WPS5985

Policy Research Working Paper 5985

Weather Based Crop Insurance in India

Daniel J. Clarke
Olivier Mahul
Kolli N. Rao
Niraj Verma

The World Bank
Financial and Private Sector Development Vice Presidency
Non-Banking Financial Institutions Unit
&
South Asia Region
Finance and Private Sector Development Unit
March 2012

Abstract

The weather index insurance market in India is the world's largest, having transitioned from small-scale and scattered pilots to a large-scale weather based crop insurance program covering more than 9 million farmers. This paper provides a critical overview of this market, including a review of indices used for insurance purposes and a description and analysis of common approaches to design and ratemaking. Products should be designed based on sound agronomic principles and further investments are needed both in quantifying the level of basis risk in existing products, and developing enhanced products with lower basis risk. In addition to pure weather indexed products, hybrid products that combine both area yield and weather indices seem promising, with the potential to combine the strengths of the individual indices. A portfolio approach to pricing products, such as that offered by Empirical Bayes Credibility Theory, can be significantly more efficient than the standalone pricing approaches typically employed in the Indian market. Legislation for index insurance products, including consumer protection legislation, should be further enhanced, for example by requiring disclosure of claim payments that each product would have made in the last ten years. The market structure for weather based crop insurance products could better reward long-term development of improved product designs through product standardization, longer term contracts, or separating the roles of product design and delivery.

This paper is a product of the Non-Banking Financial Institutions Unit of the Capital Market Practice, Finance and Private Sector Development Vice Presidency; and Finance and Private Sector Development Unit, South Asia Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org.
The authors may be contacted at omahul@worldbank.org and nverma@worldbank.org.

WEATHER BASED CROP INSURANCE IN INDIA[1]

Daniel J. Clarke, *Department of Statistics, University of Oxford*

Olivier Mahul, *Program Coordinator, Disaster Risk Financing and Insurance Program, Non-Banking Financial Institutions Unit and Global Facility for Disaster Reduction and Recovery, World Bank*

Kolli N. Rao, *Chief Risk Officer, Agricultural Insurance Company of India*

Niraj Verma, *Senior Financial Sector Specialist, South Asia Finance and Private-Sector Development Unit, World Bank*

JEL Classification Numbers:

G22, O13, O16.

Keywords:

Agriculture, crop insurance, developing countries, India, product design, pricing, weather index insurance

Sector Board:

Capital Market Practice, Finance and Private-Sector Development

---

[1]This paper was motivated by a larger program of technical work by the World Bank, requested by the Government of India and the Agricultural Insurance Company of India. This technical assistance was funded by the Swiss Development and Cooperation Agency (Phase 1, 2005), the FIRST Initiative (Phase 2, 2005–2007) and the Global Facility for Disaster Reduction and Recovery (Phase 3, 2008–2011). The authors thank M. Parshad and M. K. Poddar of AICI, as well as other government officials with whom we interacted, for useful discussions and access to data, and to Ivan Rossignol, Loic Chiquier, Stefan Dercon, Avery Cook and Ruth Vargas Hill for useful comments. Views expressed in this paper are the authors' and should not be attributed to the World Bank, University of Oxford or Government of India. Email: clarke@stats.ox.ac.uk, omahul@worldbank.org, knrao@aicofindia.com, nverma@worldbank.org.

1. Introduction

India has a strong claim to have been the birthplace of the idea of weather indexed insurance, with Chakravarti having outlined a detailed proposal for rainfall indexed insurance to be sold across India as early as 1920 (Chakravarti 1920). Although Chakravarti's proposal was never implemented, it is somehow fitting that India was the first developing country to pilot weather indexed insurance and, despite the recent spread of weather indexed insurance programs across the world, at the time of writing more farmers purchase weather indexed insurance in India than in any other country (Mahul and Stutley 2010).

The Indian weather indexed insurance market has rightly attracted attention from academic economists interested in piloting and learning from new ideas (e.g. Giné et al. 2008, Cole et al. 2009, Giné et al. 2010). However, while this research program has by design focused on a few small scale voluntary insurance programs that provide insurance to fewer than 10,000 farmers in total, little has been written about the recently scaled-up, largely compulsory, publicly subsidized program, the Weather Based Crop Insurance Scheme (WBCIS). In the 2010-11 agricultural year over 9 million Indian farmers held WBCIS policies with premium volume of over US $ 258 million and total sum insured over US $ 3.17 billion.[2]

The implementation of these large scale programs has stimulated a program of technical work on supply side aspects of weather indexed insurance, such as how to systematically design and price products in a robust, statistically efficient manner. In particular, while products were designed and priced on a standalone approach in early pilots, as is common in markets for weather derivatives, these approaches have matured into portfolio-based approaches that are more appropriate for insurers with large, well-diversified portfolios. This paper outlines the Indian experience of scaling up a national weather indexed insurance program and suggests a roadmap for future research on the supply of weather indexed insurance policies.

The rest of the paper is organized as follows. Section 2 provides an overview of the market for weather insurance in India. Section 3 presents the forms of weather index insurance products that have been sold in India and discusses basis risk, consumer protection legislation and market structure. Section 4 presents a portfolio-based approach to ratemaking and Section 5 concludes.

2. The market for weather insurance in India

India is not new to experimenting with crop insurance. In 1999 the Government of India launched the National Agricultural Insurance Scheme (NAIS), the successor of the Comprehensive Crop Insurance Scheme (CCIS) which had been running since 1985. In states or union territories that choose to participate in NAIS, insurance for food crops, oilseeds and selected commercial crops is mandatory for all farmers that borrow from financial institutions and is voluntary for non-borrowing farmers without loans. However, despite the large public subsidy a significant majority of India's farmers have remained uninsured largely due to issues in design, particularly the long delays in claims settlement (Hazell 1992, Mahul et al. 2011) and basis risk.

The combination of high vulnerability of India's farmer households and low penetration of NAIS has proved fertile ground for innovations in the provision of agricultural insurance. One well documented innovation was the introduction of weather index insurance, where the claim payment to farmers is an explicit function of weather parameters such as rainfall, temperature and humidity as recorded at a local weather station. With claim payments based on objective, transparent,

[2]All figures have been converted from INR to USD using the exchange rate of Indian □45 to US $1.

manipulation-resistant readings, weather indexed insurance offered lower moral hazard and adverse selection, as well as quicker claim settlement than yield-based schemes.[3] The main challenge of weather-based approaches to agricultural insurance is that, by offering claim payments based on weather at a contractual weather station, weather indexed insurance offers little protection against localized events, such as hailstorm or cloudburst, and may not capture some aggregate events that affect a whole area, such as an outbreak of pestilence or disease. This imperfect correlation between the index and a farmer's loss, which can result in the farmer receiving no claim payment despite having experienced a severe crop loss, is known as *basis risk*, and can act to limit demand.

The first weather insurance product in India, and indeed in the developing world, was a rainfall insurance contract underwritten in 2003 by ICICI-Lombard General Insurance Company for groundnut and castor farmers of BASIX's water user associations in the Mahabubnagar district of Andhra Pradesh. This pilot, supported by technical assistance from the World Bank and documented in Giné et al. (2005), spurred rainfall insurance product offerings from other insurers, such as IFFCO-Tokio and the public insurer Agriculture Insurance Company of India (AICI), leading to a high rate of growth in the number of farmers insured between 2003 and 2007 (Table 1). Perhaps more surprising was that this rate of growth was high despite a low level of product renewal from farmers; Cole et al. (2009) report that only 28% of farmers in Andhra Pradesh who purchased insurance in the three-year study period purchased coverage for more than one year.

Table 1: The Indian weather index insurance market

Agricultural Year	Farmers insured	Sum Insured (USD millions)	Commercial premium volume (USD millions)[1]	Claims paid (USD millions)	Claim payments as a multiple of commercial premiums
2003-04	1,000		<0.1	<0.1[2]	
2004-05	11,300		0.2	0.1[2]	
2005-06	112,500		1.6	0.2[2]	
2006-07	181,900		1.6	1.0[2]	
2007-08[3]	678,425	398	33.1	23.9	72%
2008-09[3]	375,100	208	18.6	14.2	77%
2009-10[3]	2,278,407	1,093	99.9	62.0	62%
2010-11[3]	9,278,000	3,174	258.9	125.0	48%

Note: 1. Commercial premium includes both farmer premium and government premium subsidies.
2. Kharif season only.
3. WBCIS only.

The market for weather indexed insurance in India fundamentally changed in 2007 with the launch of the Weather Based Crop Insurance Scheme (WBCIS), the pilot scheme weather indexed insurance scheme of the Indian government. Before 2007, states could either choose to opt in to NAIS, in which case insurance purchase would be compulsory for farmers that borrowed from financial institutions and voluntary for other farmers, or opt out. From the 2007-8 agricultural year states had the additional option of choosing WBCIS as an alternative to NAIS.

