Agricultural insurances based on meteorological indices: realizations, methods and research challenges

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Abstract

In many low-income countries, agriculture is mostly rainfed and crop yield highly depends on climatic factors. Furthermore, farmers have little access to traditional crop insurance, which suffers from high information asymmetry and transaction costs. Insurances based on meteorological indices could fill this gap since they do not face such drawbacks. However full-scale implementation has been slow so far.

In this article, we first describe the most advanced projects that have taken place in developing countries using these types of crop insurances. We then describe the methodology that has been used to design such projects in order to choose the meteorological index, the indemnity schedule and the insurance premium. We finally discuss for the main research issues. In particular, more research is needed on implementation, assessment of benefits, how to deal with climate change, spatial variability of weather and interactions with other hedging methods.

Keywords: Agriculture, insurance, climatic risk.

1 Introduction

In traditional crop insurance, the insurer pays an indemnity to the farmer when crops are damaged, typically by drought, hail or frost (the so-called 'multirisk' crop insurance). Since the farmer benefits from an information asymmetry vis-à-vis the insurer, the latter must resort to a costly damage assessment to check at least part of the claims. Such insurances exist only where they are largely subsidized by the government. We can quote as examples PROPAGRO in Brazil, INS in Costa Rica, CCIS in India, ANAGSA and the FONDEN programme in Mexico, PCIC in the Philippines, Agroseguro in Spain, and FCIC in the USA, for which every respective government pays for more than half of the premiums (Miranda and Glauber, 1997; Molini *et al*., 2007).

Insurances Based on Meteorological Indices (IBMIs) may constitute an interesting alternative, especially for developing countries. The difference with traditional crop insurance is that indemnification is not triggered by damage to the crop, but by the level of a meteorological index, which is itself correlated to crop yield. IBMIs are analogous to weather derivatives, which reduce the impact of a harmful weather on firms whose margins widely depend on climate. Those financial products appeared in the 1990s, first distributed to energy suppliers.

The main advantage of IBMIs over traditional insurance is that there is no need for damage assessment. Thanks to the absence of information asymmetry (Goodwin and Mahul, 2004) the principal (the insurer) does not have to check the agent's (the insured farmer) statement. Moreover, IBMIs allow a quick payment of the indemnity (Alderman and Haque, 2006), provided that the organization producing the weather data is efficient enough, as noticed by Giné *et al*. (2008) on the Indian case.

The downside is the so-called basis risk, i.e. the fact that the correlation between crop yield and the meteorological index cannot be perfect. Indeed the relationship between weather and yield is complex and depends on field-specific features such as the slope, the soil quality, and the availability of alternative water sources. Moreover, many hazards, which are not directly related to weather (e.g. pests), impact yields, especially in developing countries. Hence a farmer insured against a bad weather can still suffer from a bad harvest. He will be worse off than without insurance since he will have paid the insurance premium. Finally, a high spatial variability of the weather (section 3.4 below) also contributes to the basis risk since it would be too costly to install a rain gauge, let alone a complete weather station, in every field.

The scientific literature on IBMIs is developing quickly. The principles of IBMIs were initiated by Halcrow (1948) and developed by Dandekar (1977). The idea was then proposed for developing countries (Skees *et al*., 1999) and a formal framework was provided by Mahul (2001). Several recent articles present the main IBMIs implemented: Barnett *et al.* (2007); Barnett *et al.* (2008); Collier *et al.* (2009); Hellmut *et al*. (2009); Hazell *et al*. (2010); DeJanvry *et al*. (2011). Others focused on a particular project or region: for example, Berg *et* *al*. (2009) focus on Burkina Faso; Giné *et al*. (2007, 2008) on India; Hess and Syroka (2005) on Malawi; Mahul and Skees (2007) on Mongolia and Turvey (2001) on Ontario (Canada). Some articles deal with one aspect of the IBMIs: Barnett *et al*. (2008) with the ability of IBMIs to tackle poverty traps, Chantarat *et al*. (2007) with their contribution to famine prevention, Hochrainer *et al*. (2007) with their robustness to climate change. Ex-post studies have developed in recent years but are still quite limited due to the recent development of such products: Cai *et al*., 2009 in China; Fuchs and Wolff 2011 in Mexico and Hill and Viceisza, 2009 in Ethiopia.

In this paper, we provide a general overview of the methods used and difficulties faced by IBMIs. In a first section, we describe the main IBMI experiments in developing countries, i.e. in India, Malawi and Ethiopia. In part two, we present the methods used to design the key features of an IBMI. In the third part, we draw an agenda for research on IBMIs.

2 The main experiments in developing countries to date

Most IBMIs implemented in developing countries insure individual farmers. Malawi and India are currently the countries which have gathered the most experience in this context up to now. In this part, we also present a rather different kind of IBMI, which was implemented in Ethiopia at a 'macro' scale.

