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ABSTRACTS

The papers appearing in this special issue were originally presented at the 101st Seminar of the European Association of Agricultural Economists (EAAE) titled "Management of Climate Risks in Agriculture," held in Berlin, Germany, July 5–6, 2007. Abstracts of three additional seminar papers (published elsewhere) are also included here.

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Preface

Agricultural Finance Review (*AFR*) provides a forum for discussion of research, extension, and teaching issues in agricultural finance. This publication contains articles contributed by scholars in the field and refereed by peers.

Volume 43 was the first to be published at Cornell University. The previous 42 volumes were published by the United States Department of Agriculture. *AFR* was begun in 1938 by Norman J. Wall and Fred L. Garlock, whose professional careers helped shape early agricultural finance research. Professional interest in agricultural finance has continued to grow over the years, involving more people and a greater diversity in research topics, methods of analysis, and degree of sophistication. We are pleased to be a part of that continuing development. We invite your suggestions for improvement.

AFR was originally an annual publication. Starting with volume 61, Spring and Fall issues are published. The *AFR* web page can be accessed at http://afr.aem.cornell.edu/. Abstracts of current issues and pdf files of back issues since 1995 are available.

The effectiveness of this publication depends on its support by agricultural finance professionals. Grateful appreciation is expressed to the W. I. Myers endowment for partial financial support. Thanks are also due to Faye Butts for receiving, acknowledging, and monitoring manuscripts, and Judith Harrison for technical editing.

Manuscripts will be accepted at any time.

Calum G. Turvey, Editor
Bruce J. Sherrick, Associate Editor

Martin Odening and Ernst Berg
Guest Editors

Foreword
Agricultural Finance Review Special Issue: "Management of Climate Risks in Agriculture"

It is well known that weather risks are a major source of uncertainty in agriculture. Drought or excess rain is responsible for poor harvests all over the world. Perhaps the most obvious impact of weather risk is on crop yields, but its relevance is not limited to crop production. The performance of livestock farms, the turnover of processors, the use of chemicals and fertilizers, and the demand for many food products also depend on the weather. Hence, large segments of agribusiness are affected by weather risks.

Although weather risk is a traditional theme in agricultural economics, it seems promising to take a fresh look at this topic. On the one hand, due to global climate changes, the volatility of weather and the occurrence of extreme weather events increase, in turn further contributing to volumetric risk. This leads to destabilization of farm incomes, which can become particularly acute in developing countries. On the other hand, with the emergence of international weather markets, new opportunities arise to handle these risks. Instruments such as weather insurance or derivatives or catastrophe (CAT) bonds are available to transfer weather risk to the capital market. While many transactions are based on over-the-counter bilateral contracts, standardized products are also currently traded on formal exchanges—e.g., the Chicago Mercantile Exchange (CME).

While weather risk management evolved from the energy sector, there is considerable promise for applications to agriculture and agribusiness. From theoretical foundations to practical applications, developing an understanding of weather markets, the traded instruments, and their relation to traditional weather insurance is a challenging task for agricultural economists.

In recognition of the importance of weather risk management in agriculture, an international seminar was organized to provide an overview of the state of the art in this field of research. The seminar was held at the Humboldt-University Berlin on 5–6 July 2007, under the auspices of the European Association of Agricultural Economists (EAAE). This special issue of the *Agricultural Finance Review* contains a selection of the papers presented at that seminar. Before inclusion, the papers were each reviewed by two referees. In addition, at the back of this special issue we include abstracts of three selected seminar papers which are published elsewhere.

This volume opens with an overview about the historic development of weather risk markets provided by Michael Roth, Christina Ulardic, and Juerg Trueb. The authors further highlight critical success factors needed for a prospering market. Jette Krause addresses the problem of predicting agricultural yields under climate change. Using a Bayesian approach, she shows that cereal yields exhibit growing deviations from an increasing trend. The contribution of Robert Finger and Stéphanie Schmid is at the interface between crop science and economy. They integrate biophysical simulations in an economic model in order to assess the weather sensitivity of wheat production and to evaluate adaptation strategies such as changes in production intensity and irrigation.

The next two papers examine traditional insurance from different perspectives. Alberto Garrido and David Zilberman empirically estimate insurance demand models based on insurance records of more than 50,000 farmers in Spain. A major finding is that farmers' insurance demand can be largely explained by indemnities they experienced in the past. Geoffroy Enjolras and Robert Kast (see abstract, p. 219 of this *Journal* issue) develop a theoretical model that allows determining the optimal structure of insurance contracts in the presence of systemic risk and idiosyncratic risk. Their findings reveal that a combination of participating and nonparticipating contracts is most efficient, since this allows an implementation of the risk-mutualization principle and the risk-transfer principle.

A sequence of four papers analyze farm-level applications of weather derivatives and index-based insurance. Daniele Torriani and her colleagues investigate the hedging effectiveness of weather derivatives in maize production in terms of a reduction of a value-at-risk measure. They conclude that considerable loadings on the fair premium could be charged compared with a situation without hedging. Oliver Musshoff, Norbert Hirschauer, and Martin Odening report similar findings when deriving the willingness to pay for index-based weather insurance in an expected-value-variance framework. Joshua Woodard and Philip Garcia focus on the important issue of weather derivatives' basis risk. Their results show that geographic basis risk can significantly reduce the hedging effectiveness of weather derivatives. This, however, should not preclude the use of geographic cross-hedging, particularly with increasing spatial aggregation of the risk exposure. Apart from weather risk, other risk factors, particularly price risk, should be taken into account when quantifying the marginal contribution of weather derivatives to the risk exposure of farms. This is one of the main messages of the paper by Ernst Berg and Bernhard Schmitz who develop a whole-farm model for that purpose.

Calum Turvey extends the scope of the previous papers by including farms' financial risk. He demonstrates that weather-linked bonds and other risk-contingent credit instruments can be useful tools for balancing weather-induced increases in business risk against the financial risk of a leveraged firm. Moreover, pricing formulas for weather-linked bonds, operating loans, and mortgages are developed. Pricing issues of weather derivatives are also discussed in the contribution of Wei Xu, Martin Odening, and Oliver Musshoff (see abstract, p. 221 of this *Journal* issue). They adopt the concept of indifference pricing as an alternative to risk-neutral valuation and equilibrium models.

The last four papers of this volume discuss actual and potential applications of alternative risk-transfer instruments for mitigating the economic consequences of weather hazards in lower income countries. Jerry Skees, Barry Barnett, and Anne Murphy discuss how natural disasters can be insured and reinsured using innovative instruments like catastrophe bonds. Their explanations involve experiences from several pilot projects that have been conducted by the World Bank. Focusing on drought risk, Sommarat Chantarat and her colleagues develop a weather index-based insurance product that could be used by governments or NGOs to improve humanitarian response to slow-onset disasters. A similar approach is pursued by Vasco Molini et al. (see abstract, p. 223 of this *Journal* issue). Subsequent to a description of present social safety nets in Northern Ghana, the authors construct a weather derivative with a flexible functional form and test its performance by means of simulations. Finally, Jerry Skees subsumes the progress and challenges associated with the use of index-based risk-transfer products in lower income countries.

We thank all participants of the EAAE Seminar for their interesting contributions and papers. Thanks are also extended to the reviewers who helped to improve earlier versions of the papers. Financial support from the Rentenbank (Frankfurt a.M.) for organizing the seminar and publishing these proceedings is gratefully acknowledged. Special thanks go to Reinhold Wilhelm and Gabriele Wuerth for supporting the conference management.

