Chapter 1
The Value of Information in Index Insurance for Farmers in Africa

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Abstract Index insurance is a relatively new approach for providing climate risk protection to low-income farmers in developing countries. Because this insurance is implemented in data-poor environments, information constraints and uncertainty substantially affect the products. Since insurance is a tool that can be used to exchange uncertainty in the market, the level of information available directly alters prices, with insurance protection for climate risk and insurance protection for information uncertainties about climate risks both being components of the final price. Using data, methodologies, and contracts for index insurance applications in Africa, the chapter presents this concrete component of the value of information by quantifying the value of improved data in lowering insurance prices. It provides a brief overview of index insurance in developing countries and discusses the value of remote sensing in informing the index and the role of climate trends.

Keywords Agricultural insurance • Index insurance • Value at risk • Value of information • Rainfall simulation

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1.1 Introduction

Smallholder farmers in Africa are severely hurt by droughts and other climate-related events. Most of the literature about the value of information in agricultural production focuses on the production benefits that can be obtained when farmers use the information to alter their behavior to be more cautious in years that are likely to be bad, and more aggressive in years that are not likely to be bad (see literature review by Meza et al. 2008). In the past, smallholder farmers in Africa have had essentially no access to insurance. New types of insurance, such as index insurance, are becoming available to these farmers. Recent literature extends the work on the value of information in production decisions to include important features of insurance (Carriquiry and Osgood 2008; Osgood et al. 2008; Cabrera et al. 2006). The value of information gains an additional and very concrete component, the effect of information on the cost of insurance.

We describe a very different component in the value of information driven by the availability of insurance, the value of information through reducing the cost of insurance. We present this component through pricing exercises of index insurance projects that we have been involved with. For the discussion we use the actual data, software, and formulas used in the insurance programs to explicitly quantify this component of the value of information.

Traditional loss-based indemnity insurance has been extremely difficult to implement in most of the world, leaving most farmers without coverage. There are several challenges with traditional insurance that have prevented it from being workable in many contexts. Traditional agricultural insurance requires a large amount of information on the probability of losses in order to be applied. In many situations, this information is not available. It requires that an adjuster visit the field where a loss is reported, which becomes prohibitively expensive for farmers with small plots in remote locations who have relatively small amounts insured. Loss-based insurance is also fraught with perverse incentives leading to moral hazard and adverse selection. If a farmer receives a payout when there are crop losses, the farmer has an incentive to let crops die. Similarly, farmers who are more likely to have losses are more likely to purchase insurance. Since insurance companies never have complete information about farmers and their actions, these problems often undermine the viability of the insurance. The value of information differences between strategically acting farmers and insurers is addressed in game theory work on asymmetric information, including specific work on agricultural insurance (Luo et al. 1994; Skees et al. 1999).

Index insurance is a relatively new approach intended to address those problems so that insurance may be made more broadly available. For this type of insurance, the payout is based on measurements of an index that is likely to lead to crop loss. Most commonly, this index is a function of cumulative rainfall during critical parts of the agricultural production season, with payouts triggered during droughts, when the cumulative rainfall falls below a predetermined threshold. Using this strategy, historical rainfall data can be used to determine the probability of a payout. Although this information is very often limited, it is typically much less limited than information on yield losses themselves. In addition, payouts can be made based on the weather measurement without requiring an adjuster to incur the cost of visiting each field. The perverse incentives are addressed because the payout is not based on the farmer's behavior. There is no benefit to the farmer through the strategic reduction in yields.

Those benefits come with a substantial cost. Because the insurance provides payments on the rainfall as opposed to the loss, it cannot totally protect a farmer from loss. Farmers may have losses due to pests, flooding, wind, or even differences in rainfall between the measured amount and what the farmer experiences on her field. The disconnect between payouts and losses is called basis risk, and it is a central theme in the index insurance literature. Because of basis risk, index insurance does not function well as comprehensive insurance protection. Instead, it is better suited for incrementally reducing the risk that a farmer faces in the most cost-effective manner. Policy documents that describe index insurance issues include (Hellmuth et al. 2009; Hazell et al. 2010), and (Barrett et al. 2007) provide a review and synthesis of the academic index insurance literature.