2.1 India

India introduced traditional crop insurance in 1965 and IBMIs in 2003. It was the first country to introduce IBMIs at a commercial scale and is still the one which covers the highest number of farmers. The first implementation in 2003 was initiated by the private sector; more precisely, it was a joint initiative of the insurance company ICICI Lombard and the microfinance institution BASIX, with the help of the Commodity Risk Management Group (CRMG) of the World Bank (Hazell *et al*., 2010). It began in Andhra Pradesh, covering groundnut and castor oil against drought on three phenological phases of the crop. This programme expanded over time and covered, in 2008-09, around 10,000 farmers over 8 states in India. On average, during the six years of operation, 15% of farmers received an indemnity and the loss ratio (indemnities/premiums) amounted to 65%.

A second programme, a public one, covers a much higher number of farmers (1.6 million in 2009), it is called the Weather Based Crop Insurance Scheme (WBCIS). However, for the large majority of them (around 90%), insurance was compulsory since it was included in a package with a loan for agricultural inputs. Moreover, a maximum 80% of the premiums are subsidized by central and state governments, depending on the crop. As a consequence, the loss ratio amounts to 0.7 if calculated with the unsubsidised premium, versus 2.3 with the subsidised one, according to Chetaille *et al*. (2011). Indemnifications are triggered by a deficit or the presence of unseasonal rainfall during the Kharif (monsoon season) and also high temperatures and frost during the Rabi, the winter (mostly irrigated) growing season.

Although Indian experiences with IBMIs are often presented as a success, the results of the policy have to be put into perspective in regard to the low premiums actually paid by the farmers (less than US$ 5 per acre, Giné *et al*., 2007) and very low observed subscription rate when premiums are not subsidised. This somewhat disappointing result led to statistical studies about insurance take-up and especially its determining factors (Cole *et al*., 2009; Giné *et al*., 2007; Giné *et al*., 2008, cf. section 3.1). Giné *et al*. (2010) offers a detailed review of the Indian rainfall index insurance market.

2.2 Malawi

In Malawi, two projects jointly offering an IBMI with an inputs loan were run by the Insurance Association of Malawi and designed by the CRMG and IRI (cf. section 3.5.2). The initial objective was to limit loan default payment, which precludes the development of these credits. Indeed, when the rainy season is bad, so is the yield and farmers are unable to repay the credit. For this reason, the maximum payout corresponds to the total loan value. Four of the 22 weather stations showing satisfying quality standards in terms of missing values (providing 40 years of rainfall data) were used for determining a Water Requirement Satisfaction Index (WRSI, cf. section 3.1.2).

The first pilot programme (launched during the 2005-2006 season) concerned groundnut producers and was distributed in association with a cooperative of local growers. It was extended to maize producers the next year and a second programme for tobacco growers was launched. The first round concerned less than 900 farmers and the second one about 2000 (of which 1710 were groundnut farmers, Barnett and Mahul, 2007). During the 2007-2008 growing season a contract farming company exporting tobacco took the pilot over and insured more than 2,500 tobacco and maize growers, abandoning groundnut contracts.

The impact of these programmes on income could not be estimated due to a good rainy seasons during their implementation. The use of costly inputs rose compared to the previous years but, surprisingly, insurance did not have a positive impact on inputs loan take up (Giné and Yang, 2009). However, as pointed out by the authors, this result could be explained by some peculiarities of the experiment setting.

2.4 Ethiopia

In Ethiopia, a pilot programme was initiated by the World Food Programme (WFP) in 2006, and received technical assistance from the Food and Agriculture Organization (FAO) and the World Bank. The premium was offered by the WFP major donors and the product was insured by the reinsurance company AxaRe (now ParisRe). If any indemnity had been triggered, it would have been redistributed by the Ethiopian government to approx. 67,000 households (Barrett *et al*., 2009) that cultivate wheat, millet, cowpea and maize. The index was based on the cumulative rainfall, determined using a network of 26 weather stations across the country. The complex annual rainfall pattern in Ethiopia highlighted the need to examine growing strategies in detail. Indeed, in some regions there are two distinct rainy seasons, which induce two possible farming strategies depending on the timing of the first one: farmers can either choose to sow one long-cycle crop or to sow two different short-cycle crops.

In 2009 local IBMIs pilot projects were run in Ethiopia where the insurance market is developing, currently composed of one public and 10 private firms. One such example is the Horn of Africa Risk Transfer for Adaptation (HARITA) project in the Tigray region, designed by the International Research Institute for Climate and Society (IRI, Earth Institute, Columbia University) and launched by Oxfam America, the Rockefeller foundation and SwissRe. It is based on satellite imagery data. A second one was undertaken in the Oromia region supported by the WFP. Both projects directly target growers.