— Martin Odening, Ernst Berg,
and Calum G. Turvey

Critical Success Factors for Weather Risk Transfer Solutions in the Agricultural Sector: A Reinsurer's View

Michael Roth, Christina Ulardic, and Juerg Trueb

Abstract

Agricultural yield and commodity prices are very sensitive to weather patterns such as drought, excessive rain, or frost. Consequently, unseasonable weather can cause major losses for players in the agricultural value chain, including input providers, farmers, commodity traders, and food processors. In this paper information recorded by PriceWaterhouseCoopers on behalf of the Weather Risk Management Association is complemented by Swiss Re's market intelligence to examine demand patterns for weather risk transfer solutions. There is a particular focus on the evolution of demand from the energy sector compared to the agricultural sector as a means of identifying the critical success factors needed for a prospering market. Our findings show that recent growth in the weather risk transfer market is mainly related to speculative trading in the energy sector. Stakeholders in the agricultural sector around the world are growing increasingly interested in weather risk transfer products. However, the lack of exchange-based instruments in this field, the relatively high basis risk between weather indexes and agricultural yield, the fact that agricultural markets are still highly regulated, and inadequate information and training are all impeding the growth of this business.

Key words: agricultural sector, demand patterns, weather risk transfer

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The largest exposure of the agricultural sector is related to systemic risks such as widespread drought conditions, frost, and heat waves. Using loss data gathered by the National Crop Insurance Service (NCIS) from insurance companies participating in the U.S. crop insurance market (the world's largest market providing extensive coverage for a large geographic area), we estimate that about 80% of losses recorded during 1981–2003 result from large-scale weather risks impacting yield over a prolonged period—i.e., drought (47%), wet conditions (22%), frost (13%).

Within the last few years, drought-related losses have occurred in the United States (2002), Europe (2003), and Australia (2006). For example, the hot and dry summer of 2003 caused an estimated loss of revenue to the agricultural sector in Europe of about €10.7 billion (Swiss Re, 2004).

The introduction of Multi-Peril Crop Insurance[1] (MPCI) schemes gave farmers the ability to protect themselves against nearly all systemic risks. This coverage is widely used in the United States, Canada, Spain, Portugal, and Israel—largely due to government subsidies. Other stakeholders in the agricultural sector, such as input providers, commodity traders, food processors, and farmers, working in the majority of the worldwide agricultural markets, have only limited or no access to

[1] In general, MPCI products provide a very wide coverage for crop yields with only few risk exclusions, and therefore are well suited to cover systemic risks such as unseasonable weather patterns which impact over a period of time.

MPCI coverage. Therefore, they likely require other solutions to manage their exposure to weather risks. Furthermore, farmers in markets where MPCI coverage is available typically carry deductibles of 25–50% of the average expected yield, and hence even those farmers are (albeit to a lesser extent) exposed to the vagaries of the weather.

During the second half of the 1990s, U.S. energy trading companies such as Enron, Aquila, and Koch developed weather derivatives. These energy traders were quickly joined by banks and reinsurance companies who introduced the concept of weather derivatives and weather insurance—referred to as weather risk transfer instruments in this paper—to other industry sectors, such as agriculture, construction, or tourism.

Agricultural sector stakeholders have had access to weather risk transfer instruments for the last 5–10 years. Consequently, it is of interest to compare the development of market demand for such instruments in the energy sector with demand in the agricultural sector. We have done this by comparing the development of weather risk transfer instruments for both industry sectors using data recorded by PriceWaterhouseCoopers (PWC) during its annual survey of the weather markets on behalf of the Weather Risk Management Association (WRMA) and market intelligence derived from Swiss Re teams acting in the agricultural and weather markets. Our analysis reveals some success factors considered to be critical for the further growth of weather risk transfer business within the agricultural sector.

Demand Patterns in the Weather Risk Transfer Market

PWC has conducted a yearly survey of the weather risk transfer market since 2001. The survey is based on portfolio information provided by professional market participants on a confidential basis. Each survey covers April 1 to March 31 of the following year, and records aggregated characteristics of transactions incepting during that period. For multi-year transactions, only one calculation period is recorded. While not all professional market players are covered by the survey, we consider it to be reasonably representative of market developments (for further details, see www.wrma.org).

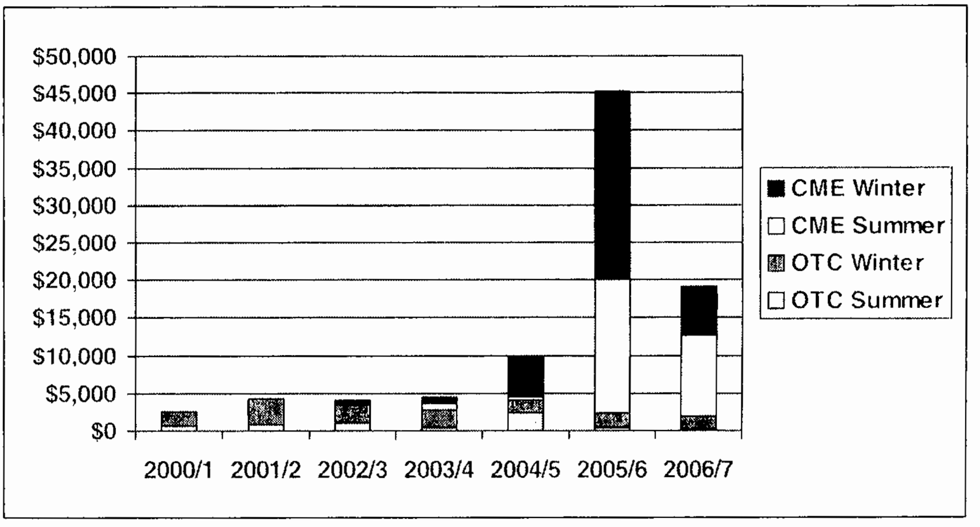
In addition to the sources noted above, our comments are based on the market intelligence of Swiss Re's agricultural and weather teams. Both teams have long-standing market experience, act globally, and have a solid market presence. We estimate the agricultural team's market share to be slightly more than 10% of the agricultural reinsurance market with higher shares in emerging markets. The weather team's market share is estimated to be about 30% of the over-the-counter (OTC)[2] market; the team is also one of the most active market participants in the Chicago Mercantile Exchange (CME) based degree-day[3] trading.

An analysis of PWC's most recently published market survey reveals the following (Figure 1):

- The weather risk transfer market shows healthy growth, recording an aggregated notional value of US$19.2 billion for 2006/7. This is well above the US$2.5–9.7 billion range recorded for 2001/2 through 2004/5; however, there is a significant reduction in size relative to the survey period 2005/6. Market intelligence indicates that the peak value recorded for the survey period 2005/6 is mainly due to the build-up and liquidation of the weather portfolios of three large U.S.-based speculators.

[2] OTC business refers to contracts directly closed between two counter parties. Business recorded in this category can be either in the form of derivative or insurance and reinsurance contracts.

[3] Here we refer to the trading in CME swaps and options which use cooling and heating degree-days as underlying indexes.



Source: PriceWaterhouseCoopers (2007, p. 18).
Notes: Winter contracts are defined by an inception date between November 1 and March 31 of each year; summer contracts are defined by an inception date between April 1 and October 31 of each year.

