efficient would be 89%. The microinsurer in 2005 also displays an output shortfall for output 2 (581,165), showing that this level of investment has no effect on efficiency. The level of investment needs to be increased by at least 581,165 units to become wholly efficient.

Comparison of frontier efficiency methodology and key performance indicators

During the time we were conducting this research, the microinsurance practitioners from the *Performance Indicators Working Group* asked us to compare our efficiency results with the existing key performance indicators since this is a research area of special interest to microinsurance practitioners. Are microinsurers 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.[18]

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

Note: 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 comparison of the key performance indicators shows a very distinct ranking of the microinsurers and no clear pattern of either excellence or its opposite. The rank correlations between DEA, SFA, and the key performance indicators are relatively low, too; all are below 0.40 and in some cases even negative, indicating that insurers that are good in one category, perform poorly in the other. There are hardly any microinsurers in our panel that receive a consistent ranking using the key performance indicators, which again illustrates the high level of heterogeneity in this sample. Most of the programs are non-profit organizations with a strong customer orientation; financial performance is not their primary goal. For example, looking at the net income ratio, which is usually used as an indication of profitability, only 9% of the data

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

points in our panel show acceptable results for this ratio (according to Wipf and Garand (2008) an acceptable net income ratio would be in the range of 0-10%).

Even with constant monitoring, managing a microinsurer based exclusively on key performance indicators is problematic since choosing an appropriate set of performance indicators, not to mention trying to define what is good performance and what is not, is very difficult and any such choices made will necessarily involve a tradeoff between specific financial and social goals. In this context, frontier efficiency techniques could be very useful in supporting management decisions and providing unambiguous guidance for increasing the performance of a microinsurer. For example, with DEA, the tradeoff between different inputs and outputs is the result of an optimization and benchmarking against other microinsurers (and as such objective), whereas relying on more traditional performance indicators necessarily requires a subjective choice and weighting of different indicators. The DEA results also provide guidance on which inputs (outputs) to decrease (increase) in order to enhance efficiency, information not directly obtainable from key performance indicators. We thus believe that frontier efficiency techniques can be a valuable addition to the existing set of performance indicators.

5. Conclusions

This is the first paper to use frontier efficiency analysis for measuring the performance of microinsurance programs. Early research on performance measurement in microinsurance focuses on traditional financial ratio analysis; however, we argue that frontier efficiency provides a new, powerful performance measurement technique and a valuable addition to the existing performance measures in the field. Efficiency techniques might be helpful in overcoming the ambiguities of traditional financial ratios, as they summarize different characteristics of the firm in a single and easy to interpret performance indicator. Furthermore, the techniques can accommodate the important social function that many microinsurers have.

In the empirical section of this paper we illustrated efficiency estimates for 21 microinsurance programs in Africa, Asia, and Latin America for the years 2004 to 2008 based on data provided by the *Microinsurance Network*. The empirical findings reveal significant potential for improvement with regard to productivity and efficiency for many programs.[19] The results also illustrate the diversity of different microinsurance providers in terms of performance and emphasize the relevance of benchmarking in identifying "best practices" across different microinsurance providers, countries, and institutional forms. We argue that the use of SFA models is currently superior to the application of DEA for microinsurers due to data availability and quality. SFA best incorporates the shortcomings of the data in the microinsurance industry. However, DEA models, especially their very specific utility for management decision making, will become increasingly more applicable as the industry develops.

Several limitations should 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 one of the very few dataset that have been collected on microinsurers to date, it is still relatively small. Furthermore, the analyzed microinsurers are in different stages of development, i.e., some are still in the start-up phase while others have been up and running for several years. These differences are reflected, e.g., in the low amount of output provided by some schemes, which biases their efficiency scores. Nevertheless, we argue that the efficiency scores can be useful for benchmarking if these limitations are kept mind. We thus interpret the empirical section of this paper as a first step along the path of applying frontier efficiency to microinsurance.

A natural next step 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 both the start-up and experienced phases could provide more insight into the efficiency of microinsurers at different stages of the life cycle. A larger dataset might also be used to conduct a cross-frontier analysis of non-profit and for-profit microinsurers to draw

[19] As mentioned, Eling and Luhnen (2009b), in an analysis of commercial insurers, found 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.

conclusions on the potential use of different production technologies. Once a broader database is available, the efficiency values could be used to derive management advice and recommendations as to optimal inputs and outputs. As we show in our analysis of shadow prices and slack variables, such an analysis is already feasible with the extant dataset, but given the relatively small sample we think that future research is necessary to strengthen and confirm these managerial implications.