[3] The Indian experience suggests that 'tamper-proof' automatic weather stations reduce, but do not remove, the risk of insurance fraud: in the 2010-11 Rabi season there were reports of insured farmers fraudulently placing ice cubes around temperature sensors of automatic weather stations to trigger claim payments for low temperatures.

Table 2: Premium subsidies for commercial crops covered under WBCIS

Commercial Premium	Subsidy for commercial crops
<2%	No subsidy
2%-5%	25% of commercial premium, with minimum of 2%
5%-8%	40% of commercial premium, with minimum of 3.75%
8%+	50% of commercial premium, with minimum of 4.8% and maximum of 6%

WBCIS enjoys substantial government subsidy, with farmer premium rates capped at 1.5% for wheat and 2.0% for other *food* crops (cereals, millets, pulses and oilseeds) and defined subsidy rates for other, *commercial,* crops (Table 2), although subsidy rates for commercial crops are typically lower than the subsidy rates enjoyed by the NAIS. With WBCIS offering lower, more predictable costs to state government and quicker claim payments to farmers, some large states have experimented with WBCIS as an alternative to NAIS.

As might be expected, the introduction of a largely compulsory, heavily subsidized program led to a substantial increase in premium volume and number of farmers insured from 2007-8 onwards, with between-year volatility mostly caused by large states changing their decision about whether to opt in to WBCIS or not (Table 1). A significant majority of farmers covered under WBCIS are compulsory, borrowing farmers rather than voluntary, non-borrowing farmers.

One key difference between WBCIS and NAIS is that under WBCIS private sector insurance companies are allowed to compete with the public insurer to offer the subsidized products.[4] Competition is at the district level, with state governments choosing a single provider for each district. Private insurance companies have been allowed to offer voluntary cover since 2007 and cover to borrowing farmers, for whom insurance purchase was compulsory, from Rabi 2009-10. For the 2009-10 agricultural year, private insurance companies sold policies amounting to over 20% of the entire WBCIS portfolio by premium volume, with the remainder sold by the public insurer AICI.

With only four years of matched premium and claim payment data it is not possible to make strong statements about the loss ratio, the ratio of claim payments to commercial premium since it is challenging to differentiate between favorable weather experience and expensive products. Over the 2007-2010 agricultural years, the unweighted average loss ratio was 65% and the unweighted producer loss ratio, the ratio of claim payments to farmer premiums, was approximately 130%; that is to say that for every □1 of farmer premium paid in each of the four years, □1.3 of claims were paid in each of the four years. This is lower than the producer loss ratio of 300% for borrowing farmers purchasing NAIS cover between 2000 and 2008 (Mahul et al. 2008).[5] However, with only four years of claims data, the most recent of which happened to be among the best of the past decade, this may not be representative of the future average producer loss ratio.

3. Weather insurance product design

The primary aim of designing an index for agricultural insurance should be to minimize basis risk, the risk that the index does not accurately capture farm-level losses. In particular, it is important to ensure that the product makes appropriate claim payments in years that are unusually bad for

[4] Under the modified NAIS private sector insurance companies also compete with the public insurer.

[5] The producer loss ratio for nonborrowing farmers purchasing NAIS cover between 2000 and 2008 was 640%. This disparity illustrates the impact of adverse selection in an insurance program without risk-based pricing: non-borrowing farmers chose to purchase cover when it was actuarially more valuable.

farmers. An index that captures the vast majority of bad years is likely to be attractive to farmers, but a weather index insurance product that cannot be relied on to make claim payments in very bad years will be unattractive to the most risk averse farmers, even if it is subsidized, and may be unattractive to all farmers (Clarke 2011).

For a given index, a designer may construct a product with a target probability of claim payment. For example, a designer may aim to make frequent small claim payments or infrequent large claim payments. While classical insurance theory provides strong motivation for the latter there may be other reasons for wanting to make frequent claim payments, such as building trust that claims will be paid, possibly as a promotional strategy for the product. Regardless of the target claim payment frequency, the product should aim to make claim payments in all very bad years.

For a specific functional form, or collection of functional forms, for a weather index the precise parameters could be chosen based on the judgment of an agronomist, a formal crop model, or statistical analysis which aims to maximize the correlation between claim payments and yield losses.

Functional forms for weather indexed insurance product design

Many types of products have been tried for weather index insurance in India. A selection of these product forms are described below and in the appendix. However, as discussed at the end of this section it should be noted that there has been a striking absence of rigorous statistical analysis to help insurers choose the best index in a specific environment.

In theory, the more degrees of freedom available to a product designer, the more freedom the designer has to reduce basis risk. However, complex products do not necessarily have low basis risk. While many alternative product forms have been sold in India, very little is understood about the level of basis risk in different products or whether more complex products do actually exhibit lower basis risk. Since minimizing basis risk is a key aim of weather indexed insurance product design, more work in understanding what products exhibit lower basis risk would be helpful, as would research into the degree to which an increase in the density of weather stations can decrease basis risk.

Total seasonal rainfall index

Chakravarti (1920) envisaged a rainfall insurance product in which claim payments would be due if the total rainfall during a season was less than a given threshold (Mishra 1995). More generally, the claim payment from a total seasonal rainfall indexed insurance product is typically a step function of the total rainfall in a given season. For such products, total rainfall is often expressed as a fraction of *normal rainfall*, calculated to be the historical average rainfall.

Although sold by AICI in 125 locations over 10 states in Kharif 2005 (e.g. see Appendix

Table 3), rainfall indices based on total seasonal rainfall quickly fell out of favor due to the following limitations. First, such indices ignore the significance of rainfall distribution and focus solely on the total rainfall received during the crop season. A significant number of incidences of large-scale crop losses in India have been the result of long dry spells, and these may not be reflected in total rainfall. Second, by assuming that only average rainfall affects crop yields, the approach disregards both the phenological stages of crop growth and the observation that any rainfall beyond the field capacity of the soil is redundant for crop growth.[6]

Weighted rainfall index

[6] Field capacity is typically defined as the amount of soil moisture or water content held in soil after excess water has drained away and the rate of downward movement has materially decreased.

A weather product based on normal seasonal rainfall is a special case of a weighted rainfall index, where all the weights are chosen to be the same. In general, a weighted rainfall index may be defined as

$$Weighted\ rainfall\ index = \sum_{t \in \{days\}} \omega_t (r_t - \bar{r}_t), \tag{1}$$

where ω_t denote the weights, r_t denotes realized rainfall and $\bar{r}_t$ is typically chosen to be the average historical rainfall. Products based on such indices have been sold by ICICI Lombard in Kharif 2003 and AICI and IFFCO Tokio in Kharif 2004 and 2005 (see Table 4).

Weighted rainfall indices offer more flexibility to a designer than indices based on total seasonal rainfall, but suffer from similar limitations. In particular, a weighted rainfall index provided scope for cross-subsidization across different rainfall periods. For example, a large volume of rainfall in a period of low significance (weight) could compensate for poor rainfall in a period of high significance (weight). Application of daily caps (ceilings) for rainfall volume could partly address this constraint at the cost of further complicating the index.

Multiple phase weather index

In response to the farmer feedback collected after the first pilot, ICICI Lombard developed a rainfall index with multiple phases for the Kharif 2004 season, described in Giné et al (2010). For such an index the growing season is divided into sequential phases of varying duration, typically chosen to correspond to the crop-growth stages as defined by crop calendars and other reference sources for agronomy. For each phase, the schedule of payments is typically piecewise linear in the total rainfall in the phase, reflecting the water requirements of the crop in that phase, and with payments only if the total rainfall in the phase is sufficiently low (or high).

For example, Table 5 provides an example of a product for which payments are triggered if the total rainfall in the phase r_p is below the rainfall trigger $Trigger_p$, linearly increasing to the maximum payment of $Rate_p \times (Trigger_p - Exit_p)$ for $r_p \geq Exit_p$. Such a schedule would lead to a claim payment as follows:

$$\begin{aligned} &Deficit\ rainfall\ index\ with\ phases \\ &\quad = \sum_{p \in \{phases\}} Rate_p \times \max\left[0, Trigger_p - \max\left(r_p, Exit_p\right)\right] \end{aligned} \tag{2}$$

This design could be more intuitive to potential policyholders by clearly associating each critical crop-growth phase with a distinct rainfall insurance structure, and provides scope for interim payouts instead of having to wait till the completion of policy period. However, multiple-phase rainfall insurance index may not capture long dry spells, particularly for phases with durations exceeding a fortnight.