There are also many other programmes in pilot phase, in development or discontinued. These programmes were exhaustively listed in Hazell *et al*. (2010).

3 Methodological issues

3.1 Meteorological indices

To minimize the basis risk, the chosen meteorological index has to be a good predictor of yields, and especially of bad yields. While products insure against cold temperatures or frost (South Africa), others against excess water during harvest (India, Nicaragua, Rwanda and Tanzania) or against floods (Indonesia and pilots in Vietnam and Thailand), but most of them insure against a lack of rain. Hence, we only examine the last category in this section.

3.1.1 Basic rainfall indices

The cumulative rainfall during the growing season (which, in the tropics, typically corresponds to the rainy season) is the simplest quantifier of water availability. However, the impact of a lack of rain depends on its importance and the crop growth phase. Hence, in practice, the growing season is split in several sub-periods and an indemnity is paid whenever a lack of rain occurs in one of these sub-periods, or only in the sub-periods considered the most important for plant growth. It was the case in Malawi and India (cf. section 1.3 and 1.4). The amount of rainfall that triggers the payouts (the "strike") as well as the amount of indemnity differ across the sub-periods and are based on agro-meteorological knowledge. Moreover, very light daily rains (typically < 1 mm/day) and daily rains exceeding a given cap (60 mm/day in most of the World Bank insurance schemes) are generally not taken into account in the cumulated rainfall. Indeed, very light daily rains generally evaporate before being used by the plant, while rains exceeding a given cap run off and cannot be used either.

Such simple indices were applied in India and during the first Malawian experiment. They were also used in the Ethiopian scheme where payments were triggered by a low cumulative rainfall from March to October, compared to the 30-year average. Crop specific indices were calculated by weighting 10-days periods cumulative rainfalls according to their relative impact on yields.

The Available Water Resource Index (AWRI; Byun *et al*., 2002), based on effective precipitations of the previous days, is a slight improvement on the cumulative rainfall. In short, available water is estimated by simulating reduction of soil water stocks due to runoff, evapotranspiration and infiltration. Reduction is represented as a weighted sum of previous rains on a defined period (often 10 days) with time-decreasing factors.

Both indices are better predictors of yields if they are determined using the actual sowing date (or a sowing window) to trigger the beginning of the growth cycle. Imposing an arbitrary sowing date or window in the insurance policy increases the basis risk hence reduces the benefit of the IBMI. However, inquiring after actual sowing date would be very costly. Hence, in practice, especially in India and Malawi, the sowing date used to determine the crop growth phases is imposed by the insurer (a fixed period in Malawi and triggered by the occurrence of a precise cumulative rainfall level in India).

3.1.2 Water stress indices

Water stress indices are based on the idea that crop yields are proportional to the satisfaction of crop needs for water resource. The WRSI (Water Requirement Satisfaction Index) is the reference water stress index. It is defined as the ratio of actual evapotranspiration (ETa) to maximum evapotranspiration (ETc). ETa corresponds to an estimation of the quantity of water actually evaporated while ETc corresponds to the quantity of water that would evaporate if the water requirements of the plant were fully satisfied. This index was developed by the FAO and used in different IBMI schemes in India and in Malawi. Since crop sensibility to water stress depends on its growth phase, most of the insurance contracts consider those phases and take in account different references values of WRSI as triggers, depending on the phase considered. For groundnut and maize, contract parameters are defined on three growing phases. For tobacco, the growing period was divided in 17 blocks of two weeks. Rainfall level of each block is compared to the crop requirement for this particular growth stage and included in the weighted sum in order to compute the index corresponding for the whole period.

3.1.3 Drought indices

Those indices use temperatures and rainfall to determine air and/or soil dryness. The Selyaninov drought index, also called Selyaninov Hydrothermal Ratio, and the PED index only captures the air dryness. Both have been used by Breustedt *et al*. (2004) in an ex-ante IBMI scheme study designed for Kazakhstan. Their calculus has the convenience of only requiring rainfall and temperatures data. The Palmer Drought Severity Index (PDSI: Palmer, 1965) was used for the study of an insurance scheme in Morocco (Skees, 2001). It requires temperature, latitude, water retention capacity of soils and precipitations data, usually on a ten day basis.

3.1.4 Satellite imagery data

Satellite imagery data allows computing vegetation indices such as the Leaf Area Index or the Normalized Difference Vegetation Index (NDVI). The latter evaluates crop canopy photosynthesis – more precisely light absorption – calculated from the difference between near infrared and red beams, divided by their sum: NDVI = (NIR-RED)/(NIR+RED).