For this discussion, we will look at two recent index insurance pilot projects in Africa in which we have participated. One is the second-year (2006) implementation of index insurance for groundnut farmers in Malawi, led by the World Bank ARMT (formerly CRMG), and the other is the launch year (2009) of the Horn of Africa Risk Transfer for Adaptation (HARITA) index insurance project in Adi Ha Ethiopia, led by Oxfam America. Throughout this work, we will draw from reports and policy documents that we have developed as we have assisted in the design and pricing of these products (Osgood et al. 2007; Chen et al. 2010; Dinku et al. 2009; Hellmuth et al. 2009).

1.2 Value of Information in Insurance Price

The cost of insurance is driven by the expense of the financing necessary to ensure payouts, as estimated by the probabilities of payout events. There are two components to the price. The first is simply the expected payout. The insurance premium must be sufficient to cover the average amount of money being paid out. In addition to the average payout, the insurance company must maintain sufficient capital on hand to cover extreme payouts. Insurance companies will choose (or be required by regulations) to keep sufficient liquidity to be able to pay for the largest event expected with a reasonable frequency. Often, this frequency is set to every 50 or 100 years, which is equivalent to holding enough money to cover the 98th or 99th percentile event.

Commonly, this money is borrowed from the insurance company shareholders, so the interest paid is the return on the shareholders' investment in the company. It is money that is held specifically to manage risk, as opposed to be put into investments (such as agricultural inputs) that would provide returns through production.

This is a fundamental cost of risk management. An individual farmer faces a similar choice whether he purchases insurance, maintains savings for a rainy day (in our case, a drought), or borrows to cover losses after the drought has occurred. It is the basic trade-off of how much money to keep liquid in case there is drought versus the money that is put at risk for higher returns, invested in inputs to a productive activity that may experience a loss.

From a risk financing perspective, the primary difference between the insurance company and the farmer is that the insurance company can build a large portfolio of unrelated (or even negatively correlated) risks, such that the amount of money that must be held to cover the farmer's 99th percentile event is less than the farmer would have to reserve. Premiums received each year by the insurance company can also be used as payouts that year, which reduces the amount of money that must be borrowed.

Information quality affects the fundamental cost of insurance. The amount of money to be reserved for risk protection is driven not only by the risks that are faced, but also by the amount of information about the risks that are faced. If the size of the 99th percentile event is not well known, more money must be held to cover a conservative estimate of 99th percentile events that might occur. Even if the average payout is known with certainty, the premium must reflect the range of average payouts that may occur. Otherwise, the insurance company cannot responsibly commit to honoring the insurance contract. As information improves about the probabilities of payouts, that information can reduce the cost of insurance, so that overly conservative levels of reserves and premiums are not required.

Insurance costs have additional components, including the administrative costs of providing insurance and the delivery costs of registering clients and delivering their payouts. Because those components do not reflect information issues and were not explicitly included in the calculation of the actual Malawi insurance cost from our numerical example, we will ignore them here.[1]

Often the cost of insurance is presented as the "actuarially fair" component, which is the simplest accounting calculation of average payouts plus "loading," all of the risk financing, uncertainty, and other costs. The actuarially fair price is "free" insurance—that is, on average, all the money paid to the insurance company is returned to the client. Loading is often expressed in terms of its percentage relative to the actuarially fair price. Insurance is also commonly presented in terms of percentage of maximum liability. This is the size of the premium in relation to the maximum possible payout size. Although this is a convenient indicator for calculating actual premium values for different maximum liabilities, it provides no information about the value that the client is receiving because it does not reflect the frequency or size of actual payouts and can be strategically manipulated to give the appearance of insurance value.[2]

A standard equation for premium (p) calculations is $p = \mathrm{E[Payout]} + r(\mathrm{VaR} - \mathrm{E[Payout]})$ (Osgood et al. 2007), where r is the effective rate of interest paid on the risk reserve funds. E[Payout] is the size of the average payout (including zero payout years) and VaR is the value at risk, the size of the 99th percentile event.

[1] For the Malawi premium calculation, the interest rate on the money held to be able to pay for the 99th percentile event was increased slightly to reflect administrative and delivery costs.

[2] For example, if a \$10 premium is paid for a policy with a maximum liability of \$100, the percentage price is 10 % for a contract that provides (full) payouts 10 % of the time (an expected payout of \$10, or zero loading) as well as for a contract that provides (full) payouts 1 % of the time (an expected payout of \$1, or a loading of 900 %).