Perhaps more importantly multiple-phase rainfall indices do not fully capture the conditional impact on rainfall in different phases on yields, instead implicitly assuming that the crop productivity in a particular phase is independent of the crop health and rainfall in the previous phase(s). For example, if the index defined in equation (2) is used to determine claim payments, a farmer will only ever receive the maximum claim payment of $\sum_p Rate_p \times [Trigger_p - Exit_p]$ if there is sufficiently low rainfall in *all* phases; complete crop loss in one phase is not sufficient to trigger a maximum claim payment even if it is sufficient to destroy an entire crop.

Designers have experimented with two ways of introducing conditionality between phases. First, products usually include a maximum claim payment for the policy which is smaller than the sum of maximum claim payments for each phase. A maximum claim payment may therefore be triggered by exceptionally poor weather in one or a small number of phases. Second, a product may allow

rainfall to be *carried over* between phases, to try to capture the soil moisture at the start of the phase (see Table 6).

Consecutive Dry Days (CDD) Index

Another approach to capturing adverse rainfall events is to construct an index equal to the maximum consecutive number of *dry days* within a specified period, where a dry day is defined as a day with total rainfall below a threshold value.

$$\begin{aligned} &Consecutive\ dry\ days\ index \\ &\quad = maximum\ number\ of\ consecutive\ days\ with\ r_{actual} < r_{threshold} \end{aligned} \tag{3}$$

This cover offers protection for long dry spells and can be sold as a standalone product or in conjunction with other indexed cover, particularly rainfall volume based products. For example, Table 7 characterizes a consecutive dry days product where the index uses a daily threshold of 2.5mm, and with claim payment a step function of the index, with claim payment of □750 if the index is between 17 and 24 days, □1,500 if the index is between 25 and 29 days and □2,000 if the index is greater than or equal to 30 days.

Some consecutive dry days products use a trigger of 0mm (see Table 8), although the agronomic merits of such products are unclear; a dry spell of 30 days, with rainfall of 2mm on day 15 would still most likely result in a large crop loss, but would not trigger a claim payment for the product defined in Table 8.

Excess/Untimely Rainfall Index

Heavy and continuous rainfall within a short period has the potential to cause severe physiological damage to crops, particularly during the maturity and the harvest phases when excess rainfall makes many crops highly susceptible to attacks by pestilence and disease. The indices that have been designed to capture wet spells are similar in nature to those already described for deficit rainfall, dependent on consecutive rainy days, aggregate rainfall over a period of between two and four consecutive days, or a piecewise linear function of rainfall in each phase. For example Hess et al. (2005) report on a rainy days product for Mahabubnagar, Andhra Pradesh for which $r_{threshold}$ was 10mm of daily rainfall and a claim was triggered if the rainy day index was four or more. The most recent products seem to be mainly based on aggregate rainfall over a period of two, three, or four consecutive days.

Low temperature or frost indices

Temperature can have a significant impact on yields (Lobell et al. 2011) and Indian insurers have experimented with indices based on weather station temperature readings, particularly for the Rabi (winter) crop.

Northern parts of India are particularly exposed to the risk of low temperatures or frost which can cause severe crop loss in a short space of time for crops like potato, chick-pea and mustard. Indices have been designed to offer some protection against adversely low temperatures, typically defined as a function of the minimum temperature in the cover period (for example, see Table 11).

High temperature indices

Complex temperature-based indices have been designed to offer some protection to farmers against adversely high temperatures, particularly for wheat crop. For example, AICI and the Indian Agricultural Research Institute (IARI) designed a phase-based high temperature index for wheat crop in Rajasthan for the Rabi 2007 season, where the claim payment to farmers in respect of each phase was a function of the mean temperature for that phase (Table 9). As another example, ICICI Lombard sold a product for wheat crop in 2010 for which claim payments depended on excess daily temperature, rather than excess average fortnightly temperature (Table 10). However, while it is

known that high temperatures can reduce wheat yields, very little is known about the level of basis risk in high temperature indexed products.

Weather Indices for Pests and Diseases

Indices have been developed in India to try to capture exposure to pestilence or disease, such as aphid infestation or potato blight and are typically based on relative humidity (see Table 12), or a combination of relative humidity, temperature and rainfall (Tables 13 and 14). Such indices are typically complex and, to an even greater degree than other indices, there has been little analysis of the degree to which such indices capture yield shortfalls.

Basis risk

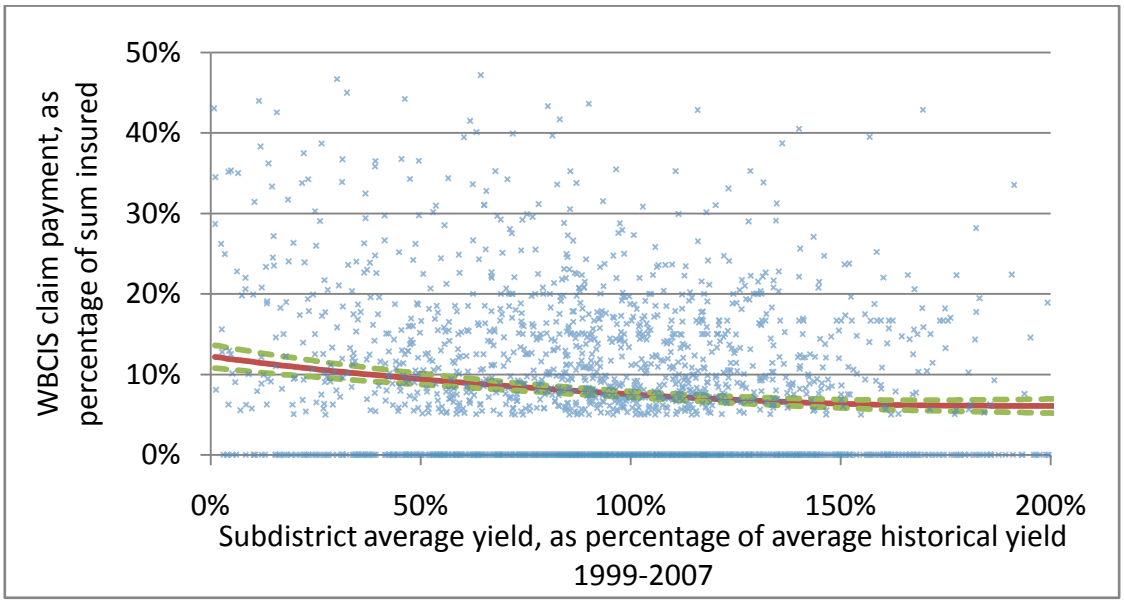
One key requirement of any index-based approach to agricultural insurance product design is that the claim payments from the indexed product are sufficiently correlated with yield losses of individual farmers, particularly in those years with significantly poor yields. In other words, products must have limited basis risk between the index and the actual individual yield loss.

Preliminary statistical analysis has been conducted for the relationship between average subdistrict yields and weather indexed claim payments for all 270 WBCIS products sold in one state in one year, spanning 13 districts and 12 crops. Applying the product characteristics to available historical weather data we obtain the claim payments that would have been paid in each of the nine years from 1999 to 2007. These historical burn costs may then be compared with subdistrict average yields, where each yield measurement is normalized by the average yield between 1999 and 2007 for the respective crop in the respective subdistrict.

Figure 1 presents a scatter plot of the empirical joint distribution of claim payments and subdistrict average yields, and a kernel plot of the average claim payments conditional on the yield. The relationship between WBCIS claim payments and yields appears to be rather weak, with low average claim payments in the event of extreme yield losses; the leftmost point estimate of the kernel regression indicates that in the event of a zero yield, the average WBCIS claim payment is only 12% of the sum insured while in the event of yields being twice the historical average, the average WBCIS claim payment is 6% of the sum insured.

Considering the entire empirical joint distribution, the average Pearson product-moment correlation coefficient is -14% and the average Spearman's rank correlation coefficient is -13%. (In both cases a more negative coefficient indicates lower basis risk.) While these correlations are the correct sign, the magnitudes are quite low. Moreover, for some crops the average correlation is the wrong sign, with lower yields associated with lower claim payments.