Figure 1. Total Notional Value of Weather Risk Contracts: 2000/1–2006/7 ($US millions)

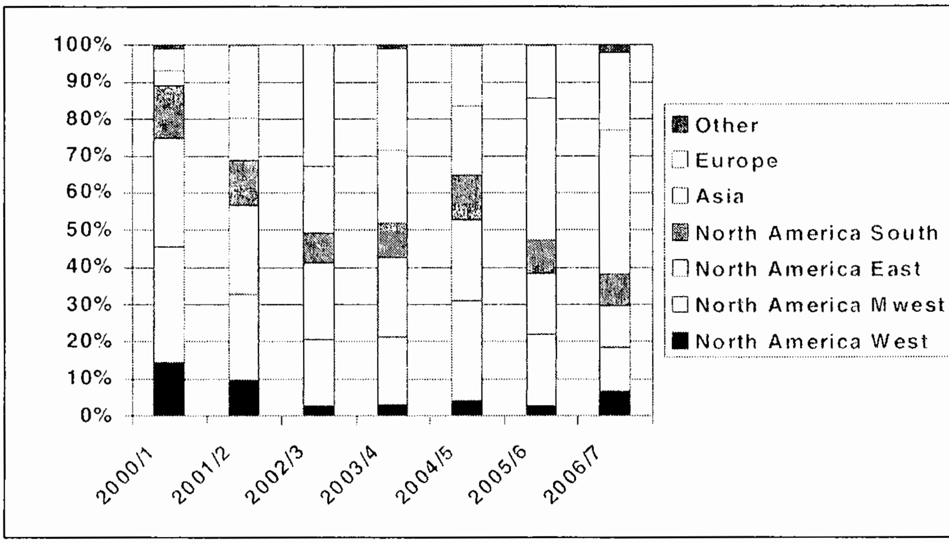
- There is a bifurcation of the market into CME business and OTC business. Since the introduction of CME products in 2002/3, there has been strong growth in CME trading. Since about 2004/5, OTC business has been shrinking. Market intelligence indicates this is mainly due to the success of CME trading which has allowed former OTC market participants to shift their activities to CME and profit from easier execution and increased price transparency.

- CME business mainly involves speculative traders in the U.S. energy sector. These market participants use weather risk transfer products in conjunction with commodity price risk products to enter into cross-commodity strategies. Market participants are attracted by CME as they can profit from the Exchange's clearing house, eliminating counter-party credit risks. Additionally, products are standardized and liquid. Finally, we note there is no analogue development related to cross-commodity trading between weather and agricultural commodities.

- OTC business is primarily related to non-standardized structures tailored to the end users. This market segment suffered from a reduction in notional values. However, because it is of particular interest to the agricultural sector, it is worthy of closer examination.

In the discussion below, we analyze the PWC survey for expansion with respect to geography and industry segments of end users entering into OTC contracts. To track these developments, we use the number of contracts by region rather than the notional amounts to avoid distortions related to the difference in valuation of goods and services covered in developed versus developing markets. Based on this metric, the PWC survey records the following:

- There is a significant geographic expansion of business, with a roughly 40/40/15/5 percentage split for North America/Asia/Europe/Rest of World, respectively, recorded during the latest survey period versus a corresponding 90/4/5/1 split recorded in the 2000/1 survey (Figure 2).



Source: PriceWaterhouseCoopers (2007, p. 26).

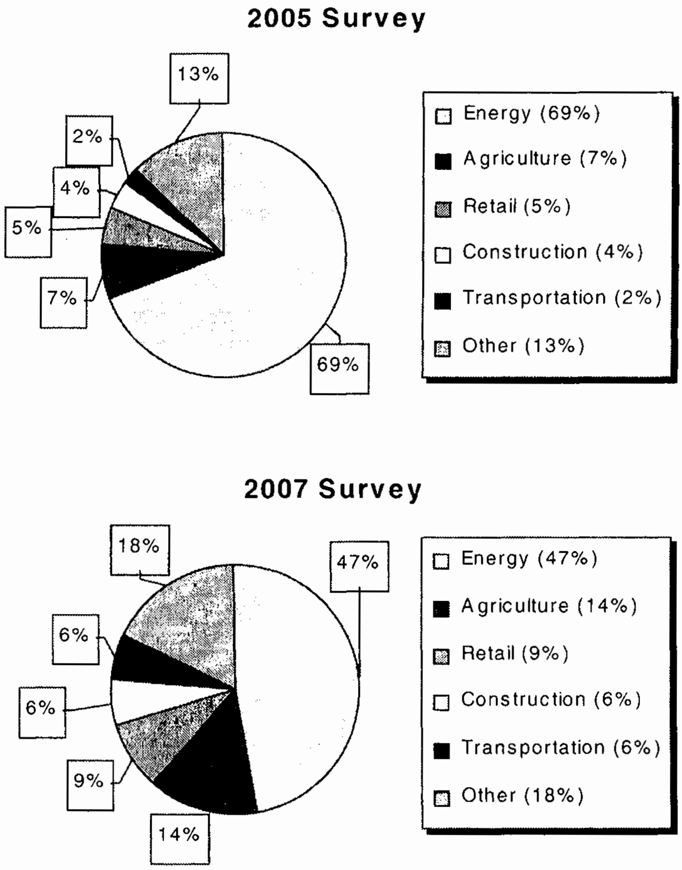
Figure 2. Distribution of Total Number of Contracts (CME and OTC) by Region: 2000/1–2006/7

- There is a doubling of the percentage of end-user business potentially attributable to end users[4] in the agricultural sector within the last two survey periods (Figure 3). This finding is in line with developments in Swiss Re's own client base where the majority of the business covering weather risks outside developed countries (North America, Europe, Japan, Australia) is with counter parties in the agricultural sector.

So far, we have used historical weather market data to explain agricultural sector demand patterns. We note, however, that demand patterns are also influenced by farmers' traditional risk management strategies and market regulations. For example, farmers, both in developed and developing countries, often diversify their sources of income. It is estimated that within the EU, 29% of farmers receive income from off-farm activities [Futures and Options Assn. (FOA), 2005, p. 42]. Furthermore, within the EU, the Common Agricultural Policy grants subsidies by guaranteeing minimum prices to producers and paying directly for crops planted. The system is currently being reformed comprising a phased transfer of subsidy to land stewardship from 2005 to 2012 (European Commission, 2007). In the United States, the U.S. Department of Agriculture (USDA) is required by law to subsidize over two dozen commodities yielding farmers extra money for their crops and guaranteeing a price floor.

With the World Trade Organization Doha Development Round currently stalled, trade-distorting support measures still protect farmers to a large extent from price volatility, which makes risk transfer products seem less important. However, there are also some markets that have recently engaged in measures fostering the use of weather risk transfer products. In India, for example, the government has asked the Agricultural Insurance Corporation (AIC) to start a weather-based crop insurance scheme on a pilot basis in two or three states, in consultation with the respective concerned state governments, as an alternative to the indemnity-based National Agricultural Insurance Scheme (NAIS).

[4] Note that counter parties in the OTC derivative business may not necessarily be identical to end users.



Source: PriceWaterhouseCoopers (2005 and 2007).
Note: Reported values weighted by number of trades reported by respondent.

Figure 3. Split of Transactions Recorded by Industry Sector for Potential End Users, 2005 and 2007

To foster this development, the government will allocate about €18 million in 2007/8 (Banknetindia, 2007). Finally, we note that many stakeholders in agriculture are still unaware or lack understanding of modern financial risk transfer instruments.

Based on the above findings, we draw the following preliminary conclusions.

- First, the growth in weather risk transfer business is primarily related to speculative trading in the U.S. energy sector. It is interlinked with exchange-based trading, i.e., the ability to exclude counter-party credit risk, standardization, and liquidity. Furthermore, trading is not dependent upon end user demand, but rather motivated by exploiting market inefficiencies that can be captured by cross-commodity trades. As demonstrated by the strong episodic expansion of market size during the 2005/6 survey period, speculative trading has the potential to trigger enormous market growth.

- Second, there is no speculative cross-commodity trading between weather and agricultural commodities. There are various reasons for this. For example, there is no simple relationship between agricultural commodity price action and temperature or rainfall, and there is no exchange-based trading in rainfall-related instruments.

- Third, during the 2000/1–2006/7 survey periods, OTC business shrunk in size but expanded in terms of geography and industry sectors involved. Our own market experience suggests there is increasing demand from stakeholders in the agricultural sector based in emerging markets—mainly Asia, South America, and (to a lesser extent and often in the context of fighting poverty) in Africa. Indeed, a recent study on agricultural risks in emerging markets (Swiss Re, 2007) highlights the market potential in this sector and sheds some light on the role of weather risk transfer instruments for these markets.