Typically, insurance price calculations are proprietary, as they reflect the risk handling specifics of the insurance company. In addition, they are commonly affected by the cost of reinsurance negotiations between the insurance company and reinsurer.[3]

The Malawi transaction is an interesting case study to illustrate value of information issues in insurance. Because it was the first index insurance product of its type in Africa (and one of the first in the world), a great deal of effort was taken to make sure that processes were simple, open, and transparent so that the important features of insurance would be clear to participants and observers. In the Malawi example, smallholder farmers in several villages purchased several thousand contracts for insurance costing approximately $2 to insure microloans for groundnut and maize production. Many of these farmers had no previous access to credit, being mostly outside the cash economy. As with most insurance, for these types of projects, it is important that the premiums reflect the true risk costs as accurately as possible. Otherwise farmers will take actions that are too risky or too conservative when they respond to the insurance price incentives (For more information on the project, see [Osgood et al. 2007; Hellmuth et al. 2009; Bryla and Syroka 2009]).

Because the Malawi insurance product was provided jointly by a consortium of insurers and no reinsurance was used, premium calculations were not proprietary negotiations between insurance interests. Instead, the cost of the premiums was determined by the project partners using publicly circulated formulas. The price was calculated as $p = \mathrm{E[Payout]} + 0.06\ (\mathrm{VaR} - \mathrm{E[Payout]})$. Because the Malawi data set had approximately 50 years of rainfall data, the 98th percentile was used to estimate the VaR.[4]

For the 2006 Malawi transaction, because the historical data set was relatively long, the cost of uncertainty about the payout probabilities was not charged to farmers. The price was calculated by calculating what payouts would have been if the index had been applied to the historical rainfall data, a process often referred to as historical burn pricing. This was selected for the initial years of the pilot because it allowed extremely transparent pricing. The intent was that pricing would become more sophisticated as project partners gained familiarity with the concepts involved.

One concern for future pricing was that it responsibly account for uncertainty in calculations, particularly as sites with much smaller data sets were included. In addition, idiosyncratic prices are generated from using historical burn pricing based on the single historical realization of rainfall, since much of the price was

[3] Reinsurance is purchased by insurance companies from global reinsurance companies, which handle very large events that would overwhelm an individual insurance company. Reinsurance companies address these risks through a global portfolio of varied insurance company clients and other investments.

[4] Following the pricing process, partners decided to use the largest payout year that would have occurred using the approximately 50 years of rainfall data to estimate the 98th percentile. This choice was made to make the explanation of the premium simpler and more transparent for early stages of the project; it did not meaningfully change the cash premiums paid by farmers.

determined by the single largest event in 50 years. In essence, pricing based solely on historical data assumes that any amount of rainfall not exactly observed in the past has a zero probability of occurring. A more robust process would estimate distributions of the index from a large number of realizations.[5]

The World Bank therefore commissioned the International Research Institute for Climate and Society (IRI) to develop rainfall models that could realistically generate large numbers of synthetic 50-year time series that could be combined to estimate an appropriate insurance price. This rainfall model is designed to reflect the uncertainty in the probability of rainfall so as to determine a responsible level for reserves and premiums. Because this analysis is less transparent than historical burn calculations and requires insurance partners to be familiar with the assumptions and weaknesses of the models, it was implemented in the form of an educational software tool. It was packaged along with the other analysis software in the online Weather Index Insurance Educational Tool (WIIET, http://iri.columbia.edu/WIIET) so that implementing groups would have full access to the contract design and pricing analysis tools, and capacity could be built for local design and pricing in these types of projects. We use that software for our illustrative example of the value of information in insurance.

Initial pilot sites were selected based on the availability of data. However, for scaling of the project, typical sites must be considered even if they have fewer data. When correctly including the value of information in the premium, many sites with fewer data may have premiums that are substantially more expensive. However, if these premiums are still workable, then the insurance can still be a valuable product. In the insurance-loan-input package, the insurance cost was approximately $2, the input cost was approximately $25, and the interest on the loan was around $7. The insurance price included 17.5 % tax on the premium. The value of the crops at the end of the season was typically about three times the cost of the inputs (Osgood et al. 2007).

Many farmers were so severely constrained in their input availability prior to the project that doubling or tripling of yields was reported. For this production system, an increase in the premium from $2 to $4 or even $5 may still lead to a useful product if it unlocks dramatic production gains. In addition, the premium calculations will allow the government to understand where the generation of improved information is worthwhile (e.g., investments in recovering and digitizing manual rain gauge recordings). The key is calculating the correct premium so that the prices reflect the true value of information and appropriate trade-offs can be made.