The NDVI can barely discriminate between pastures and cultivated areas and it is calculated with a delay period because of the potential presence of clouds. It is quite well adapted to biomass assessment but not to yield assessment. This technique is thus more frequently used for large-scale food crisis early warning, livestock management, and forecasts of forage production. It has been implemented by Agriculture Financial Services Corporation (AFSC) in Alberta (Canada), Spain, and Mexico for grassland and forage insurance (Hartell *et al*., 2006) and by the Word Bank in 2005 in Mongolia (Mahul and Skees, 2007) for livestock. However improvements in this field are very quick so that imagery resolution increases regularly and new technologies could emerge in the near future.

3.1.5 Mechanistic crop models

Mechanistic dynamic models simulate crop physiological growth depending on available environmental factors. Their precision in yield estimation is greater in theory, but they need very detailed input data. Such data are rarely available for large areas especially in developing countries.

The DSSAT model is used by Osgood *et al*. (2007) in East Africa and Diaz Nieto *et al*. (2006) in Nicaragua. It is however difficult to use such complex models (Osgood *et al*., 2007) because of a high sensitivity to parameter calibration. Nevertheless they can be used to assess the shortcomings of other methods. They also allow yield simulation under higher levels of inputs than those actually used by the farmers, which is useful since IBMIs may create an incentive to increase the level of inputs that cannot be observed ex-ante (cf. section 3.2.3).

3.1.6 Index choice criteria

Minimizing the basis risk, particularly cases in which farmers endure losses without receiving an indemnity (which we will referred to hereafter as the type II error basis risk), is the main criterion to compare those indices. The correlation between yields and index values is the simplest way to deal with such a choice, but more complex objective functions exist and are discussed in section 3.2.2. In order to improve the attractiveness for farmers it is fundamental to evaluate the correlation between yields and index values for low yields, i.e. for situations in which an indemnity should be paid. In many situations there is not enough historical data about observed yields of the farmers, the only way to assess the interest of an index is thus using simulated yields data by a crop model (Kapphan, 2011).

However, complexity limits the transparency and acceptability of IBMIs and data availability is also often limited, especially in developing countries. Thus there is a trade-off between index transparency, readability for farmers, data availability and simplicity on the one hand, and the index ability to reflect low yields (or minimize the type II error basis risk) on the other hand. If the insurance target is the farmer, simplicity is important, but if the target is a financial institution willing to insure its agricultural portfolio exposed to weather shocks, the product can be more complex.

3.2 Insurance policy design

3.2.1 Typical indemnity schedule

The typical indemnity schedule can be defined by three parameters (Vedenov and Barnett, 2004). The threshold level of the meteorological index, called the strike (*S*), triggers payouts for insured farmers. A slope related parameter (λ with $0 < \lambda < 1$) determines the exit, i.e. the index level: $\lambda.S$, from which payouts are capped to a maximum (*M*). Figure 1 displays the two opposite insurance contract shapes with λ equalling 0 and 1 (the latter corresponding to a lump sum transfer *M)* and an intermediary case. The contract shape is based on the fact that crop growth depends positively on the weather index (e.g. water availability), from a maximum stress meaning zero yield to a point where water is no longer a limiting factor of crop growth.

Figure 1: Usual shapes of IBMI policies

In many IBMI experiments, the indemnity schedule is more complex. In particular, as explained above (section 2.1.3), partial payouts are calculated for each crop growth phase, and the total indemnity is the total of these partial payouts. This is the case in Malawi (Osgood *et al*., 2007) and Senegal (Mahul *et al*., 2009) and many schemes in India. A maximum insurance payout is defined for each growth phase and the sum of insurance payouts can also be capped for the whole growing period.

3.2.2 Optimization of policy parameters

Due to the complexity of the relation between yields and water availability, in most cases, the indemnity schedule and the parameters are set without a formal mathematical optimization process. They are based on expert knowledge, simulations and sensibility analysis. Typically, the strike is set according to agronomists' views of under what level rainfall starts to be a limiting factor for crop yield, and the maximum payment may be set at the value of inputs (fertilizers, seeds, pesticides…) or at the value of the crop in a normal year. For instance, the strike is set according to an agronomic relation linking yields and water availability in Vedenov and Barnett (2004).

In certain cases, some of the parameters are explicitly optimized. The objective function differs among authors. Some maximize an expected utility function featuring risk aversion, more precisely a Constant Relative Risk Aversion (CRRA) function (Berg *et al*., 2009). Others minimize the semi-variance of income after insurance (Vedenov and Barnett, 2004). Income after insurance is the value of observed yield plus the indemnity minus the premium, and the semi-variance is the squared difference of yields inferior to the long-run average yield, relative to this average. Finally, Osgood *et al*. (2007) minimize the square of the difference between payouts and expected losses, the latter being defined as yields under the first quartile of simulated yield distribution.