- Finally, the agricultural sector is more heavily regulated than the energy sector in many developed markets, and farmers engage in a range of risk management strategies other than risk transfer instruments offered by financial service providers.

Stakeholders in the Agricultural Sector and Their Demand for Weather Risk Transfer Instruments

Having reviewed the aggregated market information, we now discuss transaction-specific features related to the agricultural sector's demand for weather risk transfer products. More specifically, we focus on client segments and their motivation, followed by a discussion of the index definitions and the risk components covered.

The client segments involved in the traditional indemnity-based agricultural insurance business are mainly farmers, direct insurance companies servicing retail customers, and reinsurance companies taking aggregate risk positions. Additionally, in some markets, services are provided by brokers and underwriting agencies specializing in the distribution/ placement of risks and structuring/pricing of products.

The development of index-based risk transfer products could attract additional client segments. More specifically, there is demand from input (seed, fertilizer, pesticides) providers, financial service companies, and aid organizations such as the World Food Program (WFP) or non-governmental organizations acting in emerging markets, as well as grain handlers and processors of food and bioenergy.

The motivations of these client segments are manifold. Input providers and grain handlers are mainly trying to smooth weather-induced demand patterns for their goods (input providers) and services (grain handlers). Additionally, input providers are generally acting in saturated markets. Consequently, they attempt to gain a competitive advantage by differentiating their product offering through bundling with weather risk transfer instruments. For example, seed companies have bundled weather risk transfer products with seed bags so their clients can cover the expenses for the seed in case of a drought. Financial service companies and governmental and non-governmental aid organizations use weather risk transfer products as a substitute or complementary risk transfer instrument for indemnity-based agricultural insurance. Finally, food processors use weather risk transfer products to cover increased costs related to a lack of quantity and/or quality of raw material needed for their processes.

Weather risk transfer instruments typically attempt to cover a shortfall in yield using weather indexes as a proxy. Sometimes, indexes are also defined to cover weather conditions that lead to a reduction in the quality of agricultural products.

While the first products were based simply on the aggregate amount of precipitation during a certain period, the market has since become increasingly sophisticated. Today, index definitions typically feature:

- a variable inception date defined as a function of the amount of rainfall during about 10 days prior to inception of coverage against dry conditions during planting;

- a combination of precipitation and temperature measurements used as input variables for the index definition during subperiods related to the various growth phases (establishment, vegetative, flowering, yield formation, ripening) to cover weather risks specific to each growth stage; and

- an index calculation defined as the weighted sum of index contributions during the above-mentioned subperiods.

Despite these rather complicated index definitions, the typical correlation between such an index and agricultural yield is around 60–80%. Additionally, as the geographic distribution of rainfall is more complicated than the distribution of temperature, the correlation of weather indexes tends to deteriorate quickly the farther they are from weather stations. Again, this is increasing the basis risk related to weather risk transfer products for the agricultural sector.

There are several developments to overcome these limitations. For example, market participants rely on a combination of temperature, rainfall, and soil information to calculate the amount of water available to a plant. Moreover, remote sensing data are being increasingly used to compensate for the lack of a coarse network of weather stations.

In contrast to the above situation for the agricultural sector, the weather risk transfer instruments used for the energy sector typically profit from a high correlation between temperature-based indexes and retail energy consumption—often above 90% for gas and about 80–90% for power.

We therefore have strong reason to believe that the basis risk related to the use of weather risk transfer instruments for the agricultural sector is one of the main obstacles for end users to enter into weather risk transfer instruments. However, we note that there is also basis risk related to indemnity-based products resulting from inaccuracies associated with the loss adjustment process peculiar to these products.

Conclusions

The introduction of weather index-based risk transfer instruments has broadened the range of market participants involved in the traditional agricultural insurance market. Additionally, index-based products complement and/or substitute indemnity-based products, especially in emerging markets that lack reliable loss adjustment processes.

However, we have identified a few critical factors for an acceleration of market growth: the high basis risks typically observed between certain weather indexes and agricultural yield, trade distortions such as subsidies to production and exports, as well as lack of information and/or inadequate training.

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A Bayesian Approach to German Agricultural Yield Expectations

Jette Krause

Abstract

Agricultural yields depend on an encompassing set of technical and environmental factors. The development of such factors often is not fully observable, and their interactions and impacts on yields have not been completely understood. This paper proposes a Bayesian method for forming agricultural yield expectations based on past yields. With this method, the development of expectations on yield trend and variability over time is retraced, and expectations for the future are derived. German winter wheat, corn, and aggregated cereal yield data from 1950 through 2006 on the national scale are used for updating. It is shown that the expectation that yields follow a stable positive linear trend with increasing variance becomes the dominant hypothesis by 1990, and gains a final weight of more than 99% for all crops considered.

Key words: agricultural yields, Bayesian learning, Bayesian updating, climate change, expectation, risk, trend, variance

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Jette Krause is a research assistant with the Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany. The author thanks Anne Biewald and Carlo C. Jaeger for supporting this work, and two anonymous reviewers for their helpful comments. Data were kindly provided by the German Federal Statistical Office. Responsibility for any errors remains with the author. Supplementary material for this paper, including the updating script and graphics showing additional updating results for western German federal states, is available online at http://www.pik-potsdam.de/members/jkrause/agriculture.

Agricultural production depends strongly on climatic conditions and weather patterns. Outputs are positively or negatively influenced by weather conditions throughout the growing period. As weather variations in Germany were perceived to be moderate over the past decades, uncertainty regarding agricultural outputs seemed to be minor and few precautionary measures were implemented to manage risks. However, extreme events in recent years, such as the heavy rainfalls in 2002 and the drought of 2003, caused substantial yield losses. These events drew attention to the vulnerability of German agricultural yields to possibly changing weather conditions.

Research on both future weather and environmental conditions (e.g., Beniston, 2004; Schaer et al., 2004) and their effects on agricultural output (e.g., Batts et al., 1997; Hulme et al., 1999) is advancing, yet currently it is unclear whether climate change has influenced past yields, and presently no way of determining the future net effect of climate change on agriculture exists. There are still a number of interactions that are not adequately described by crop and pasture models (Tubiello et al., 2007), and mechanistic understanding of the determinants of regional crop yield changes remains insufficient (Ewert et al., 2005).

Nevertheless, farmers, governments, insurance companies, or weather market agents must make decisions—what crops to grow, which agricultural policy to implement, what agricultural insurances to offer, or which weather derivatives to buy or sell. In a situation of uncertainty about future yields, decisions on adaptation measures or risk management strategies are driven by individual expectations. For scientific analysis of decision making under uncertainty as well as for practical purposes of supplying decision support, the way such expectations can be built and improved is crucial.

The objective of this paper is to present a Bayesian approach to assess German agricultural yield expectations, and to discuss the results derived from it. This approach is useful given the considerable uncertainty about factors influencing future yields, and no complete methodology for forecasting them.

The approach presented here is relatively straightforward and uses only yield data and some prior knowledge as inputs. Consequently, results can be interpreted (for example) as the expectations a farmer might form when observing annual yields, or as an assessment a decision maker might perform under time pressure. Findings can complement knowledge on yield development from experimental and simulation studies in a useful way.

Results as derived here sketch tendencies of past yield development, and allow the derived expectations to be extended into the future. However, they contain evidence of changing weather conditions only as far as it may be manifested in past yield data. The approach in itself does not allow us to determine to what extent, if any, such influences have been present, nor can it take into account knowledge on possible future changes. Therefore, the extendability of expectations derived here must be judged in the light of what is known about future development of agricultural yields, especially under climate change.

Bayesian methods are currently being applied in a vast variety of fields of research. To my knowledge, however, they have not been previously employed for determining agricultural yield expectations. Dose and Menzel (2004) developed a Bayesian method for analyzing climate change impacts in phenology, and Schleip et al. (2006) have applied it to phenological data for different trees and herbaceous plants. They use Bayesian methods to determine which of three model types considered (constant, linear, one change point) fits best to phenological data, and to derive a change point probability distribution.