Tables 1.1 and 1.2 are raw output from the WIIET software, applied using the Malawi 2006 implementation data and parameters for a maize contract in the capital city, Lilongwe. To illustrate the typical information problem, we present the full 44-year data set and compare it with only the last 9 years, reflecting what might be available at a marginal scale-up site. Table 1.1 presents the historical burn output. The historical data were used for the index formula to calculate payouts and

[5] In addition to the importance of addressing purely statistical pricing issues, it is worthwhile to address physically based processes, such as climate change. This is discussed in Sect. 1.3.

Table 1.1 Price calculations on historical data

	1961–2005 data	1996–2005 data
prem.cash.98 %	86.366	84.181
prem.frac.98 %	0.086	0.084
v_at_var.98 %	484.840	410.800
mean.pay	60.932	63.333
var.pay	20268.577	24350.000
max.pay	576.000	470.000
num.years	44.000	9.000
num.pays	11.000	2.000

Table 1.2 Price calculations with modeled rainfall accounting for information quality

	1961–2005 data	1996–2005 data
prem.cash.98 %	132.27	175.20
prem.frac.98 %	0.13	0.18
v_at_var.98 %	702.05	785.23
mean.pay	95.90	136.26
var.pay	33641.46	48750.91
max.pay	1000.00	1000.00
num.years	989.00	999.00
num.pays	360.00	452.00

the pricing equation was applied. In this table, the maximum liability is set to 1,000 (Kwacha) for illustrative reasons.[6] The premium is expressed as a cash value as well as percentage of the maximum liability. The estimate of the 98th percentile payment is presented as the v_at_var.98 %, as well as the mean payout, the payout variance, the maximum payout, the number of years in the data set, and the number of nonzero payouts. It can be seen from the table that the simple historical burn pricing does not reflect information differences between the two data sets. That is, even though we should be less certain about the rainfall process from using only 9 years of data as opposed to 44 years, the historical burn analysis isn't sensitive to the amount of data used to price the contracts, so the resulting contracts are very similar.

Table 1.2 presents WIIET software output using the module that statistically models rainfall. This model is designed to address some of the statistical issues inherent in pricing using only a single series of historical data. It estimates parameters of a statistical model for rainfall based on the observed data, and when the model is used to simulate additional realizations of rainfall, the simulations are sensitive to the amount of data used to fit the model in the first place. In other words, the model and its associated rainfall simulations account for (1) the natural variation in rainfall (which would still be substantial even if we had exact knowledge of

[6] In 2006, 145 Kwacha was worth about $1, and typical maximum liabilities were approximately 4,000 Kwacha, depending on the specific input package insured.

the true data-generating process); and (2) the uncertainty associated with the parameters of the model, which adds extra variability to the simulated realizations.[7]

We stress that estimating the parameters of the rainfall model without measuring the uncertainty of their estimates does not lead to sensible simulations. To appropriately account for the amount of information observed, it is necessary to preserve the uncertainty in the estimation of the statistical rainfall model parameters. As with any statistical inference, when the parameters of the rainfall model are estimated, the estimates are accompanied by standard errors, which reflect how confident we are in the accuracy of our estimates. For a short rainfall time series, the standard errors will most likely be larger, reflecting less information. As the number of years of observed rainfall increases, standard errors will tend to decrease, reflecting the higher accuracy of estimation. The standard errors of the parameters therefore reflect the set of possible models that may be the true process, which nevertheless cannot be determined based on the available information. In the context of index insurance contract prices, we are most concerned with standard errors related to the estimate of the average payout and the 99th percentile of the payout distribution.

In summary, to price contracts that are appropriately sensitive to the amount of observed data on which they are based, one uses the standard errors. In essence, one first draws from the error distributions to generate a set of parameters that could describe the rainfall-generating distribution. Then, one draws from the distribution of rainfall itself. In this way, both the variability of the rainfall and the amount of information about the variability of rainfall are captured.

The statistical rainfall model in the WIIET software performs this process, reflecting both the variability of rainfall and the amount of statistical information in its generated realizations using a Bayesian statistical model (see WIIET user guide, at http://iri.columbia.edu/WIIET). In Table 1.2, the difference in information between the short 1996–2005 data series and the longer 1961–2005 data series is evident in the substantially increased variance as well as the higher estimate of the size of the 98th percentile event. The average payout is also higher because payouts are due to rainfall levels in the lower tail of the distribution, which is influenced by the increases in variance due to model uncertainty. The frequency of payouts also increases because a higher proportion of years may have sufficiently extreme rainfall levels to trigger payouts.