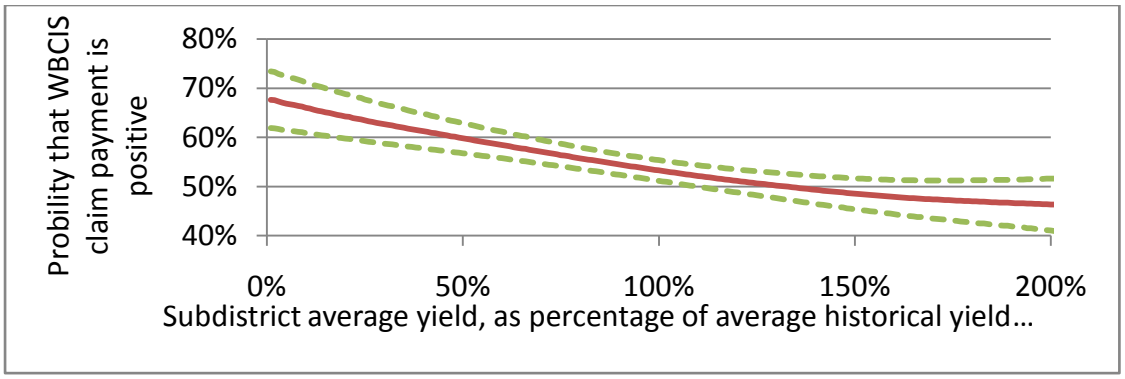
Figure 1: Scatter plot and kernel regression: claim payments against yields, for all weather indexed products sold in one state in one year



Note: The lines show the point estimate and 95% confidence intervals for an Epanechnikov kernel with a bandwidth of 0.8.

On this basis we estimate that conditional on total crop loss, that is an area average crop yield of zero, there is a 1-in-3 chance of receiving no claim payment from the WBCIS (Figure 2). This may arise because of perils not captured by the weather station data, such as localized weather, pestilence or disease, or weather events not adequately captured by the index used in the WBCIS product. Conversely, there is a high risk of farmers receiving a positive WBCIS claim payment, even in years with good yields. For example, again reading off from the kernel regression point estimate in , conditional on the yield being twice the historical average the WBCIS products included in this analysis paid claims with probability of 45% (Figure 2).

Figure 2: Kernel regression: probability of positive claim payment against yields, for all weather indexed products sold in one state in one year



Note: The lines show the point estimate and 95% confidence intervals for an Epanechnikov kernel with a bandwidth of 0.8.

However, the interpretation of this analysis requires care due to three data limitations. First, the yield data are based on crop cutting experiments which may not be wholly reliable. In past years the results from crop cutting experiments determined the claim payment due to farmers under the NAIS, and there are concerns both about measurement error and that some yield figures may have been underreported to trigger claim payments (Mahul et al. 2011). However, there is limited

evidence of over-reporting of yields, and so while the extreme left hand sides of Figures 1 and 2 may be underestimated, the right hand sides, which suggest that much of the WBCIS premium pays for claim payments in good years, are likely to be more reliable.

Second, we do not consider individual farmer yields in this analysis, but rather area average yields. While farmers with farms very near to the weather station may experience lower basis risk than the average farmer in the sub-district, WBCIS claim payments are expected to correlate more closely with area average yields than individual farmer yields. This would bias the above figures in the direction of underestimating the extent of basis risk between most farmers and the WBCIS claim payments.

Finally, significant investments in weather station infrastructure have been made in the last few years by both the public and private sectors, increasing the number of weather stations per district. Since one source of basis risk is likely to arise from the distance between a farmer's plot of land and the contractual weather station (spatial basis risk), this increase in granularity of weather stations might be expected to reduce basis risk. The degree to which this might happen is an open empirical question.

Consumer protection

While academics may not have a clear idea of the level of basis risk in a particular product, farmers are likely to be even less well equipped to be able to judge whether a product is good or not. In most contexts insurers have incentives to design products that can be understood by their clients. However, the combination of the compulsory nature of WBCIS for borrowing farmers and role of states in selecting between insurance companies has acted to reduce the incentives to design simple, transparent products that are understood by the ultimate clients, the farmers. Contracts are therefore typically complex and a farmer is unlikely to even have a good idea about what the claim payments from the product would have been in the recent past. Poor understanding is particularly detrimental to farmers who are eligible but not compelled to purchase WBCIS insurance.

One potential regulatory response would be to mandate that all weather indexed insurance contracts include a ten year history of what the claim payments would have been, using data from the contractual weather station. If such weather data is not available then data from the nearest government-approved weather station should be used, with an explicit caveat. Requiring insurers to disclose such information would allow farmers to assess whether there were claim payments in bad historical years, and may be considered as a similar type of regulation to requiring that banks state yields for loans in standardized forms, for example as an APR. Hill and Robles (2011) reports on a pilot in Ethiopia in which such information disclosure led to greater understanding of the products by farmers.

Such regulation would, of course, offer incentives to insurers to design products for which the average claim payment over the last ten years was high but the expected claim payment in future years was low. While this is regrettable, the advantages to consumers from such regulation seem likely to outweigh any such disadvantages.

Another cause for concern are reports that insurance companies are designing and pricing products based on historical weather data but then adjusting the length of the sales window based on up-to-date weather forecasts for the season, with shorter sales windows where payouts are expected and longer sales windows where payouts are not expected. Such practices might be expected to increase insurer profits but are bad for farmers and premium subsidy-paying central and state governments, and should be addressed by regulators and government.

Market structure

Some authors have noted that there has been less innovation in product design following the introduction of WBCIS, despite the large amount of data available. This may be caused by an increase in competition having reduced the private benefits from designing improved indices. States could limit this by tendering for WBCIS contracts in two phases: first a firm could be hired on a multiple-year contract to design weather products across the state; and second, insurers could compete on price or other specified dimensions to offer the stated products. Alternatively, states could tender for multi-year contracts with an insurance provider to design and offer products.

At present there is no uniform procedure adopted by state governments on the selection of insurance providers. It would be prudent to consider establishing and following a sound and transparent policy in insurance provider selection. Decisions about weather indexed insurance products are complex and there is a strong rationale for creating a technical support unit to support central and state governments in making informed decisions about insurance product design, and in choosing between insurance providers. Incidentally, formation of such a unit was one of the key suggestions of a recent evaluation study conducted on WBCIS on behalf of the Government of India (Government of India 2011).

4. Ratemaking for Weather Based Crop Insurance

As for any insurance product, the price of a weather indexed insurance product should reflect the expected cost to the insurer. Moreover, while it is important for estimates of the expected cost to be statistically unbiased, neither systematically too high or too low, it is also important the estimates are statistically efficient, so that the price for any one product is not significantly 'wrong'. It is commonly assumed that indexed weather insurance products are not subject to adverse selection against the insurer, as the insurer typically has access to long time series data that is at least as good as any information possessed by potential purchasers. However, this relies on the insurer making the best use of available data. If, as seems common across India, ratemaking procedures are statistically inefficient, insurers may be exposed to adverse selection.

Standalone approaches to ratemaking

In India, weather index insurance policies are typically rated on a standalone basis, with each calculation based on up to 30 years of historical weather data for the respective contractual weather station. First, weather data would be cleaned and analyzed for any trends which might lead to systematic increases or decreases in average claim payments over time. This cleaned, and possibly de-trended, data would then be applied to the specific contract to be priced, and the claim payments that would have been paid had that contract been in force, the *burn cost*, would be calculated for each year for which historical data exists. The *Historical Burn Rate* for the contract is then estimated as the arithmetic average historical burn cost divided by the sum insured. This is known as a Historical Burn Analysis (HBA), the simplest method of weather contract pricing.

The premium rate is then set to be the historical burn rate, adjusted by various loading factors to account for the cost of capital and administrative expenses, for example. Syroka (2007) suggests the following formula for WBCIS products:

$$Premium\ rate = (HBR + DUF + CL) \times (Administrative\ Load) \qquad (4)$$

where the Historical Burn Rate (HBR) denotes the arithmetic average burn cost for the contract in question, the Data Uncertainty Factor (DUF) is a load to account for any missing data, the Catastrophe Load (CL) accounts for the cost of acquiring risk capital, and the Administrative Load

includes any loading for administrative expenses. In practice the DUF is often chosen to be between 10% and 20% of the HBR and the CL is often calculated as

$$CL = \alpha \times \left(\max_{year} \left[\frac{Burn\ Cost_{year}}{Sum\ Insured} \right] - (HBR + DUF) \right), \tag{5}$$

where α is the insurer's cost of capital.

Standalone approaches to ratemaking are similar to those used in international weather derivative markets and may be appropriate while insurers have a small portfolio of weather indexed products due to their simplicity and cautious loading. However, they suffer from disadvantages, particularly for a large well-diversified portfolio, such as that of the current WBCIS.