3.2.3 Computing the expected value and distribution of the indemnity

The insurance premium depends on the expected value of the indemnity and on a measure of the probability distribution of payouts, i.e. indemnities (cf. section 2.2.4 below). There are two methods to determine these values; Historical Burn Analysis (HBA) and Historical Distribution Analysis (HDA) also called index modelling.

HBA is the simplest method. Index realizations, for instance the cumulative rainfall or the length of the rainy season in days, are calculated from meteorological historical data (possibly cleaned and detrended, cf. section 3.3.1 below) and converted into payouts. HBA gives a first indication of the mean and range of possible payouts of a weather contract, from which parameters such as the expected value and the standard deviation of the payouts can be calculated. Moreover, HBA does not require an assumption on distribution function parameters, in contrast to HDA. The disadvantage of HBA is that it provides a limited view of possible index outcomes: it may not capture the possible extremes, and it may be overly influenced by individual years and measurement errors in the historical dataset (World Bank, 2005).

HDA consists in fitting a statistical distribution function to the index historical values and converting values from this distribution to payouts. This distribution and the contract parameters have to be assumed. The expected payout and the measures of the risk such as standard deviation and VaR_{99} (cf. section 2.2.5 below) can be calculated either by Monte-Carlo simulations from the distribution or, in the case of simple distributions and indemnity schedules, analytically (World Bank, 2005). Even if not present in the historical series, rare events are handled in a better way with this method. Moreover outliers and measurement errors have less impact on results than with HBA.

The only formal comparison of the accuracy of the two methods seems to be a working paper by Jewson (2004) who concludes that HDA is significantly better than HBA when there is little uncertainty on the statistical distribution assumed in the HDA method.

3.2.4 Loading factor calibration

The insurance premium is higher than the expected indemnity (except if the insurance is subsidized) since it includes the administrative costs as well as the cost of the risk taken by the insurer. We only discuss the second aspect here.

The cost of the risk for the insurer depends positively on the correlation of this particular risk with the other components of the risk portfolio (Meze-Hausken *et al*., 2009). It is also worth mentioning that reinsurance is able to cap the risk taken by national insurance companies who suffer from covariance within their portfolio. Finally a key element that affects the loading factor is the availability of historical data. For example, the loading factor for a policy which uses a new weather station will be higher than that for a policy with a long series of historical data. On the basis of these idiosyncratic elements, two methods are derived for evaluating the additional cost of risk taking (Henderson, 2002):

• In the Sharpe ratio method, the margin is proportional to the standard deviation of cost ($\delta(i)$, with i the indemnities) for the insurer:

$$\alpha \times \delta(i) \tag{1}$$

Where α is the Sharpe ratio.

• In the Value at Risk (VaR) method, this margin is proportional to a risk of a defined occurrence probability. For example, VaR_{99} is the cost of the event that occurs with a probability of 1%:

$$\beta \times [VaR_{99} - E(i)] \tag{2}$$

The latter method is more adapted to high risk with low probability but cannot be applied with HBA (cf. section 2.2.3 above) since the number of events is too low. An ex-post statistical analysis on a case study in India conducted by Giné *et al*. (2007) showed that a large part of the payouts are due to extreme events: half of them in that case were due to the worse 2% climatic events. According to Hartell *et al*. (2006), α is chosen between 15% and 30 % and β between 5% and 15% (and between 5% and 7% according to Hess and Syroka, 2005 and Osgood *et al*., 2007 who draw on IBMI case studies). For instance in the case of Malawi, the VaR method applied with a factor β of 5% leads to an increase of 17.5% of the premium over the actuarial rate and a final premium rate of 11% (Hess and Syroka, 2005).

4 Research challenges

4.1 Implementation issues and institutional aspects

First of all, a pre-existing distribution network (e.g. of a financial institution) reduces marketing costs. This factor and farmers' trust in supplying institutions could be understood as the major factors of the success of Indian programmes. There is indeed a crucial need to explain the very low subscription rate in pilot projects. The relevant literature mainly highlighted the effect of human capital or other capacity barriers in empirical works. In particular, Giné and Yang (2009) pointed out the role of educational background in the particular case of a joint supply of insurance and loan in Malawi.

The first reason provided by farmers that could explain the low take-up is the misunderstanding about the product (Giné *et al*., 2008). The authors also found that the take-up rate falls with the extent to which household credit constraint binds and more surprisingly with a self-reported risk aversion indicator. One could indeed think of insurance as a risk-pooling tool which would be more interesting to risk-averse farmers. However the presence of type II error basis risk could overwhelm the latter effect so that more risk-averse farmers are less likely to adopt insurance (Clarke, 2011).