According to the calculations, the premiums would have to increase approximately 30 % to reflect the reduced level of information if only the past 9 years had been available, compared with the full 44-year data set. The value of the additional information in the longer data set was approximately 30 % of the premium. Although this is a substantial increase in cost, increasing premiums from approximately \$2 to \$3, it is relatively small compared with the other costs in the production

[7] The simulation is set to generate the number of realizations that would most closely sum to 1,000 years of total years generated. This size was selected for feasibility of computation on a web server in a classroom environment.

package (totaling a little over $30) and very small compared with the improvements in the value of farmers' production.

It is also interesting to compare the two tables to see how failing to account for the cost of less information can lead to artificially low premium levels. The insurance was priced using the 98th percentile value at risk and provided payouts approximately 25 % of the time. Because of this, one might expect substantial uncertainty about the mean and VaR of the payouts even with the full 44 years of rainfall data. One can see that including the value of information in the premium calculations leads to more than a 50 % increase in the insurance price for the 44-year data set and an approximate doubling of the price for the 9-year dataset. Therefore it is clear that information can be very valuable in this context, having a value roughly equal to the insurance purchased by Malawian farmers in 2006.

Improving the quality of information is not the only method available to reduce the costs of uncertainty. It is often possible to make products that are less vulnerable to uncertainty, reducing its costs. If insurance payouts are limited to a maximum liability that occurs frequently in the historical data set, the existing information may be sufficient to characterize the distributions effectively. If this restricted insurance product is valuable, then the farmer may save a substantial amount of money over the product with infrequent large payouts. For products such as life insurance, it is unlikely that this restriction would be workable. However, for insuring the costs of agricultural inputs and associated loans, it may be that full payments approximately 10–20 % of the time might be useful. This might be particularly true in situations for which the 1- in 100-year event would be a catastrophe so severe that massive government intervention might be more appropriate than having low-income smallholder farmers finance their own disaster relief. These are insights that the Malawi implementation has provided to help improve microinsurance projects.

1.3 Satellite Information in Index Insurance

One project informed by the experience of Malawi is the 2009 HARITA insurance pilot in Ethiopia, in the village of Adi Ha. For this project, the goal was to develop an insurance product that could be easily implemented in the typical data-poor context faced across much of Africa. A central goal of the project was to build a robust and transparent process for installing a new rain gauge and phasing insurance in at that gauge, once the information was sufficient to derive workable premiums. A site was selected for which there was no official historical rainfall measurement available. Instead, a set of informal, short-length (7-year) datasets had been collected by local extension personnel. Official datasets existed, ranging from about 10 years of data to nearly 50, but those were for sites that were dozens of kilometers away and may have had different amounts of rainfall. In addition, given climate change, it was important not only to reflect the statistically based value of information in the products, but also to account for uncertainty in physical processes such as long-term anthropogenic climate change and the decadal climate variations characteristic of the region (Hellmuth et al. 2009). It was therefore valuable to increase the capabilities of the rainfall models to make sure that they reflected these additional uncertainties and trends.[8]

One year prior to the insurance transaction, the project installed a new, automated weather station on the site and began collecting data. To design the insurance contract and determine thresholds and approximate prices, it was necessary to have some historical information. A satellite estimate of rainfall was deemed the best representative source of information for design because the other sources at the site had not been operating long enough to capture years that were known to be droughts, and the official rain gauges from other locations were known to have somewhat different seasonal timing and average amounts of rainfall.

The index structure was simplified to reduce its vulnerability to errors in the satellite information and short data sets. The rainfall level required for maximum payments was set such that at least one full payment would have happened within the past 15 years, and that most payments would be substantial compared with the full payment. The contract details were repeatedly verified by an elected farmer design team for agreement with vulnerable times of the year, for drought years, and for the timing of the drought during a dry year.