First, estimating the expected cost to the insurer of each product separately is statistically inefficient, and can lead to rating being oversensitive to statistically insignificant features of historical data. For example, consider two deficit rainfall products that must be designed for nearby weather stations. Suppose that the underlying distribution of rainfall patterns at the two weather stations is identical, but that one station has had one year in the last thirty years with very low rainfall but the other has not. Under a standalone approach to ratemaking it would be difficult to offer the same product at the same price for both stations, even if the difference in rainfall histories was not statistically significant. This is because the burning cost approach does not give any indication as to whether differences in rainfall histories are statistically significant or not.

Second, while a weather derivatives trader might want a substantial Data Uncertainty Factor in their pricing rule, to protect against a better informed counterparty adversely selecting against them, this is likely to be less of a concern for an insurer selling weather indexed products to large numbers of farmers, who do not have access to historical weather data and for most of whom purchase is compulsory. For a large personal lines insurance portfolio like that of the WBCIS it may be appropriate to allow for any statistical censoring of data at a portfolio level as one component of the Catastrophe Load, rather than separately loading each product based on an individual Data Uncertainty Factor. If missing data is believed to be missing at random then no adjustment to the Catastrophe Load would be necessary; calculated pure premium rates would be unbiased estimates of the true expected loss ratios and the Catastrophe Load would adequately allow for the cost to the insurer of any aggregate data uncertainty. If it is believed that, across the portfolio, years with bad rainfall are less likely to have been recorded than years with good rainfall then pure premium rates could be biased downwards and the portfolio Catastrophe Load should be increased to reflect this bias. Correspondingly, if it is believed that, across the portfolio, years with bad rainfall are more likely to have been recorded than years with good rainfall then pure premium rates could be biased upwards and the portfolio Catastrophe Load should be decreased to reflect this.

Third, the Catastrophe Load should be set to account for the costs of acquiring risk capital for the portfolio. The above approach, based on the maximum historic burn cost for each product, targets the amount of capital required for that product to withstand the worst event for that product for which there is data. This depends on the number of years of historic data available in a somewhat arbitrary way, and does not allow for the level of diversification in the portfolio. A more appropriate approach would be to estimate the total cost of acquiring risk capital to withstand, for example a 1-in-200 year event, and then spread that cost across products.

The above disadvantages suggest that a portfolio approach to ratemaking, where multiple products are jointly rated, could be more efficient than a standalone approach, while allowing insurance providers more flexibility to offer standardized products based on agronomic principles. Premium calculations would be more robust to statistical outliers, and would better reflect the level of diversification in the portfolio, and so commercial premiums would be a better reflection of the true expected cost to the insurer.

A portfolio approach to ratemaking

The remainder of this section outlines one potential ratemaking methodology, implemented for part of the WBCIS portfolio by the public insurer AICI.[7] The basic formula for the premium rate is

$$Premium\ rate = (PPR + CL) \times (Adminsitrative\ Load) \tag{6}$$

where the Pure Premium Rate (PPR) is an estimate of the expected claim payment from the product, the Catastrophe Load (CL) accounts for the cost of acquiring risk capital, and the Administrative Load includes any loading for administrative expenses. Figure 3 provides an overview of the methodology.

Both the standalone and portfolio approaches to ratemaking involve calculation of an estimate of the future claim payments from products: the Historical Burn Rate (HBR) and the Pure Premium Rate (PPR), respectively. Both estimates are unbiased but the PPR is likely to be closer than the HBR to the actual expected future claim payment. The increase in efficiency comes from exploiting the spatial structure of weather patterns.

There are a number of ways of incorporating the spatial dimension of data into statistical procedures, such as Hierarchical Bayes methods. However, these approaches may be challenging to implement and meaningfully scrutinize when there is limited actuarial capacity. One approach to increasing the statistical efficiency of pricing as compared to the standalone approach is that of credibility theory, under which historical burn rates are smoothed within collectives of products, with the degree of smoothing determined by a credibility factor. Of particular interest is the credibility factor approach derived by Bühlmann (1967), which offers the best linear approximations to unconstrained Bayesian estimates.

Bühlmann's Empirical Bayes Credibility Theory is a linear process, and thus extreme outliers can present difficulties requiring special attention. A technique commonly used in conjunction with credibility weighting is to cap large losses before the application of credibility theory. Capping burn costs then adding back the probability mass may be actuarially sound as infrequent events lack statistically credibility. A properly chosen cap may not only add stability, but may even make the methodology more accurate by eliminating extremes.

The resulting Pure Premium Rate (PPR) calculation on a portfolio basis does not increase or decrease rates relative to the Historical Burn Rate (HBR) calculation; the total weighted average PPR is the same as the total weighted average HBR. Rather, the portfolio approach involves a re-spreading of rates between products where any difference in rates is judged to be statistically insignificant.

The Pure Premium Rate

Insurance products would first be grouped into Risk Collectives (RCs) and Balance Back Collectives (BBCs). A RC should contain similar products that are based on different sources of weather data. A BBC should contain one or more RCs, for which extreme claim events are expected to be similar in nature. For example a RC could include all products for a given crop sold in the same state and a BBC could include all products sold in a collection of states in the same agronomic region. The grouping of products into collectives requires both expert judgment and practical considerations.

First, the HBR is calculated for all products in the same Balance Back Collective, as for the standalone approach.

[7] A similar methodology, implemented for part of the mNAIS portfolio by the public insurer, is described in (Clarke et al. 2011).

Second, the Weighted Average Burn Cost (WABC) for the BBC is calculated to be the weighted average HBR over all products in the BBC, where weights are the expected sum insured for the upcoming season.

Third, a cap is applied to each burn cost history to remove statistical outliers. For each burn cost history, the Burn Cost Cap (BCC) is calculated to be the Xth percentile burn cost, where X is a number chosen by the insurer, typically between 90 and 100. The Product Base Rate (PBR) is then defined as the average capped burn cost for that product. The PBR is the average of capped burn costs, where the cap is applied to individual historical burn costs.

Fourth, the Weighted Base Rate (WBR) is defined as the weighted average of PBRs for all products in the same Risk Collective. The weights are taken to be equal to estimates of insurance purchase in the coming season.

Fifth, the credibility formula for the Base Rate (BR) is given by

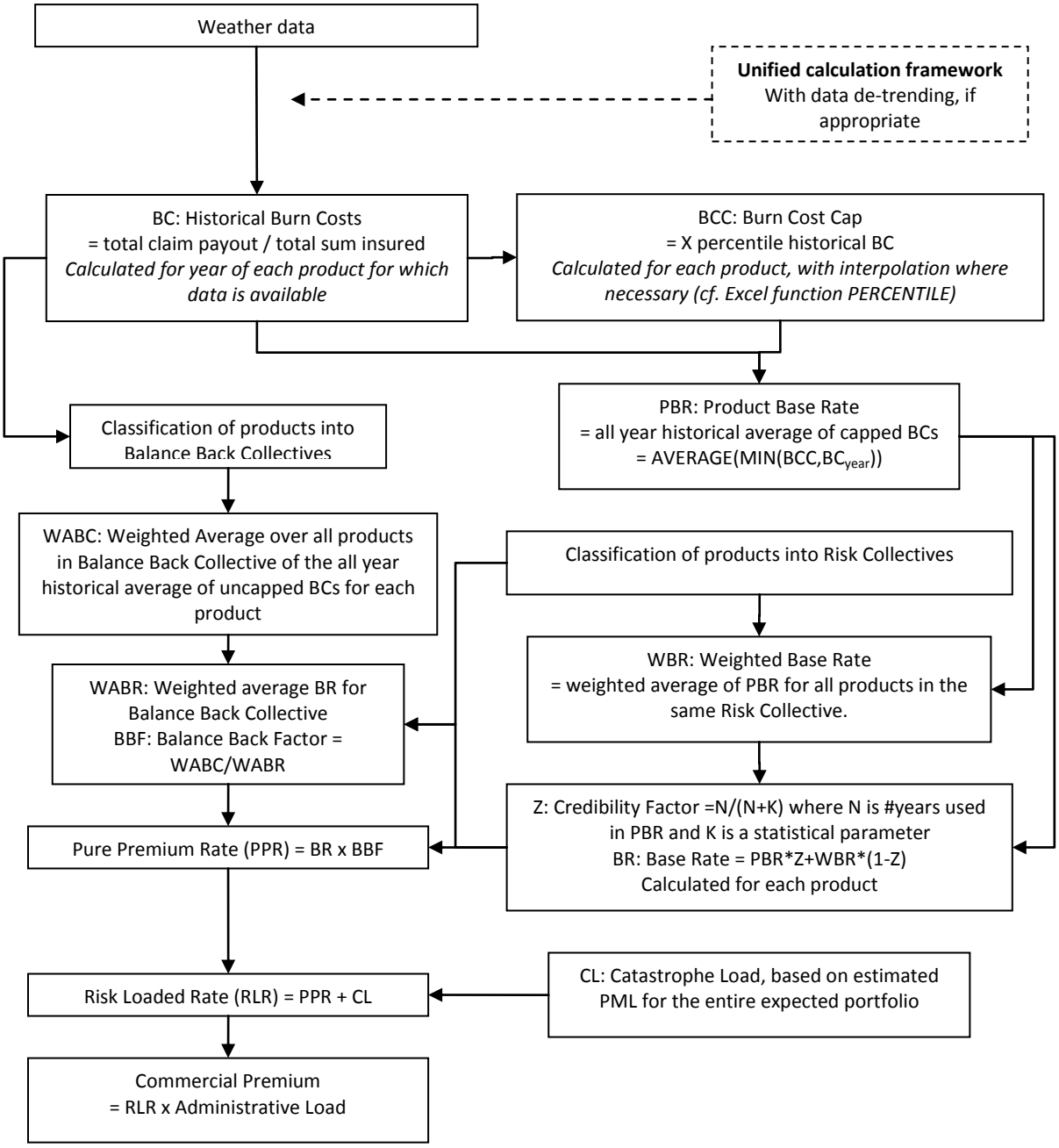
$$BR = PBR \times Z + WBR \times (1 - Z), \tag{7}$$