Moreover, uncertainty about product reliability reduces insurance demand and all the more for risk-averse farmers. Therefore many ongoing studies concentrate upon trust, readability of the underlying index and the contract, transparency of the process from index measure to funding (Dercon *et al*., 2011; Cai *et al*., 2009). For instance Cole *et al*. (2009) highlighted the trust in the supplying institution and credit constraints as explanations of low take-up rates.

Farmers' acceptance and perceptions about the product are also at stake in explaining the low take-up rates. Patt *et al*. (2009) listed recent field studies and theoretical models explaining insurance attractiveness and the trust of farmers who insist on commercial supplier honesty and his or her will to improve production conditions. Patt *et al*. (2010) compared the impact of traditional communication tools such as oral or written presentations of indexed contracts relative to role-playing games on two groups of farmers, controlling for their respective educational level. The experiment was designed for this purpose and took place in two different sites in Ethiopia and one in Malawi. They found a high correlation between insurance understanding and the desire to take up but no evidence of any superiority of role-playing games compared to oral or written presentations. According to the authors, the misunderstanding of insurance policies after training could be due to an insufficient educational background.

There are also many institutional barriers restraining IBMI implementation. In particular it is crucial that the country institutional framework and regulatory environment be adapted to private insurers, e.g. allowing contract enforcement at low cost (Carpenter and Skees, 2005;

Henderson, 2002). South Africa, India (Indian Insurance Regulatory and Development Authority, IRDA), Peru and the Philippines (Insurance Commission of the Philippines: Insurance Code of 1974) adapted their respective legislation to facilitate private micro-insurance initiatives (Wiedmaier-Pfister and Chatterjee, 2006). A total lack of contract law enforcement in Malawi — where contract farming is not particularly defined from a juridical point of view — did not prevent IBMI implementation. However, in some places (for example in Senegal: Mahul *et al*. 2009), insurance rules has not allowed its implementation so far.

4.2 Assessment of the benefits

4.2.1 Quantifying the benefits of a lower income variability

IBMI literature almost exclusively includes ex-ante analyses, and the rare ex-post empirical analyses are either very descriptive (Giné *et al*., 2007) or focused on the explanation of participation (Giné *et al*., 2008) and technology adoption (Hill and Visceisza, 2009; Giné and Yang, 2009).

Ex-ante analyses are either based on expected utility or on the minimization of a risk indicator. Berg *et al*. (2009) relied on expected utility maximization and found an increase of certainty equivalent income of about 0.5% to 3% in the case of Burkina Faso, depending on the cultivated crop: gains for millet and sorghum growers are very low, but gains for groundnut and maize growers are more significant. Vedenov and Barnett (2004) minimized several risk indicators, including the semi-variance of the insured revenue and the value-at-risk (VaR). Both papers also demonstrated the risk of over-fitting the data when the same dataset is used for optimizing the contract parameters and for quantifying the benefits: in several simulations, an IBMI yields a seemingly good outcome when applied to the dataset on which it was optimized, but it results in a much poorer outcome when applied to another dataset for validation. Berg *et al*. (2009) found a poorer outcome for groundnut but not for maize, when applying cross validation, potentially suggesting that maize yield is more depending on the cumulative rainfall over the rainy season than groundnut.

Breustedt *et al*. (2008) reviewed the main tools used for evaluating risk reduction through IBMIs, among which the mean-variance approach, the stochastic dominance indicators (first or second degree), the downside loss indicators (mean root square loss, variance of losses etc.) and expected utility functions featuring risk aversion. They highlighted the scarcity of work which addresses farm-level yields and the need for analyses of risk reduction at the level of individual farmers.

4.2.2 Production intensification

Limited wealth and risk aversion prevent farmers from implementing risky strategies that are more productive on average: the use of fertilizers, improved cultivars, etc. Binswanger and

Rosenzweig (1993) estimated the average shortfall in farm profit of poor Indian farmers that undertake low risk / low yields productive choices due to risk aversion, to be 30%. Farm models and a broader understanding of the ways farmers manage risk are thus also needed to acknowledge how to foster the use of intensifying techniques that seem to be a cornerstone in increasing yields in low-income countries.

Insured farmers could be encouraged to undertake more risky growing strategies and thus to adopt new technologies and invest in fertilizers. Encouragement to intensify the production process is part of the interest of such products in spite of their assessment complexity in absence of large scale empirical data. There is a real need for ex-post impact assessment taking into account those endogenous impacts of IBMI implementation.

Yield time series with different levels of fertilizers and different crops and varieties can be simulated by crop models for estimating potential production under various weather conditions. Such models are typically calibrated on the potential yields observed in experimental stations. However, in developing countries, actual farm yields are much lower than potential yields observed in experimental stations. There are various reasons for this: pests, lack of available labour at crucial stages, low availability of inputs, etc. For instance quality mineral fertilizer distribution seems to be quite slow to emerge; see Duflo *et al*. (2009) for a review of potential underlying mechanisms. It would thus be useful to give more attention to the capacity of crop models to simulate production under smallholders' conditions and possibly implement statistical validation methods on crop model using farm data.