Remote sensing was used in the index design. Remotely sensed vegetative greenness measures, such as Advanced Very High Resolution Radiometer Normalized Difference Vegetation Index (available since 1981) were used to verify whether drought years were evident. Regional greenness measures have been used as indexes in other insurance projects, such as the 2007 Millennium Village Project insurance transaction in Kenya and Ethiopia, an International Livestock Research Institute livestock oriented project in Kenya in 2009, and an ongoing U.S. Department of Agriculture Risk Management Agency livestock product. The application of these products is challenging, since the vegetation observed by the satellite is often not the crops but instead surrounding trees and grasses. In addition, many crops can be green even when they produce little grain. Also, variations due to solar angle, dust, different sensors, and satellite angle may be as large as variations due to drought. More modern satellites address some of these problems through additional spectral bands. However, because these improved satellites have limited data sets that do not extend very far back in time,[9] they are used for validation and understanding the level of information that they provide, typically in situations for which the contract holder has a broad range of risk management options to address shortcomings in the remotely sense data. For example, in the Millennium Village Project, the remote sensing index was purchased by the development project itself, rather than by the individual farmers. The strategy was for the project to use the index in responding to farmer development issues during drought years.

[8] This is a nontrivial challenge, and the development of formal models is currently still in process.

[9] See the technical annex to Hellmuth et al. (2009) at http://iri.columbia.edu/publications/id=1008

Another satellite product use in index insurance is remotely sensed estimates of rainfall. This output has been used much less extensively than vegetative greenness, typically to validate ground measurements or to assist in index design. This is most often performed by using satellite measurements of the temperature at the top of clouds to estimate rainfall.[10] This technique is much more effective at determining whether rain fell than estimating the actual amount, and the quality of estimates is limited by the quality of the ground information used for calibrating the rainfall prediction models. These measures often have relatively high levels of error for daily rainfall but are much more accurate when used to determine average rainfall over a month or so.[11] This phenomenon occurs for many data sources, including ground measurements at different locations. Although daily rainfall between two points or data sets may differ, over time, the differences average out. The Adi Ha indexes were therefore designed to be simple sums over a 1–2-month period[12].

The National Oceanic and Atmospheric Administration Climate Prediction Center Africa Rainfall Climatology satellite rainfall estimate was used as a starting point for the design of the index. This data set has a historical record of 15 years. Although limited when compared with a 50-year data set, when used with the simplified index strategy, this record was long enough to observe several major payouts, including full payouts. Therefore, the satellite record provided basic information necessary for index design, provided the costs due to the value of information were not prohibitive.

The benchmark index was developed using the ARC data set and compared with farmers' reports. The index was refined to obtain the best agreement. In addition, the official ground rainfall measurements were ranked by year in terms of rainfall during critical times in the growing season, and the vegetative remote sensing measures were ranked by year in terms of greenness following the critical rainfall periods. Indexes were evaluated in terms of how well the payout years were reflected in the relevant lower quantiles of the other data sets. Typical agreement was between 60 and 70 % of the payout years, with some datasets agreeing completely in annual ranking. For the first years of the Adi Ha implementation, this process was performed manually. More rigorous statistical models to combine the information in the different measures and to quantify the level of uncertainty are currently being developed and evaluated.

The HARITA project followed the Malawi implementation by a couple of years, and the sophistication of the agricultural microinsurance industry had grown.

[10] More modern satellites use additional information, but their coverage is limited and does not extend very far back in time.

[11] See http://iri.columbia.edu/publications/id=1008

[12] There was one additional feature to these simple contracts. In order to assure that rainfall must be relatively uniform over the contract period, each ten day period had a cap, above which additional rainfall was not included in the total. In this way, a two month period of drought can still trigger the index payment, in spite of a single large rainfall event at the end of the contract period.

Reinsurance had become standard for index insurance pilots, and the focus on simplicity in pricing as calculated by project partners had shifted toward more accurate prices negotiated between the insurer and reinsurer, informed by data and technical analysis provided by project partners.

The initial plan was to have the satellite-based index priced for the new automated station that had been installed the prior year, based on the data available during the past year. It was assumed that smallholder farmers would not be comfortable with using satellite observations in an insurance product, and that the satellite product might not have the necessary accuracy compared with a ground measurement.

After its pricing analysis, the reinsurance company said that the price of a product based on the ground observations would be extremely high if there was only a single year to link the two datasets because of the excess costs associated with the very limited information. The company reported that an index triggered directly by the ARC satellite estimates of rainfall would have a much lower price because much more information was available. The farmers and project partners discussed the options and relative prices. It was decided that it would be worthwhile to use the satellite-only product in the first year, with a goal of transitioning toward the ground measurements once sufficient ground information had been gathered. This was the first time that smallholder farmers had been directly offered a product based on satellite estimates of rainfall.