Another promising avenue for future research is 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 industry are necessary to develop a theoretically sound and acceptable set of input and output indicators.

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 reporting 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 inputs and multiple outputs (see, e.g., Coelli and Perelman, 1996; Coelli, 2005). Our rationale for choosing this specific functional form is its broad acceptance in *stochastic frontier analysis* in insurance (see, e.g., Cummins and Weiss, 2000). 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 in our model to account for technological change over time. A random error term v_{it} is included in Equation (A1), which is assumed to be normally distributed. We account for inefficiency using the term u_{it}, which is assumed to follow a truncated normal distribution. In a one-stage approach (conditional mean approach), firm-specific variables are employed to model the mean m_{it} of u_{it}, which as such directly manipulates the shape of the efficient frontier (see, e.g., Battese and Coelli, 1995; Greene and Segal, 2004; Eling and Luhnen, 2009b). The regression model for m_{it} is:

$$m_{it} = \delta_0 + \delta_1 a_{it} + \delta_2 b_{it} + \delta_\rho c_{i\rho} + \delta_5 d_{it} + \delta_6 f_{it} + \delta_\theta g_{i\theta} + \delta_\gamma q_{i\gamma} + \delta_\delta w_{i\delta}, \tag{A2}$$

where a_{it} is a dummy variable reflecting profit orientation (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), and $c_{i\rho}$ are two dummy variables with ρ=1,2 reflecting the size categories small and medium. The size category large is excluded to avoid singularity and serves as the reference category. d_{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 contract design 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. $q_{i\gamma}$ are region dummy variables with γ =1, 2 representing Africa and Asia; Latin America is the reference category. $w_{i\delta}$ are four time dummy variables with δ=2005,…, 2008; 2004 is excluded.

To calculate cost efficiency, we specify a translog stochastic cost function:

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

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 (p_{Ki} in this case) and dividing all input prices and the dependent variable (C_{it}) by this input price. The remaining model specifications that include the distributional assumptions on v_{it} and u_{it} are specified analogous to the technical efficiency SFA model.

Data envelopment analysis

Technical and cost efficiency in DEA is measured assuming VRS (see, e.g., Banker, Charnes, and Cooper, 1984; Cooper, Seiford, and Tone, 2007). Technical efficiency e_i of an insurer i is estimated by:

$$e_i = (s^T y_i - u_0)/r^T x_i \,, \tag{A4}$$

where y_i is a vector with outputs y_{ji}, $j = 1,\ldots, z$. x_i is a vector with inputs x_{ki}, $k = 1,\ldots, w$. s^T is the transposed vector of output weights and r^T the transposed vector of input weights. u_o accounts for VRS and may be positive, negative, or zero. All y_i and x_i are assumed to be positive. We obtain optimal input and output weights for the maximization of efficiency by solving the following optimization problem for each insurer i:

$$\begin{aligned} & \max_{\mathrm{s,r,u_0}} \; e_i = (s^T y_i - u_0)/r^T x_i \,, \\ \text{subject to} \quad & (s^T y_\tau - u_0)/r^T x_\tau \leq 1 \; (\tau = 1, \ldots, n), \\ & s_{ji} \geq 0, r_{ki} \geq 0 \;\forall\, j = 1, \ldots, z, k = 1, \ldots, w,\; u_0 \text{ free in sign.} \end{aligned} \tag{A5}$$

The first condition of the fractional program (A5) limits the ratio e_i of weighted outputs to weighted inputs to a maximum of 1. The corresponding linear program is easily obtained by imposing the constraint $r^T x_i = 1$, implying that the weighted sum of inputs is standardized:

$$\begin{aligned} & \max_{\mathrm{s,r,u_0}} \; e_i = s^T y_i - u_0 \,, \\ \text{subject to} \quad & r^T x_i = 1 \,, \\ & s^T y_\tau - r^T x_\tau - u_0 \leq 0 \; (\tau = 1, \ldots, n), \\ & s_{ji} \geq 0, r_{ki} \geq 0 \;\forall\, j = 1, \ldots, z, k = 1, \ldots, w, u_0 \text{ free in sign.} \end{aligned} \tag{A6}$$

References

Aigner, D. J., C. A. K. Lovell, and P. Schmidt, 1977, Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics*, 6: 21-37.

Aly, H. Y., R. Grabowski, C. Pasurka, and N. Rangan, 1990, Technical, Scale, and Allocative Efficiencies in U.S. Banking: An Empirical Investigation, *Review of Economics and Statistics*, 72(2): 211-218.

Banker, R. D., A. Charnes, and W. W. Cooper, 1984, Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science*, 30(9): 1078-1092.