Jaeger et al. (forthcoming) analyze whether the occurrence of the 2003 heat wave can be attributed to climate change. They define four different hypotheses on temperature trends associated with either anthropogenic climate change or no anthropogenic climate change, and calculate their weights by Bayesian learning using Swiss temperature data.

The Bayesian approach adopted here is formally similar to that used by Jaeger et al. (forthcoming), but the individual hypotheses are not linked to either climate change or no climate change. Indeed, such a linkage is not feasible here, because the specific point of departure of this analysis is that it is impossible to state what the overall impact of climate change on agriculture will be. Instead, general changes in the yield trend and variability around this trend are investigated here, using hypotheses that allow us to look for a potentially nonstationary yield development. To what extent the present results relate to changing weather or climatic conditions, or to other factors, is left to a discussion of the current literature. While the hypotheses presented are rather coarse, they are acceptable given that the intent is not to provide numerical forecasts (though technically, the resulting distributions and their weights could be used to do so), but instead to analyze tendencies associated with past and future yield expectations.

In the following section, the Bayesian approach is described, the present model is specified, and results are presented. In a subsequent section, these results are linked back to relevant current literature.

A Bayesian Assessment of German Agricultural Yield Expectations

Bayesian updating allows comparison of different hypotheses we take into account to determine how plausible they are, given the information we have. Depending on the choice of hypotheses, we do not necessarily select one hypothesis and discard the others; rather, the best distribution may result in a weighted mixture of various hypotheses.

Technically, Bayesian learning is carried out by computing the likelihood of each hypothesis considered with regard to available data and by adjusting the hypothesis' weight accordingly. Subjectively chosen hypotheses, possibly related to expert opinions an individual considers, with initial probabilities assigned to them on the basis of individual experience and knowledge, enter as initial expectations. This assessment is updated through a formal learning algorithm, whereby initial probabilities can be revised in the light of the data. The updating process, based on Bayes' theorem, provides a rational way of reasoning and adapting expectations. It allows extending the decision-theoretical approach to cases of uncertainty (Kreps, 1988). Applying this approach to agricultural yields will show how past yield data have driven expectations.

In order to apply Bayesian learning, we must first determine what data set to use. We then need priors, i.e., a predefined set of hypotheses on possible developments with initial weights attached to them, which can be constructed using data analysis as well as prior knowledge. These elements are provided below. The updating process is then described and results are presented.

Yield Data

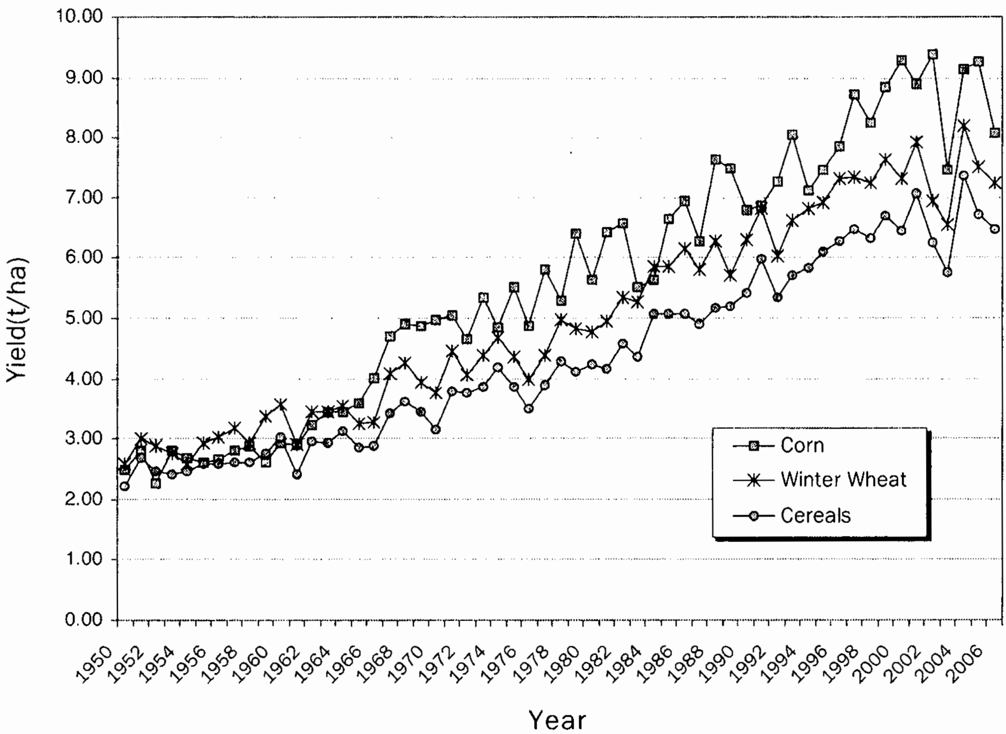
In this paper, German (NUTS 0/national level) agricultural yields per hectare from 1950 through 2006 are used, as provided by the German Federal Statistical Office (www.destatis.de). Data for the years prior to the German reunification have been calculated ex post by the Statistical Office. Three crop types are considered—winter wheat, grain corn which includes corn cob mix (ccm) as of 1987 (referred to as "corn" throughout the text for simplicity), and cereals as an aggregate. Figure 1 displays the yield development of these crops over the 1950–2006 study period.

Winter wheat was chosen because it is the single largest contributor to German cereal yields. In 2006, winter wheat was cultivated on 3.1 million hectares of farmland and produced an overall yield of 22.1 million tons. In the same year, 3.2 million tons of grain corn and ccm were harvested from an area of 0.4 million hectares. Cereals as an aggregate, comprising wheat, barley, rye, grain corn and ccm, triticale, and oats, yielded 43.5 million tons, using an overall area of 6.7 million hectares of farmland (Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz, 2006).

Constructing Priors

The Bayesian updating process can shift weight among hypotheses, but will not be able to reveal tendencies that are not included in the set of hypotheses. Thus, it is important to define hypotheses carefully with regard to real-world features. For the present purpose, assumptions on the nature of the trend and on the distribution of deviations must be made, and one has to allow for changes in these features.

Statistical tests with fitted linear, quadratic, third-order polynomial, and exponential trend functions reveal that a linear trend is a reasonable assumption. R^2 values for the linear function are about 0.95 for all crops considered, and they are in the same range for all other trend functions. The residuals from the linear trend function show no evident pattern, although there is a tendency to produce more positive than negative residuals. As no attempt at quantitative forecasting of



Source: Author's representation, based on data available from the German Federal Statistical Office (contact at www.destatis.de).

Figure 1. German Agricultural Yields for Corn, Winter Wheat, and Cereals, 1950–2006

yields will be made on the basis of this analysis, using a simple linear trend model appears justified.

Moreover, literature confirms that a linear trend function provides a valid approximation for yield data of the past decades. Calderini and Slafer (1998) report that German wheat yields exhibit a linear trend from a breaking point in 1952 on. This is in accord with Hafner (2003) who finds a prevalence of linear growing trends in corn, rice, and wheat yields during the last 40 years for 188 countries.

To specify how data deviate from the trend, a normal distribution with zero mean is chosen here, as systematic variation is described by the trend function. Theoretically, the choice of a normal distribution is justified through the central limit theorem. The error component in observed agricultural yields has many minor causes, such as the quality of seeds, the amount of fertilizers used, the care a farmer takes, technical standards, soil properties, temperature and precipitation conditions, frost, hail or storms, the possible influence of pests, and so on.

Most of these components (except different aspects of weather conditions, which may be related) are approximately independent, allowing deviations from the trend to be modelled as normally distributed. This assumption seems to be an acceptable, though imperfect approximation of data for cereal and wheat yield residuals (which concentrate close to zero with maximum positive and negative deviations in the same range, but a tendency of showing a positive sign more often then a negative one), but less appropriate for corn yield residuals (the distribution of which shows two peaks and slightly larger positive than negative values, but less of a tendency to show positive signs more often than negative ones).