Following the 2009 contract period, it was found that the satellite estimates were within a few percentage points of the rainfall measurements at the new station and were also within a few percentage points of the rainfall measurements made manually by the farmers themselves. One benefit of the remote sensing product is that it reflects the average rainfall over the region covered by the insurance, as opposed to the amount that falls only where the official rain gauge is located. The satellite observations are available for a much wider range of sites than the ground-based measurements. Also, the satellite information was less vulnerable to tampering or missing data.[13] In follow-up surveys, approximately 90 % of the farmers reported being comfortable with the satellite product (Peterson 2009). A decision was made to pursue a strategy in which the satellite estimates of rainfall would be the primary source of data for the index so long as the historical satellite rainfall was validated through ground measurements, farmer interviews, and satellite greenness observations.

1.4 Conclusion

We have illustrated a new, concrete value of information to African farmers through its reduction of index insurance premiums. Using the data and software from index insurance implementations in Malawi and Ethiopia, we have provided illustrations of

[13] Some of the 2009 data from the newly installed rain gauge were lost because of equipment failure.

this particular component to the value of information and have discussed the value of multiple information sources, such as remote sensing, in insurance.

Much future work remains. For projects such as HARITA, it may be that instead of transitioning to contracts using the ground-based measurements, secondary contracts could be purchased. These secondary contracts could provide a payment in the case where the satellite estimates differed from the measurements of a particular station by a predefined amount, protecting the farmer from dramatic errors in the satellite estimates without providing the full cost of insurance on the gauge. To develop this transaction, a statistical model is needed to quantify the probabilities that the satellite and rain gauge would differ, as well as the uncertainty in these probabilities. In addition, these models would be valuable in making sure that rainfall and climate uncertainties reflected in other sources but not in the satellite data could be used to increase the level of uncertainty in the rainfall modeling. Similarly, these models might be able to reduce the uncertainty in a relatively short but high-quality satellite data series using information from lower-quality but longer satellite products or ground measurements, leading to lower premiums.

The HARITA choice to rely primarily on the satellite data has raised several new questions related to the value of information. For example, there are efforts underway to have the Ethiopian national meteorological agency use its proprietary rainfall records to arrive at an ARC-like product with improved calibration and a doubling of the length of the historical record, to 30 years. This project requires funding. If the information allows premiums to be reduced substantially, that may itself show the new information to be sufficiently valuable to fund the work.

The value of information in the premiums also affects decisions about the installation of new rain gauges on the ground. If their contribution to the information can be systematically modeled, new rain gauges can be strategically located to have the highest value, and the number of expensive new stations to be installed (and maintained) can be determined. The costs of digitizing paper-based historical records can also be weighed against the value of their information in insurance premiums, as well as their value for other applications. Advances in remote sensing of vegetation can be used to validate information from other sources and flag the areas where remote sensing of rainfall or ground measurements do not adequately reflect vegetative changes.

Additional issues have arisen in the HARITA project. During the 2009 implementation, about one quarter of the insurance price was due to uncertainty about climate change. The reinsurance company observed a nonsignificant negative trend in the rainfall data for the 15 years. Although the 15-year dataset was not sufficient to determine whether this trend was spurious, real, or the result of a natural decadal process, the reinsurer held some additional resources to be able to provide payouts in case the trend was real. Rainfall models that could incorporate the physical factors connected with types of trends could allow for less conservative reserves (and therefore lower-priced contracts).

Finally, there may be scope for additional work on the strategic use of information. Contract theory work on incentive-compatible reporting and auditing may be of value for index insurance and remote sensing. In locations where long ground-based datasets are available, there are still concerns that people might tamper with the rain gauge to obtain a payout. Remote sensing information might be used to audit ground-based information even if not of the same level of accuracy. With the appropriate mechanism, the remote sensing merely needs to be accurate enough to credibly signal that people are likely to be caught if they tamper with the ground observations. Similarly, as more farmer observations are used to validate remote sensing estimates, incentives may arise to distort the information obtained. Truth-telling mechanisms (related to those in Sheriff and Osgood 2010) may provide incentives for farmers to measure and report rainfall as accurately as possible.

1. Commentary: Informational and Institutional Challenges to Providing Index Insurance for Farmers

Michael Toman[14]

Managing weather-related risk has been a long-standing challenge in Africa. Poor farmers are especially vulnerable to unexpected weather-induced crop damages or failures because agricultural output plays such a large role in family consumption, and alternative income generation opportunities are limited. For crop insurance to be effective and affordable, the pool of insured farmers needs to be large and dispersed enough that weather conditions across participating farmers are not highly correlated. Because insurance is not a familiar product, however, initial reluctance to purchase it needs to be overcome, in particular by providing credible guarantees that payouts actually will occur once premiums are paid.