Battese, G. E., and T. J. Coelli, 1995, A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical Economics*, 20: 325-332.

Berger, A. N., J. D. Cummins, M. A. Weiss, and H. Zi, 2000, Conglomeration Versus Strategic Focus: Evidence from the Insurance Industry, *Journal of Financial Intermediation*, 9(4): 323-362.

Berger, A. N., and D. B. Humphrey, 1997, Efficiency of Financial Institutions: International Survey and Directions for Future Research, *European Journal of Operational Research*, 98(2): 175-212.

Brau, J. C., C. Merrill, and K. B. Staking, 2009, Insurance Theory and Challenges Facing the Development of Microinsurance Markets, Working Paper, Brigham Young University and Colorado State University.

Caves, D. W., L. R. Christensen, and M. W. Tretheway, 1980, Flexible Cost Functions for Multiproduct Firms, *Review of Economics and Statistics*, 62(3): 477-482.

Charnes, A., W. Cooper, and E. Rhodes, 1978, Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research*, 2(6): 429-444.

Choi, P. B., and M. A. Weiss, 2005, An Empirical Investigation of Market Structure, Efficiency, and Performance in Property-Liability Insurance, *Journal of Risk and Insurance*, 72(4): 635-673.

Christensen, L. R., D. W. Jorgenson, and L. J. Lau, 1973, Transcendental Logarithmic Production Frontiers, *Review of Economics and Statistics*, 55(1): 28-45.

Churchill, C., 2006, *Protecting the Poor: A Microinsurance Compendium*. Geneva: International Labour Organization (ILO).

Churchill, C., 2007, Insuring the Low-Income Market: Challenges and Solutions for Commercial Insurers, *Geneva Papers on Risk and Insurance*, 32: 401-412.

Coelli, T. J., 1998, A Multi-Stage Methodology for the Solution of Orientated DEA Models, *Operations Research Letters*, 23: 143-149.

Coelli, T. J., 2005, *An Introduction to Efficiency and Productivity Analysis* (Boston: Kluwer Academic Publishers).

Coelli, T. J., and S. Perelman, 1996, Efficiency Measurement, Multiple Output Technologies and Distance Functions: With Application to European Railways, CREPP Discussion Paper 96/05, University of Liege.

Cooper, W. W., L. M. Seiford, and K. Tone, 2007, *Data Envelopment Analysis*, 2nd edition (New York: Springer).

Cummins, J. D., M. Rubio-Misas, and H. Zi, 2004, The Effect of Organizational Structure on Efficiency: Evidence from the Spanish Insurance Industry, *Journal of Banking and Finance*, 28(12): 3113-3150.

Cummins, J. D., and M. A. Weiss, 2000, Analyzing Firm Performance in the Insurance Industry Using Frontier Efficiency and Productivity Methods, in: G. Dionne, ed., *Handbook of Insurance* (Boston: Kluwer Academic Publishers), pp. 767-830.

Cummins, J. D., M. A. Weiss, and H. Zi, 1999, Organizational Form and Efficiency: The Coexistence of Stock and Mutual Property-Liability Insurers, *Management Science*, 45(9): 1254-1269.

Cummins, J. D., and H. Zi, 1998, Comparison of Frontier Efficiency Methods: An Application to the U.S. Life Insurance Industry, *Journal of Productivity Analysis*, 10(2): 131-152.

Diacon, S. R., K. Starkey, and C. O'Brien, 2002, Size and Efficiency in European Long-term Insurance Companies: An International Comparison, *Geneva Papers on Risk and Insurance*, 27(3): 444-466.

Eling, M., and M. Luhnen, 2009a, Frontier Efficiency Methodologies to Measure Performance in the Insurance Industry: Overview, Systematization, and Recent Developments, forthcoming in: *Geneva Papers on Risk and Insurance*.

Eling, M., and M. Luhnen, 2009b, Efficiency in the International Insurance Industry: A Cross-Country Comparison, forthcoming in: *Journal of Banking and Finance*.

Ennsfellner, K. C., D. Lewis, and R. I. Anderson, 2004, Production Efficiency in the Austrian Insurance Industry: A Bayesian Examination, *Journal of Risk and Insurance*, 71(1): 135-159.

Farrell, M. J., 1957, The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society A*, 120: 253-281.

Fenn, P., D. Vencappa, S. Diacon, P. Klumpes, and C. O'Brien, 2008, Market Structure and the Efficiency of European Insurance Companies: A Stochastic Frontier Analysis, *Journal of Banking and Finance*, 32(1): 86-100.

Gallant, A. R., 1982, Unbiased Determination of Production Technologies, *Journal of Econometrics*, 20(2): 285-323.