In summary, yield data are assumed to result from a process characterized by a linear trend and normally distributed deviations from that trend:

$$(1) \quad y_t = a_t + b_t * t + \varepsilon_t,$$

$$\text{with } \varepsilon_t \sim N(\mu; \sigma_t^2) \text{ and } \mu = E(\varepsilon_t) = 0.$$

It follows that agricultural yields at a point in time, t, can be described as a normally distributed variable of the form:

$$(2) \quad y_t \sim N(a_t + b_t * t; \sigma_t^2).$$

Based on the general form of the trend function and the distribution of yields around the trend value, a set of hypotheses can now be specified. In regard to the trend, when building expectations for the year to come, it is assumed that either the trend fitted to past data is extrapolated to the next year, or the parameter b increases or decreases by 20%. This allows us to ascertain whether continuity of the past trend is a reasonable assumption, or whether there is a major change. Analogously, variance σ^2 of deviations from the trend is assumed to stay constant or to increase or decrease by 20% with respect to the value calculated from past data.[1]

[1] The possible factors of change {1, 1.2, 0.8} have been chosen pragmatically. This is not to suggest that increases or decreases by 20% each year are seen as the only realistic perspective. Rather, the value has been chosen larger than could realistically be expected in order to guarantee the model is robust with respect to minor changes in trend or variance. Other sets of multipliers, {1, 2, 0.5} and {1, 1.05, 0.95}, have been tested. The former, even stronger set of assumptions leads to a convergence toward hypothesis no. 2 much earlier (by about 1960 for cereals, 1965 for wheat, and 1967 for corn yields). The latter, weaker assumptions favor hypotheses on increasing trend (nos. 4 to 6), where for wheat and cereal yields, the hypothesis on both higher trend and increasing variance (no. 5) gains the highest values in the end (about 65% for wheat and 85% for cereals), whereas for corn yields, the hypothesis on stable trend and increasing variance takes over in the end (nearly 80%). The nine hypotheses considered here are defined in the "Updating Results" subsection.

Combining each option for the trend with each option for variance, nine hypotheses on yield distributions for each period of the following form are generated:

$$(3) \quad y_{t,j,k} \sim N(a_{t-1} + (b_{t-1} * f_{b_j}) * t; \sigma_{t-1}^2 * f_{o_k}),$$

where $f_b = f_o = \{1, 1.2, 0.8\}$ are sets of multipliers indicating the change of the parameters b and σ^2, and j, k are indices running over the elements of f_b and f_o.

Moreover, an initial probability distribution on the hypotheses must be designated. Accordingly, an equal initial probability of 1/9 is assigned to each hypothesis based on the principle of indifference. In this manner, each hypothesis is given an equal opportunity to gain weight on the basis of data.

Updating the Priors

Now a Bayesian learning algorithm can be used to update the initial weights. In a stepwise procedure, the following process is executed for every data value from 1953 on:

- At each point τ in time, the parameters of the trend model are estimated by the method of least squares on the basis of all yield data known from previous periods. That is, values a_t and b_t in equation (2) are calculated for $t = \tau$, on the basis of yield data for $0 \le t \le \tau$, with $t = 0$ referring to the year 1950. The estimator for the variance [σ_t^2 from equation (2) for $t = \tau$] is then computed as the average squared residual from the trend.

- A set of hypotheses h_i (with $i = 1, \ldots, 9$) on yield distributions at time $\tau + 1$ is generated by applying equation (3) for all combinations of j, k.

- The posterior weights of the hypotheses are updated in a Bayesian fashion by the following rule:

$$(4) \quad P(h_i \mid e_{\tau+1}) = \frac{P(h_i \mid e_\tau) * p(e_{\tau+1} \mid h_i)}{\sum_{j=1}^{n} P(h_j \mid e_\tau) * p(e_{\tau+1} \mid h_j)},$$

where $P(h_i \mid e_\tau)$ is the prior probability[2] of hypothesis i based on all evidence available up to time τ, $p(e_{\tau+1} \mid h_i)$ is the likelihood of evidence which occurs at time $\tau + 1$ within hypothesis h_i, and the posterior probability $P(h_i \mid e_{t+\tau})$ of the given hypothesis is calculated as their product, divided by the total probability of the event $e_{\tau+1}$ over all $n = 9$ hypotheses as given in the denominator.

The result of each updating cycle is a set of hypotheses along with their posterior probabilities. They specify agricultural yield expectations for the future at a point in time.

Updating Results

Panels A, B, and C of Figure 2 show the updating results for expectations associated with German winter wheat, corn, and aggregated cereal yields, respectively. In each panel, each line connecting symbols of the same shape describes the weight that one of the nine hypotheses takes from 1952 to 2006. Hypotheses differ in the assumptions they make with regard to changes in the trend and in the variance of deviations. The nine hypotheses are as follows, where "unchanged trend" refers to a stable slope, "higher trend" means the slope increases by 20%, and "lower trend" indicates it decreases by 20%; constant variance, increasing variance, or decreasing variance indicate that variance does not change, it increases by 20%, or it decreases by 20%:

- Hypothesis No. 1: Unchanged trend / constant variance
- Hypothesis No. 2: Unchanged trend / increasing variance
- Hypothesis No. 3: Unchanged trend / decreasing variance
- Hypothesis No. 4: Higher trend / constant variance
- Hypothesis No. 5: Higher trend / increasing variance
- Hypothesis No. 6: Higher trend / decreasing variance
- Hypothesis No. 7: Lower trend / constant variance
- Hypothesis No. 8: Lower trend / increasing variance
- Hypothesis No. 9: Lower trend / decreasing variance

In 1952, all models have the same initial weight due to the chosen uniform initial prior. As of 1953, the weights of the hypotheses are posterior probabilities, conditional on all yield data from 1953 up to the respective year, as calculated by the updating program. For the different crops, results vary. What they have in common, however, is that after an initial phase of 10 to 20 years of updating where all hypotheses compete, only three to four hypotheses keep weights substantially larger than zero.[3] For winter wheat and corn yields, the updating process converges to the hypothesis that the yield trend is stable and variance increases from the early 1990s and the mid-1980s on, respectively. For cereals as an aggregate, the same outcome is reached as of 2002.

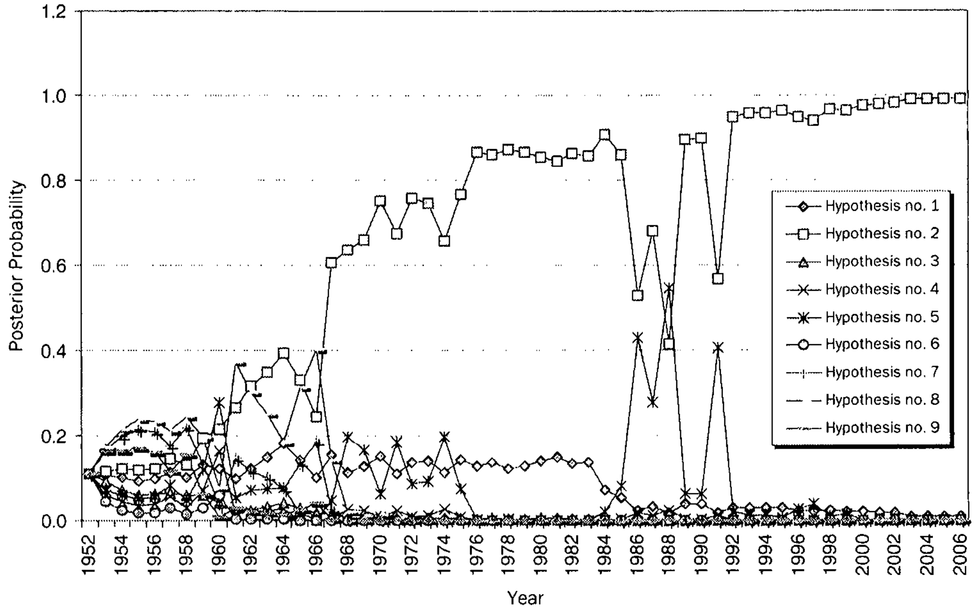
For winter wheat yields (panel A of Figure 2), hypotheses indicating that variance increases (nos. 2, 5, and 8) accumulate relatively high weights from about 1960 on. In aggregate, they have a probability of nearly 80% (often more) from 1967 on. While hypothesis no. 8 (lower trend) loses its weight by 1970, the weight of

[2] For the first updating step, the initial weights are used. For all consecutive steps, the posterior calculated in the previous updating cycle enters here.