where BR is the Base Rate, PBR is the Product Base Rate, that is the average capped burn cost for that product, WBR is the weighted average PBR for all the products in the Risk Collective, and Z is the Credibility Factor. The Base Rate is therefore a weighted average of the PBR and the WBR, where the weight is the credibility factor Z.

Credibility refers to the degree of belief in a particular source of data. Credibility is a relative concept and is greater the more relevant the data source, and the greater the number of observations in the data source.

Credibility Factor Z can range from 100% (full credibility is assigned to individual history, and therefore there is no smoothing) to 0% (no credibility is assigned to individual history, and therefore there is full smoothing). Z should be 100% when the Risk Collective provides no statistically useful information for ratemaking. Correspondingly, Z should be 0% when the individual burn cost history is statistically uninformative, compared with the history for the full Risk Collective.

Figure 3: Weather-Based Crop Insurance: Flow Chart of a portfolio approach to ratemaking



One such Credibility Factor Z was introduced by Bühlmann (1967)[8]. Denoting the historical loss from product i in year j as X_{ij} this *Empirical Bayes Credibility Factor* Z is given by

$$Z = \frac{n}{n + \mathbb{E}[\widehat{s^2(\theta)}]/Var[\widehat{m(\theta)}]} \tag{8}$$

where n and N denote the number of years of data and the number of products in the risk collective respectively, and

$$\bar{X}_i = \frac{1}{n}\sum_{j=1}^{n} X_{ij}$$

$$\bar{X} = \frac{1}{nN}\sum_{i=1}^{N}\sum_{j=1}^{n} X_{ij}$$

$$\mathbb{E}[s^2(\theta)] = \sum_{i=1}^{N}\sum_{j=1}^{n} \frac{(X_{ij} - \bar{X}_i)^2}{N(n-1)}$$

$$Var[m(\theta)] = \left[\sum_{i=1}^{N} \frac{(\bar{X}_i - \bar{X})^2}{N-1} - \frac{\mathbb{E}[s^2(\theta)]}{N}\right]^+$$

This Credibility Factor satisfies intuitive properties and is robust in a range of scenarios; Z increases if there is more data for the product itself, the variation of burn costs for each product history decreases, or the variation of PBRs between products increases.

Since extreme losses have been removed from each product's experience, it is appropriate to add them back in at a broader level, so that rates are not underestimated. These losses could be added directly to Base Rates or incorporated proportionately by way of a multiplying factor. The two approaches will be similar if the Balance Back Collectives are homogenous. Here we assume that any capped burn cost mass is spread over the Balance Back Collective. The Pure Premium Rate (PPR) is therefore given by

$$Pure\ Premium\ Rate\ (PPR) = BR \times \frac{WABC}{WABR} \tag{9}$$

The total weighted average PPR over the Balance Back Collective is therefore the same as the total weighted average HBR over the Balance Back Collective.

Catastrophe Load

The suggested approach to catastrophe loading is based on an aggregate portfolio approach. This means that the total additional premium income from the Catastrophe Load should equal the total cost to the insurer of bearing the risk of the entire portfolio.

The insurer could conduct a portfolio risk analysis to determine the total amount of risk capital required, based on an aggregate Probable Maximum Loss (PML) approach. First, one should calculate the aggregate historical losses that would have been incurred if the current portfolio had been sold in previous years. Second, one should estimate the portfolio PML for a given return period. For the suggested ratemaking methodology the PML should be expressed as a proportion of Total Sum Insured, called the Probable Maximum Burn Cost (PMBC).

The insurer could estimate the cost of securing this risk capital, allowing for the internal cost of capital and the cost of any reinsurance purchased. Where the insurer must quote premiums for

[8] Textbook treatments include Herzog (1999) and Bühlmann and Gisler (2005).

products before the entire portfolio is finalized, judgment must be applied in assessing the level of diversification in the forthcoming weather based crop insurance portfolio. The more diversified the portfolio, the lower the Probable Maximum burn cost will be. If there is some uncertainty surrounding the level of diversification in the forthcoming portfolio the insurer may wish to estimate the Probable Maximum burn cost on a prudent, or cautious, basis.

The aggregate portfolio catastrophe load can be spread between products based on their contribution to the premium income or their contribution to the Total Sum Insured. The former would lead to a loading factor to be multiplied by the PPR; the latter would lead to a load being added to the PPR. The latter, additive, approach is suggested as it allows the insurer flexibility to rate groups of products in advance of knowing the full portfolio.

The Catastrophe Load (CL) is then calculated with reference to the PMBC, the insurer's cost of capital, and the insurer's risk financing strategy. A Catastrophe Load suggested is added to the PPR for each product. For example, if the insurer wished to accumulate capital of 16% of the aggregate total sum insured, and the cost of securing risk capital were 7%, the Catastrophe Load would be 16% x 7% = 1.1%.

The insurer may wish to calculate separate Catastrophe Loads for the Kharif and Rabi seasons to allow for any difference in catastrophic risk borne. This section ignores any reduction in the Catastrophe Load to account for diversification between the Kharif and Rabi seasons. By underestimating the benefits of diversification, this approach may be considered prudent for the products analyzed.

Standardization of products as a protection against data mining

A portfolio approach to ratemaking, such as that suggested above, would allow the insurer more flexibility in designing products based on agronomic principles. If the difference in rainfall for a group of weather stations in some Risk Collective was not statistically significant, then the same product could be sold in all stations at the same, or a very similar, price. This would have been difficult to justify under a standalone methodology.

However, care must be taken if the same historical weather data is to be used for both design and pricing of weather indexed insurance products. In particular, if individual products are designed to offer as much cover as possible for a target price, where the design process makes full use of historical weather data, then unadjusted rates will be systematically too low.

For example, suppose that you are a product designer with 30 years data and wish to offer cover for a one month period in two adjacent districts. The average rainfall for the month in question is 80mm in both districts and you want to develop a trigger below which you start making payouts. Your crop model says you should make payouts below 55mm.

1. Of the worst ten historical years there are nine years with monthly rainfall of 52mm and one year with monthly rainfall of 45mm. You find you can significantly cheapen the product based on historical data by moving the trigger from 55mm to 51mm, excluding the nine years with 52mm rainfall from the payouts.
2. Of the worst ten historical years there are nine years with monthly rainfall of 61mm and one year with monthly rainfall of 45mm. You find that you can increase the trigger from 55mm to 60mm without increasing the historical average payout from the product.

Both of these are examples of data mining that would lead to the systematic under-pricing of products.

For a more concrete example, consider the following. Suppose that an index has a standard continuous uniform distribution. A product designer observes 20 independent realizations of the index, denoted $K_i, i \in \{1, \dots, 20\}$, and we may sort these realizations into increasing size, denoted $\widetilde{K}_i$

where $\widetilde{K}_i \leq \widetilde{K}_{i+1} \forall i \in \{1, \dots, 19\}$. The designer is to offer a product that pays □100 if the next realization of the index is below some trigger T and □0 otherwise. Suppose that the designer aims to offer as much cover as possible for a pure premium of □10. Now, if the designer chooses $T = \widetilde{K}_3 - \varepsilon$ for some small $\varepsilon > 0$, at this trigger the product would have paid out twice in the past. An Historical Burn Analysis would lead to an estimate for the pure premium of $\square 100 \times \frac{2}{20} = \square 10$. However, for the uniform distribution, we know that $\square 100 \times \mathbb{E}[T] = \square 100 \times \mathbb{E}[\widetilde{K}_3 - \varepsilon] = \square 100 \times \left[\frac{3}{21} - \varepsilon\right]$ which is strictly greater than □10 for small enough ε.