Adding to those challenges are the difficulties that are the focus of this chapter. Because decisions by individual insured farmers on protecting their crop yields are difficult to observe, any insurance contract based on measures of farmer-specific loss would be prone to misrepresentation, moral hazard (farmers would reduce their own protective measures), and adverse selection (those less capable of protecting themselves, and thus more costly to cover, would be more likely to buy the insurance). The chapter highlights how insurance coverage based on movement of a general index of weather conditions correlated with individual farm yields can provide reasonably effective coverage without these problems. The analysis is informed by several innovative, controlled field experiments in two African countries. The discussion of this method of analysis is itself an important contribution of the chapter.

A firm offering weather index based crop insurance still faces the challenges of assessing the risks to which its portfolio of policies is exposed, and pricing the insurance coverage accordingly so as to reduce to a minimal level the probability that large contemporaneous claims could exceed its financial reserve. It is in this context that the chapter explores how strategies to improve information about index insurance risks can have value for both the insurance company and its customers. Important findings of Osgood and Shirley include these:

- High uncertainties about payout probabilities can significantly increase index insurance cost. Such uncertainties are common in the context of drought risks, for example, given limited information and modeling available for predicting their occurrence. This presents a challenge for establishing financially sustainable premiums—low enough to be affordable yet actuarially sound.

[14] The views expressed here are the author's alone and should not be attributed to the World Bank Group or its member countries.

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- Simulation models for assessing risks are an important complement to limited observed data on droughts for assessing payout probabilities. It turns out that assessments based on past patterns alone can be very inaccurate and are not very sensitive to changes in information, since new information can only marginally alter the patterns implied by a historical data set. A modeling approach can be useful for exploring how future risks might be altered by climate change. Satellite-based information also can be very useful to improve confidence in probability estimates.
- Index insurance is not a substitute for reducing vulnerability. Drought index insurance addresses only one component of risk, so in the absence of effective insurance for other risks, such as storm or flood damage, complementary farm-level measures still will be needed for reducing vulnerability. Individual actions to reduce vulnerability to drought risks is a cost-effective complement to insurance coverage. An example is output diversification, including crops and livestock, so that planned allocations of land to different products can be modified based on predicted conditions. Here again, earth observation systems that provide better forecasts for an upcoming growing season, and more timely information about emerging threats, can be very valuable.

Osgood and Shirley are careful to note that even though improved information for assessing risks can make index insurance a better value and thus more easily marketed, it is not a sufficient condition for successful introduction of crop insurance. In light of the persistent difficulties encountered in establishing financially sustainable markets for this insurance, it may be useful to highlight some other important considerations that could even preclude the successful introduction of insurance in some circumstances.

- Constraints on liquidity limit the ability of farmers to purchase the insurance, even with modest premiums. This is an especially important consideration if farmers also have used microloans to help finance their current cultivation activity, in which case premiums to cover both farmer and lender may be considerably higher.
- Risk aversion toward using a novel product can decrease demand for insurance, even if improved probability assessments lower the cost. On the other hand, since index insurance is inherently only partial coverage, it is important that potential customers appreciate this. As illustrated by the field experiments underlying the analysis in the chapter, potential customers may require considerable information and education to evaluate the potential advantages of insurance.
- The prospect of climate change inherently reintroduces "noisy priors" for how crop risks may evolve over time, given the degree of quantitative uncertainty about climate change impacts. If crop loss insurance comes into greater use to reduce impacts of short-term climate variability, what adaptive measures by farmers are needed to reduce vulnerability to effects of climate change over the longer term?
- Public policies can weaken the development of an effective insurance market in several ways. For example, to what extent would expectations that the government will continue to provide disaster assistance reinject moral hazard into the

insurance system? Prospective purchasers also will be concerned about the strength of policies to ensure the creditworthiness of the insurers, a common concern in the financial sector of many developing countries. Ultimately, policymakers need to consider what portfolios of risk mitigation policies can have the greatest impact for a given resource cost. In addition to improved information about risks, such measures could include reducing institutional barriers to accessing insurance, and supporting measures by farmers to reduce their own vulnerability—which will also provide collective benefit by lowering economy-wide risks.

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