Gong, B. H., and R. Sickles, 1992, Finite Sample Evidence on the Performance of Stochastic Frontiers and Data Envelopment Analysis Using Panel Data, *Journal of Econometrics*, 51: 259-284.

Grace, M. F., and S. G. Timme, 1992, An Examination of Cost Economies in the United States Life Insurance Industry, *Journal of Risk and Insurance*, 59(1): 72-103.

Greene, W. H., and D. Segal, 2004, Profitability and Efficiency in the U.S. Life Insurance Industry, *Journal of Productivity Analysis*, 21(3): 229-247.

Gutiérrez-Nieto, B., C. Serrano-Cinca, and C. Mar Molinero, 2009, Social Efficiency in Microfinance Institutions, *Journal of the Operational Research Society*, 60(1): 104-119.

Hjalmarsson, L., S. C. Kumbhakar, and A. Heshmati, 1996, DEA, DFA and SFA: A Comparison, *Journal of Productivity Analysis*, 7: 303-327.

Kumbhakar, S. C., and C. A. K. Lovell, 2000, *Stochastic Frontier Analysis* (Cambridge: Cambridge University Press).

Levin, T., and D. Reinhard, 2007, Microinsurance Aspects in Agriculture, Discussion Paper, Munich Re Foundation and CGAP Working Group on Microinsurance.

Mayers, D., and C. W. Smith, 1988, Ownership Structure Across Lines of Property-Casualty Insurance, *Journal of Law and Economics*, 31(2): 351-378.

McCord, M. J., 2009, Microinsurance: Providing Profitable Risk Management Possibilities for the Low-Income Market, in: I. Matthäus-Maier and J. D. von Pischke, eds., *New Partnerships for Innovation in Microfinance* (Berlin: Springer), pp. 279-298.

Meeusen, W., and J. van den Broeck, 1977, Efficiency Estimation from Cobb-Douglas Production Functions with Composed Errors, *International Economic Review*, 8: 435-444.

Mester, L. J., 1991, Agency Costs Among Savings and Loans, *Journal of Financial Intermediation*, 1(3): 257-278.

Morduch, J., 2006, Microinsurance: The Next Revolution? in: A. V. Banerjee, R. Bénabou, D. Mookherjee, eds., *Understanding Poverty* (New York: Oxford University Press), pp. 337-355.

Morrison, C. J., and E. R. Berndt, 1982, Short-Run Labor Productivity in a Dynamic Model, *Journal of Econometrics*, 16(3): 339-365.

Nering, E. D., and A. W. Tucker, 1993, *Linear Programs and Related Problems* (London: Academic Press).

Pastor, J. T., 1996, Translation Invariance in Data Envelopment Analysis: A Generalization, *Annals of Operations Research*, 66: 93-102.

Pulley, L. B., and Y. Braunstein, 1992, A Composite Cost Function for Multiproduct Firms with an Application to Economies of Scope in Banking, *Review of Economics and Statistics*, 74(2): 221-230.

Roth, J., M. J. McCord, and D. Liber, 2007, The Landscape of Microinsurance in the World's 100 Poorest Countries, Report of the Microinsurance Centre, Appleton.

Shephard, R. W., 1970, *Theory of Cost and Production Function* (Princeton: Princeton University Press).

Simar, L., and P. W. Wilson, 1998, Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models, *Management Science*, 44(11): 49-61.

Stanton, K. R., 2002, Trends in Relationship Lending and Factors Affecting Relationship Lending Efficiency, *Journal of Banking and Finance*, 26: 127-152.

Welch, B. A., 1947, The Generalization of "Student's" Problem when Several Different Population Variances are Involved, *Biometrika*, 34: 28-35.

Wilcoxon, F., 1945, Individual Comparisons by Ranking Methods, *Biometrics Bulletin*, 1: 80-83.

Wilson, P. W., 1995, Detecting Influential Observations in Data Envelopment Analysis, *Journal of Productivity Analysis*, 6: 27-45.

Wipf, J., and D. Garand, 2008, Performance Indicators for Microinsurance: A Handbook for Microinsurance Practitioners. Luxembourg: Appui au Développement Autonome (ADA).

Yuengert, A. M., 1993, The Measurement of Efficiency in Life Insurance: Estimates of a Mixed Normal-Gamma Error Model, *Journal of Banking and Finance*, 17(2-3): 483-496.

Zhang, Y., and R. Bartles, 1998, The Effect of Sample Size on the Mean Efficiency in DEA with an Application to Electricity Distribution in Australia, Sweden and New Zealand, *Journal of Productivity Analysis*, 9(3): 187-204.