4.2.3 Modelling poverty traps mechanisms

Poor households face a double constraint constituted of a tied budget (limited access to credit market) and a subsistence imperative. In order to meet minimum nutritional needs, households often under-invest in productive capital, including in human capital through health and education expenditures. Indeed facing risk creates an incentive for poor households to stock non-productive subsistence assets (food) with low-return and low-risk (Zimmerman and Carter, 2003, cf. section 4.5.1 for a short review of the impact of other informal risk coping strategies). According to Chetty and Looney (2006), consumption smoothing mechanisms and especially their cost should thus be considered when assessing the welfare gain of any social insurance. Barnett *et al*. (2008) reviewed such mechanisms and their crucial role in designing index based risk transfer products. However, to our knowledge, no IBMI has been assessed within a formal dynamic model featuring the possibility of poverty traps.

4.3 Robustness to climate change

Due to global warming, there is an upward trend in local temperatures in almost every region. If the index of an IBMI includes temperatures but does not account for this trend, the calculation of the expected indemnity is biased. The continuation of an upward trend in temperature is very likely over the next decades, but the magnitude of this trend is highly uncertain. First, according to the last IPCC (2007) synthesis report, global warming in 2100 could be between 1.4 °C and 5.8 °C, depending both on climate sensitivity and on greenhouse gas emissions. Second, uncertainty on local warming is even higher than that on global warming.

In some regions (e.g. West Africa) rainfall data also exhibit trends, which may be due to global warming, natural climate variability and/or changes in land use. The difficulty is higher than for temperature since in many regions, such as West Africa again; climate models disagree on whether global warming will entail an increase or a decrease in rainfall. Moreover, not only the average, but also the inter-annual variability of the rainfall level may change due to global warming.

Simple detrending methods based on past data are routinely used in IBMI design (Jewson and Penzer, 2005). However, they cannot correctly account for complex non-stationarities, like the succession of humid and dry decades in the Sahel (Dai *et al*., 2004). Nor can they deal with the above-mentioned uncertainty with regard to future local climates. Hence, the presence of a trend in the data used to build the index can lead to private suppliers turning away from local markets. This was the case in Morocco (Skees *et al*., 2001) in spite of the twenty years of precipitation data and the provision promises made by the government.

Hochrainer *et al*. (2007) tested the robustness of an IBMI in Malawi using climate forecasts generated by the MM5 and PRECIS regional climate models. They questioned its long run sustainability until 2080.

Progress on this point requires a better forecast of climate change at a decadal scale, research area on which many efforts are currently focusing.

4.4 Climate spatial variability and the scaling of insurances

Risk covariance is a major source of insurance market failure in developing countries and explains the high subsidization rate of agricultural insurances, according to Barnett *et al.* (2008).

Spatial risk correlation is a major impediment of IBMI implementation. It increases income variance for the insurer, hence the insurance premium. The only ways to lower the variance of income for a given spatial variability of shocks are to insure a larger area, allowing a better pooling, and/or to transfer a part of the risk to an international insurer or reinsurer through risk layering. For instance, reinsurance was needed for drought insurance in Ethiopia. In this Ethiopian context, Meze-Hausken *et al*. (2009) studied insurance provision on 30 years and 15 stations with an HDA and conclude that pooling over the country limits the need for capital requirement.

Spatial variability reduces this problem but increases the basis risk for a given weather station density. In practice the maximum distance to the nearest weather station is set at between 20 (in Senegal) and 30 km (in Malawi, in most cases in India and in Canada according to Hartell *et al.*, 2006). Yet in some regions the spatial variability of weather is significant even at 10 km or less. This calls for increasing the density of rain gauges, which would however substantially raise IBMI management costs (installation, operation and maintenance). There is thus a trade-off between the management cost and the basis risk.

In most IBMIs, only the closest weather station is taken into account to calculate the indemnity. However, interpolation methods can also be used to infer the meteorological index realization over a geo-referenced grid (Paulson and Hart, 2006). Method complexity differs from simple and determinist ones (such as simple linear weighting, decreasing with distance of stations around or squared weighting like the Inverse Distance Weighted Averaging, IDWA) to stochastic ones as such as Kriging based on Gaussian multivariate statistical distributions.

4.5 Interactions with other hedging methods

4.5.1 Informal practices

We distinguish between risk management (or mitigation: ex-ante) and risk coping (or adaptation: ex-post) methods following Dercon (2005). Since Besley (1995) and Fafchamps (2003) already reviewed the literature on those informal methods, we only mention them briefly below.