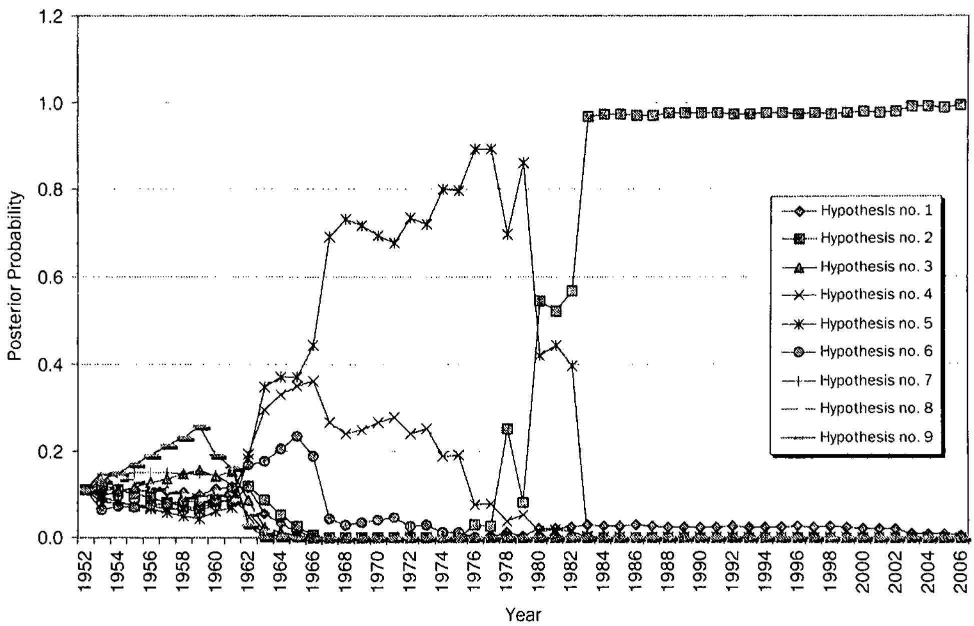
[3] For technical reasons, none of the models can ever have a weight of zero. Due to the assumption that yields are normally distributed, all yield data have a likelihood larger than zero under any of the distributions. (Likewise, it follows that no distribution can have a full 100% of weight.) As no hypothesis can completely be refuted, the updating method allows hypotheses that have been of little explanatory value in the past to be revived when changes occur. As an example, for corn, hypothesis no. 2 has very little weight around 1970, with a minimum weight of 9.5×10^{-6} in 1971, but later becomes the dominant hypothesis.

Figure 2. Posterior Probabilities for German Agricultural Yield Hypotheses: Winter Wheat (Panel A), Corn (Panel B), and Cereals (Panel C)

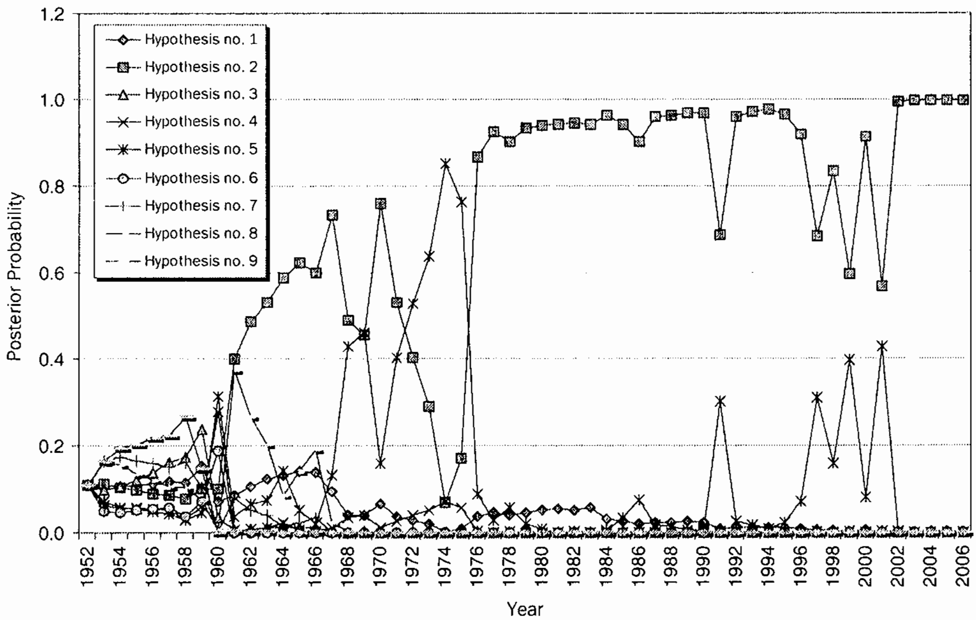
PANEL A. Updating Results Using Winter Wheat Yields, 1950-2006



PANEL B. Updating Results Using Corn Yields, 1950-2006



PANEL C. Updating Results Using Cereal Yields, 1950-2006



Source: Author's representation.

Note: The nine hypotheses (refer to listing in text narrative) specify year-to-year changes in the yield trend, and in the variance of residuals.

hypothesis no. 5 (higher trend) oscillates strongly up to the mid-1970s. After a phase of little importance, it jumps again, reaching a maximum value of more than 50% in 1988, and 41% in 1992. It then levels off and hypothesis no. 2 (constant trend), which has been the most important hypothesis from the late 1960s to the mid-1980s, once again takes over. From 1992 forward, it has a more than 90% probability; from 1998, more than 95%; and it reaches a final weight of 99.2% by 2006.

In contrast to winter wheat yields, where increasing variance is the predominant tendency from 1967 on, corn yields are most strongly characterized in an early phase of updating by a higher trend (panel B). From 1967 to 1975, the three hypotheses sharing this assumption (nos. 4, 5, and 6) together have a probability of more than 99%. Among these three hypotheses, however, no. 5, postulating a higher trend combined with increasing variance, is always the most likely during this phase with weights in the range of nearly 70% to 90% from 1967 to 1979. In the second half of the 1970s, hypothesis no. 2 begins to gain weight rapidly. It achieves more than 95% as of 1983, and more than 99% from 2003 on, reaching a weight of 99.4% in 2006.

For cereals as an aggregate (panel C), hypothesis no. 2 (stable trend and increasing variance) is the most successful hypothesis from 1961 on, when it first reaches a weight of 40%. Its importance is challenged by hypothesis no. 5 during two phases. Hypothesis no. 5 is the single most weighted hypothesis in 1969 (46%) and from 1972 to 1975, with a maximum weight of 85% in 1974. After a phase of relative unimportance, it jumps again to values of more than 30% during the 1990s and reaches 43% in 2001, but then levels off. Hypothesis no. 2 jumps to more than 99% in 2002 and maintains this high weight, finishing at 99.8% in 2006.

In summary, from at the latest 1990 on, the hypothesis of constant trend and increasing variance (no. 2) dominates over all other hypotheses for all crops under consideration. For winter wheat and corn yields, its weight is more than 95% from 1998 and 1983 on, respectively, and for all three crop types considered, it is more than 99% as of 2003. Its final weight is 99.2% for winter wheat, 99.4% for corn, and 99.8% for aggregated cereals.