Both ratemaking methodologies presented in this section would be vulnerable to this form of data mining. Both methodologies rely on either a raw or a smoothed historic burn cost approach and if this is biased downwards due to data mining in product design then average pure premium rates will also be biased downwards.

Products cannot be rated on an actuarially sound basis with this form of data mining. One could reduce the bias in rates by calculating historical burn costs for a particular product using weather data series from all nearby weather stations, and then charging a premium based on the average of the average burn costs for this product. However, this would involve cumbersome calculations and would introduce significant inefficiency in estimation; that is to say that premiums would often be either too high or too low, even if they were fair on average.

A way to guard against this form of data mining is to require that all products for a particular crop in a particular season differ only by a limited number of parameters. A standardized product could offer full cover for modeled crop loss above a specified deductible. The deductible parameter could be chosen by the insurer for each product, based on statistical principles, while the shape of the product would be determined by an agronomic model.

As another example, all Kharif maize products sold across India might include four phases of deficit rainfall cover, one phase of consecutive dry day cover, and one phase of excess rainfall cover. All such products would have identical exits, rates, maximum payments, periods, and trigger days. However, triggers for deficit rainfall cover could be uniformly increased or decreased for each maize product so that the calculated rate was within the required range. For example, if the triggers for the four phases of one maize product were {50, 70, 80, 40} then the triggers for any other maize product would be {50+X, 70+X, 80+X, 40+X} for some number of millimeters X, that could be positive or negative. X would be chosen for each product so that the Pure Premium Rate is within the target range. Such an approach would shield the design process from statistically insignificant features of historical weather data. Such dependence would not lead to data mining.

The suggested ratemaking procedure would allow insurers more flexibility in designing products based on agronomic principles. If the difference in rainfall for a group of weather stations in some Risk Collective was not statistically significant, then the same product could be sold in all stations at the same, or a very similar, price. This would have been difficult to justify under the existing ratemaking methodology.

Although the above discussion focuses on WBCIS, the importance of standardizing the shape of products, based on agronomic principles, and using historical data only to determine one or two key parameters is equally valid for any other types of products offered by insurers.

One might think of a weather insurance product as comprising a *shape* of cover in addition to a *level* of cover. The shape of cover should not be driven by individual weather data histories because, otherwise, products are likely to be underpriced. It might seem natural for the shape of cover to depend on agronomic fundamentals. In contrast, it is perfectly reasonable for the level of cover to depend on the individual weather data history. Such dependence would not lead to the form of data mining described above.

5. Conclusion

Unlike early pilots, the scaling up of weather index insurance in India has received little attention by academic economists. This paper offers an overview of the market and suggestions for future research and innovations.

First, states may wish to support long-term development of improved products that aim to minimize basis risk. A comparative statistical analysis of different products would be valuable and should be possible in India given the availability of long-term yield and weather data. This could lead to further standardization of products, based on agronomic and statistical principles, which would in turn support robust actuarial design and pricing. In addition to this analysis, the current market structure, under which insurers propose both products and prices, may not offer appropriate incentives to insurers to invest in developing improved products since innovations can be copied by rival insurers. Instead, states may wish to consider tendering in two phases, first with a multiple-year contract to design products and second with a one-season contract to sell products, or to commit to multiple-year contracts with insurance providers.

Second, governments may wish to enhance consumer protection legislation for indexed insurance products, for example, by requiring that any contract states historic burn costs for at least the last ten years. This could help farmers decide whether a particular product is good value, and whether it could be relied on to pay out in bad years.

Third, the WBCIS offers substantial opportunities to understand how to increase demand, particularly from the most vulnerable farmers. A rigorous monitoring and evaluation could be integrated into these programs to ensure that at the end of the pilot period government and states have the information they need to make decisions about the future of agricultural insurance in India.

Fourth, while this paper has focused on weather indexed insurance contracts, there is merit in further research to better understand how best to combine the information from different indices so that farmers can rely on timely claim payments in bad years. For example, an early part-settlement based on a weather index could be combined with a final adjustment based on an area yield index (Rao 2011), with weather and satellite data used behind the scenes by insurance providers to target and monitor the crop cutting experiments that form the basis for the yield index.

Finally, designing, evaluating and regulating indexed insurance products is a highly technical area and there may be a role for a central government Technical Support Unit to provide objective, technical support to states, central government and regulators. At a minimum, such a unit could provide objective analysis of the cost of and level of basis risk in products to assist states in choosing between different programs and insurance providers. However, the unit could also have a broader analytical and research function, with a mandate to study the agricultural insurance market across India and develop best practice guidelines on areas such as product design, procurement and strategies for increasing take-up.

Bibliography

Bühlmann, H., 1967. "*Experience rating and credibility*," ASTIN Bulletin, 4, 199–207.

Bühlmann, H. and A. Gisler, 2005. *A course in credibility theory and its applications*, Springer Verlag.

Chakravarti, JS, 1920. *Agricultural insurance: a practical scheme suited to Indian Conditions*, Government Press, Bangalore.

Clarke, D.J., 2011. *"A Theory of Rational Demand for Index Insurance"*, Economics Series Working Papers 572, University of Oxford, Department of Economics.

Clarke, D.J., O. Mahul and N. Verma, 2011. *"Index Based Crop Insurance Product Design and Ratemaking: The case of the modified NAIS in India,"* World Bank, mimeo.

Cole, S.A., X. Giné, J.B. Tobacman, P.B. Topalova, R.M. Townsend, and J.I. Vickery, 2009. *"Barriers to Household Risk Management: Evidence from India,"* Working Paper 09-116, Harvard Business School.

Giné, X., H.B. Lilleor, R.M. Townsend, and J. Vickery, 2005. *"Weather Insurance in Semi-arid India,"* Paper presented at the Annual Bank Conference on Development Economics, May 23-24, Amsterdam.

Giné, X., L. Menand, R. Townsend, and J. Vickery, 2010. "*Microinsurance: a case study of the Indian rainfall index insurance market"*, Policy Research Working Paper Series 5459, The World Bank.

Giné, X., R. Townsend, and J. Vickery, 2008. *"Patterns of rainfall insurance participation in rural India,"* The World Bank Economic Review, 22 (3), 539.

Government of India. 2011. "*Report on Impact Evaluation of Pilot Weather Based Crop Insurance Scheme (WBCIS)*", Ministry of Agiculture, New Delhi, January.

Hazell, P. , 1992. *"The appropriate role of agricultural insurance in developing countries,"* Journal of International Development, 4 (6), 567–581.

Herzog, T.N., 1999. *Introduction to Credibility Theory*, Actex Publications.

Hess, Ulrich, Jerry Skees, Barry Barnett, Andrea Stoppa, and John Nash, 2005. *Managing Agricultural Production Risk: Innovations in Developing Countries*, The World Bank, Agriculture and Rural Development Department, Report.

Lobell, D.B., M. Banziger, C. Magaorokosho, and B. Vivek, 2011. "*Nonlinear heat effects on African maize as evidenced by historical yield trials,"* Nature Climate Change, 1, 42–45.

Mahul, O., N. Verma, and D.J. Clarke, 2011. *"Improving famers' access to agricultural insurance in India,"* World Bank, mimeo.

Ministry of Agriculture, 2010. *"Pilot Weather Based Crop Insurance Scheme (WBCIS)"*, Government of India.

Mishra, P.K., 1995. *"Is Rainfall Insurance a New Idea? Pioneering Work Revisited*," Economic and Political Weekly, pp. 84–88.

Rao, K.N., S. Gadgil, P.R. Seshagiri Rao, and K. Savithri, 2000. *"Tailoring strategies to rainfall variability – The choice of the sowing window,"* Current Science, 78(10):1216–1230.

Rao, Kolli N., 2011. "*Weather Index Insurance: Is it the Right Model for Providing Insurance to Crops?*" ASCI Journal of Management, 41(1): 86-101.

Singh, R., 2010. *"Review of Weather-based Crop Insurance in India"* Background paper, Washington DC: World Bank.

Syroka, J., 2007. "*Index-Based Weather Insurance for Indian Farmers: Recommendations for Ratemaking",* Washington DC: World Bank.

Hill, R.V. and M. Robles, 2011. *"Flexible Insurance for Heterogeneous Farmers: Results from a Small-Scale Pilot in Ethiopia*". IFPRI Discussion Paper 1092. Washington, D.C. International Food Policy Research Institute (IFPRI).