Risk coping

Providing formal insurance could have a negative impact on informal risk coping networks, as noted by Alderman and Haque (2007). Transfers from migrants, neighbours, family or friends are well described in Fafchamps (2007), and their importance for IBMI literature has recently been analyzed by Barnett *et al*. (2008). Farmers are encouraged to pool the risks they face, for instance by using private transfers. However, Pan (2008) found evidence that transfers have a minor impact on risk pooling. Kazianga and Udry (2006) only found evidence of a very low risk sharing among households facing climatic shocks in Burkina Faso. A potential explanation is that having recourse to informal credit could also be very costly (Collins *et al*., 2009). However, insurance is not totally substitutable with private transfers that are undertaken in a limited geographic area (e.g. between village or family members unless considering remittances) since it is limiting the impact of spatially covariant shocks.

Risk management

Insurance could also replace other previous strategies such as self-insurance (savings, livestock and other stocks adjustment such as mortgage of personal goods, Collins *et al.*, 2009), crop diversification or intercropping.

Empirical studies point out the very low use of livestock as a buffer stock (Fafchamps *et al.*, 1998; Lybbert *et al.*, 2004; Lentz and Barrett, 2004; Unruh, 2008). Farmers smooth consumption by adjusting stocks of stored grain, which is also very costly. For instance stored grain undergoes very high depreciation rates associated with different degradation sources, such as moisture, rodents and insects.

Finally it could be argued that the cost of informal practices limit their attractiveness, especially compared to formal insurance products. Dercon *et al.* (2008) reviewed the studies which evaluate these costs, highlighting the need for health and crop micro-insurances. However, their potential substitution by insurance and informal risk mitigation methods could lower its take-up, especially when information about their relative costs is not easily available.

4.5.2 Inputs loan

The combination of insurance with input credits presents a double interest. First, it allows the use of the distribution networks of micro-finance institutions. Second, it mitigates the default risk for lenders, and lowers the credit interest rate, all other things being equal. The joint effect of both products with a possible farmers' default on loan is formalized by Dercon and Christiaensen (2011) for Ethiopia. Lowering the default rate reduces the potential moral hazard and adverse selection induced by loans supplied at a given interest rate. Screening and monitoring costs thus drop, lowering loan prices.

However, Giné and Yang (2009) showed evidence that a loan for high-yielding hybrid maize and groundnut seeds in Malawi does not increase the take-up rate and may even possibly lower it. To reach this conclusion they ran a randomized experiment comparing take-up rates of farmers that subscribe to a loan with a mandatory IBMI priced at an actuarially fair rate to those of a control group for whom a loan without insurance was supplied. The use of high-yielding seeds rose compared to the previous years but, surprisingly, insurance seems to have had a negative impact (a decrease of approx. 13 percentage points) on loan take-up. A potential explanation mentioned by the authors is that farmers are already implicitly insured by the limited liability serving as collateral in the loan contract. However, the low number of observations and a significantly higher educational level in the control group limit the scope of such results.

4.5.3 Seasonal weather forecasts

Seasonal weather forecasts provide probabilistic information on the next season in various regions of the world. If these forecasts become more accurate in the future, farmers could use them to adjust their productive choices. In particular, they may use more risky but potentially more productive crops or techniques in years with a good forecast. Meza *et al*. (2008) surveyed the assessments of these forecasts in agriculture.

Forecasts are necessarily imperfect and a weather-related risk often remains. In this context, insurance may be a complement for weather forecasts by allowing production intensification with limited risk. Carriquiry and Osgood (2008) and Osgood *et al*. (2008) studied the synergies of insurance and seasonal weather forecasts while Jewson and Caballero (2003) proposed two major methods for using different kinds of forecasts in the pricing of weather derivatives. However, it could be more appropriate not to supply annual insurance contracts but long term contracts with mandatory commitment for a few years instead, in order to avoid potential opportunistic behaviours that would consist in only insuring if a 'bad' season is forecasted. Future research could be devoted to this kind of contracts.

5 Conclusion

Although index-based insurances have gained increasing attention in the last ten years, a lot of research remains to be done before a robust conclusion on their potential benefit can be reached. A part of this research is mainly related to agro-meteorology (e.g. the work on new and improved indices, including the use of data from satellites) but further research is also needed, in at least five directions.

First, there is a need to explain the often low subscription rates and why they differ across projects. Cultural and institutional issues clearly matter here. Second, the quantification of benefits is still in its infancy. Third, although weather insurance is sometimes presented as an adaptation tool against climate change, global warming can threaten the viability of index-based insurances. Fourth, spatial issues such as the optimal density of weather stations and the ambiguous impact of spatial covariance deserve more attention. Last but not least, the interactions with other hedging methods should be explored further.

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