World Bank. 2007. *"India National Agricultural Insurance Scheme: Market-based Solutions for Better Risk Sharing"* Report No. 39353. Washington DC: World Bank.

World Bank. 2011. *"Enhancing Crop Insurance in India"* Washington DC: World Bank.

Appendix

Table 3: Normal rainfall index for Mahabubnagar, Andhra Pradesh (AICI, Kharif 2005)

Rainfall between 1 June and 30 September 2004 (mm)	Payment (□/mm)
0-42	21.10
42-85	21.00
85-128	20.93
128-170	20.87
170-213	20.78
213-256	20.65
256-298	20.56
298-341	20.45
341-384	20.40
384-426	20.35
426-469	18.30
469-512	16.47
512-554	14.80
554-597	13.32
597-640	11.99
640-682	10.77

Note: Average historical rainfall was 853mm

Table 4: Weighted rainfall index for Mahabubnagar, Andhra Pradesh (IFFCO-Tokio)

Month	Weight	Normal Rainfall (mm)	Weighted Rainfall
June	1.25	114.7	143.4
July	1.50	205.1	307.7
August	1.25	178.4	223.0
September	0.50	186.3	93.2
	Total:	569.8	767.2

% Deficiency	Claim Payout (% of Sum Assured)
0%	0%
10%	0%
30%	10%
40%	13%
50%	18%
60%	25%
70%	40%
80%	70%
90%	100%

Premium	4.38%

Table 5: Rainfall index with multiple phases (ICICI Lombard, Kharif 2004)

Phase	Dates	Strike (mm)	Exit (mm)	Sum Assured (□)
Establishment and Vegetative Growth	June 10 – July 14	75	20	3,000
Flowering and Pod Formation	July 15 – August 28	110	40	2,000
Pod Filling and Maturity	August 29 – October 2	75	10	1,000

Table 6: Rainfall index with multiple phases and carry-forward (AICI, Kharif 2009)

Period	10-Jun to 30-Jun	1-Jul to 31-Jul	1-Aug to 31-Aug	1-Sep to 30-Sep
Trigger I (<)	50 mm	90 mm	100 mm	60 mm
Trigger II (<)	25 mm	45 mm	50 mm	30 mm
Exit	0	0	0	0
Payout Rate I (□/ mm)	10	10	12	15
Payout Rate II (□/ mm)	70	68	58.0	52
Max. Payout (□)	2000	3500	3500	2000

Note: Rainfall of more than 2 times the trigger during a particular phase is considered for 'Carry Forward' to the next phase. In case of Phase-I, 25% of the rainfall in excess of the trigger (provided the rainfall is more than twice the trigger value) would be carried forward to Phase - II. In case of Phase - II, 30% of the rainfall in excess of the trigger (provided the rainfall is twice the trigger value) would be carried forward to Phase III. And in case of Phase III, 30% of the rainfall in excess of the trigger (provided the rainfall is twice the trigger value) would be carried forward to Phase IV.

Table 7: Consecutive Dry Days (AICI, Kharif 2009)

COVER PERIOD	1-Jul to 31-Aug		
Rainy Day Definition	Daily Rainfall ≥ 2.5 mm		
Trigger Non-Rainy Days (>=)	17	25	30
Payout (□)	750	1500	2000

Table 8: Consecutive Dry Days 2

Crop	Groundnut
Reference Weather Station	IMD Udaipur
Index Definition	Maximum Number of CDDs where a CDD is a day with rainfall equal to 0 mm
Cover Start Date	1-Jul-09
Cover End Date	10-Sep-09
Strike 1 (CDD's)	20
Strike 2 (CDD's)	30
Strike 3 (CDD's)	40
Strike 4 (CDD's)	50
Exit (CDD's)	60
Payout 1 for CDD> strike1 and <= strike2 (□)	300
Payout 2 for CDD> strike2 and <= strike3 (□)	900
Payout 3 for CDD> strike3 and <= strike4 (□)	2250
Payout 4 for CDD> strike4 and <= exit (□)	4500
Maximum payout	7500

Table 9: Temperature index with multiple phases (AICI, Rabi 2007)

Cover Objective	Heat or Rise in Mean Temperature
Cover Period	1st January to 31st March
Total Payout	Sum of the Payouts of Various Fortnights
Max. Sum Assured	□5400

Period (Fortnight)	1-15 Jan	16-31 Jan	1-15 Feb	16-29 Feb	1-15 Mar	16-31 Mar
Rise in Fortnightly Mean Temp (°C)	Payout (Percentage of Sum Assured)					
1.0	0.00	0.00	0.00	0.00	0.00	0.00
2.0	0.00	0.00	0.00	3.82	4.31	4.31
3.0	0.00	0.00	0.00	6.76	6.57	6.57
4.0	0.00	3.99	3.53	9.92	8.39	8.39
5.0	4.66	5.70	4.92	12.68	9.52	9.52
6.0	0.00	7.04	9.20	15.17	10.78	10.78

Table 10: Cumulative High Degree Deviation (HDDN) Index (ICICI Lombard, 2010)

Crop	Wheat
Reference Weather Station	NCMSL Dhar
Index	Total sum of upward deviation of average of daily maximum temperatures of every sub phase from the corresponding benchmark temperatures of every subphase, measured in degree celsius, during the cover phase. i.e. $\sum_n max[0, Average(Tmax_n) - BT_n]$, where $Tmax$ is daily maximum temperature, n is sub phase, BT is Benchmark Temperature.

Cover Phase, From	1-Jan-10
To	31-Mar-10
Strike 1 (°C)	6.50
Strike 2 (°C)	13.50
Exit (°C)	17.50
Notional 1 (□/°C /Hectare)	785.70
Notional 2 (□/°C /Hectare)	2562.70
Phase Limit (□/ Hectare)	15750.00

Sub phase			Benchmark Temperature (°C)
S. No	From	To	
1	01-Jan-10	15-Jan-10	26
2	16-Jan-10	31-Jan-10	27
3	01-Feb-10	14-Feb-10	29.5
4	15-Feb-10	28-Feb-10	31
5	01-Mar-10	15-Mar-10	34.5
6	16-Mar-10	31-Mar-10	37.5

Table 11: Low temperature index

Crop	Cumin
Reference Weather Station	Kota
Index	Minimum Temperature on any Day during the Cover Period
Strike	6°C
Exit	3°C
Notional (□/°C)	1250
Sum Insured (□)	3750

Table 12: Relative Humidity Index for Pests and Diseases

Index Objective	To protect against possible yield loss because of weather conditions conducive to occurrence of Aphid and Blight disease.
Crop	Cumin
Reference Weather Station	Bikaner
High Relative Humidity (RH) Event	A RH reading of > 65% taken at 08:30 or 17:30 hours in a day
Index	Maximum number of 5 day moving count of High RH events
Cover start date	1-Jan
Cover end date	28-Feb
Strike (High RH events)	7.0
Exit (High RH events)	10.0
Notional (□ / High RH event)	2000
Policy Limit (□)	6000

Table 13: Multiple Parameter Weather Index for Pests and Diseases (ICICI Lombard, Kharif 2006)

Crops	Potato
Reference Weather Station	Ranchi
Index	Number of Blight conducive events (BCE) within the policy period where a BCE occurs when within a period of 5 days the following conditions are observed simultaneously: There is some amount of rainfall observed in 2 consecutive days, morning and evening relative humidity is observed to be more than 85% for 2 continuous days, and the maximum and minimum temperature on a day is observed to be in between 7.2 - 26.6 °C for 4 consecutive days.
Policy duration	15-Sep to 06-Nov
Strike (No. of BCEs) >	1
Exit (No. of BCEs)>=	2
Payout (in □ for observed index of 1 BCE)	600
Payout (in □ for observed index of 2 BCE)	1000
Premium (□)	157
Policy Limit (in □)	1000

Table 14: Dual-Parameter Weather Index for Diseases

Disease Conducive Weather Index (DCWI) for Gherkin		
Cover Period	Option 1	1st Jan to 31st May
	Option 2	1st Feb to 31st May

Daily Strike	Both average Relative Humidity (RH) > 74% and minimum temperature < 18.5^{0}C.	
Index Count	Consecutive days with strike, where the count of days only restarts after gaps of two or more days without the strike.	
Loss Adjustment Factor (LAF) for Incidence Count	Incidence Count	Loss Adjustment Factor (LAF)
	1	0
	2	0
	3	0
	4	5
	5	6
	6	8
	7	11
	8	13
	9	17
	10	22
	11	28
	12	36
	13	46
	14	59
	15	75

Index Value	LAF corresponding to the Incidence Count
DCWI	Sum Total of all LAFs in the cover period
Notional (□/DCWI)	75
Max Payout (□)	10000