For all crops, hypothesis no. 1 (neither trend nor variance changes) keeps the second highest weight at the end of the updating process, but in all cases, the value after the last updating step is less than 1%. As the weight of hypothesis no. 2 comes close to 100%, the influence of other hypotheses can be ignored for predictive purposes. Consequently, these results show that the best expectation for future yield development as derived from the present approach is that yields will continue growing along a stable linear trend and show increasing deviations from that trend. This development has been dominant for much of the past two or three decades, varying among the yield types considered.

Distributions for yields in the years to come, based on all yield data available up to 2006, take the following general form:

(5) $y_t \sim N(a_{2006} + b_{2006} * t;\ 1.2^{(t-56)} * \sigma^2_{2006})$, for $t \geq 57$,

where a_{2006} and b_{2006} refer to the axis intercept and the slope of the trend function, and σ^2_{2006} to the variance calculated from yield data from 1950–2006, and $t \geq 57$ refers to successive years from 2007 forward. For the single crops, the yield distributions (with yields given in tons per hectare) are specified as:[4]

(6) $y_{t,corn} \sim N(2.159 + 0.126 * t;\ 1.2^{(t-56)} * 0.232)$,

(7) $y_{t,wheat} \sim N(2.309 + 0.099 * t;\ 1.2^{(t-56)} * 0.152)$,

and

(8) $y_{t,cereal} \sim N(2.068 + 0.086 * t;\ 1.2^{(t-56)} * 0.096)$.

Note, however, equations (6)–(8) should not be used to calculate expected yield distributions far in the future, as the assumptions made are too coarse for this purpose.

Discussion of the Results

The Bayesian method does not reveal the absolute cogency of the hypotheses considered, nor does the approach in itself give hints as to the reasons why a certain hypothesis has proved successful in the past. Therefore, in this section, updating results are related to the state of current literature.

First, results are compared to findings on yield trend and variability from other studies. Second, the plausibility of and possible explanations for the present results are checked in regard to findings about key influencing factors for German agriculture during the period of analysis. And third, literature on the prospects of future change in agricultural production conditions and their possible effects on yields is reviewed—with discussion highlighting whether the expectations derived here can serve as a reliable proxy for the nearer future. Special attention is given to the questions of whether climate change may have shaped past expectation formation, and whether simulations of future conditions allow present expectations to be maintained.

Previous Findings on Agricultural Yield Trend and Variability

The increasing linear trend comes as no surprise, as linearity has been assumed

[4] These distributions are derived from the updating procedure using data up to 2006. When new data, i.e., yields per hectare in 2007 and later years, become known, the updating procedure can be used to calculate new values for the trend parameters as well as for the variance, and expectations for the future can be improved by subsequent updating steps.

and it is evident from Figure 1 that yields have grown over time. The result of increasing variance is consistent with results from earlier studies analyzing the development of agricultural yields. Assessing the development of wheat yield stability in 21 countries, Calderini and Slafer (1998) report a positive linear trend in deviations of annual German wheat yields per area unit from a bilinear regression line for 1900 to 2000. This trend reveals that absolute wheat yield variability has been increasing.

Alexandrov and Hoogenboom (2001) show that yield variations from a polynomial trend of wheat and corn yields in Georgia, USA, have increased after 1950. Reilly et al. (2003) examine aggregate crop yields in the USA from 1866 to 1998. They find that variation for wheat and potato yields has declined linearly over the entire period of their analysis, as well as for the subperiod 1900 to 1994. Corn yields, however, show a significant linear increase in variation from 1950 to 1994. In all cases, the slopes of regression lines were quite small. The authors define the yield trend as the nine-year moving average of yields. Variation is derived as the deviation of annual yield from this trend, relative to the fitted trend value of the respective year. Thus, variation is a relative measure in their study. Since yields have increased substantially over the period of analysis, absolute variation increased as well, although relative variation barely changed. These examples show that the increases in (absolute) volatility found here are in accordance with results from previous studies.

Factors Explaining Yield Development During the Investigation Period

Three groups of factors can strongly influence agricultural production—technological advance, environmental conditions, and agricultural policy. Technological advance helps to explain a sizable portion of the positive yield trend observed during the past 50 years. Calderini and Slafer (1998, p. 340) state that "yield advances are the consequence of a complex conjunction of agronomic causes (e.g., improved cultivars, mechanization, timing of sowing, usage of fertilizers and pesticides, and better rotational practices), in addition to socioeconomic factors." Hafner (2003, p. 276) points to similar influences as an explanation for the growth of global cereal production per unit area experienced in the past 40 years, namely "genetic improvements in rice and wheat varieties and maize hybrids, and the alteration of agricultural practices such as the use of high levels of fertilizer, the use of pesticides and irrigation."

The European Environment Agency (2004) agrees that technological success was behind the increasing trend of crop yields per hectare, which was observed worldwide over the past 40 years. In a study estimating changes in crop productivity, Ewert et al. (2005) conclude that yield increases of major European crops (including cereals, wheat, and corn) since the 1960s have been largely due to technology development in a broader sense, including crop management and breeding.

While the influence of technological advance on the yield trend is straightforward, the issue of whether and how it affects the variability of agricultural yields is not so clear. Calderini and Slafer (1998) suggest that although modern wheat production systems have increased productivity, they may have caused a decrease in yield stability. They argue this is plausible because modern high-yield cultivars are more sensitive to environmental changes. From their study, however, they conclude that modern farming systems did not necessarily lead to a decrease in wheat yield stability in absolute terms, whereas yields in relative terms primarily became more stable.

Apart from technological advance, environmental conditions—e.g., temperature, precipitation, radiation, CO_2 concentration, and soil conditions—are important determinants of agricultural yields. Ewert et al. (2005) discuss effects of climate change and CO_2 on past yields, asserting that technological development clearly outweighs them. Increasing CO_2 is estimated to have caused, at most, 5% of yield increases from 1961 to 2000, while climate change effects have been even less pronounced.

Analyzing drivers for wheat yield variability in the European Union at NUTS 2 and 3 levels from 1991 to 2000, Bakker et al. (2005) discount changes in CO_2 concentration because of their insignificant effects on crop yields, and identify radiation and temperature as the main climatic conditions that may have influenced wheat yields. In combination with these climatic conditions, they also consider soil and economic variables. The authors find that yields are closely negatively related to the climatic variables considered, which also account for a large portion of variability (minimally 13%, maximally 83%), followed by economic variables (explaining 0–67% of variability) and soil variables (explaining 5–56%). Due to overlapping explanatory powers, Bakker et al. note they were unable to determine the exact contribution of each variable to variability; at higher aggregation levels, the risk of confounding explanatory variables increases, such that at the NUTS 2 level, discrimination between them was difficult or impossible to identify. Thus, it cannot be deduced from their analysis which variables may have been the most important driving forces behind NUTS 0-level yields as analyzed in the present study.

Several regional studies provide hints about the effects of weather conditions on yields in some German regions. For example, Schindler et al. (2007) investigated plant water supply in northeast and central Germany over the period 1951–2000. During this time frame, water supply over the vegetation period decreased. Precipitation decreased by an average of 22 to 50 mm, with high spatial variation. From 1996 to 2000, cereal production was limited due to water stress on 10% of the agricultural land in Saxony-Anhalt and 25% in Brandenburg.

Chmielewski and Köhn (1999) report results from a field experiment on spring cereal grain yield, conducted at Berlin-Dahlem between 1962 and 1996. Based on their findings, nearly 60% of grain yield variability can be explained by meteorological variables from April to July. Crop failures occurred in two years of their study period due to too dry and warm weather in June and July (1976), or April to July (1992). Such conditions could negatively affect the formation of most yield parameters.

Without referring to yields, precipitation and temperature changes in this direction have been detected by Hundecha and Bárdossy (2005) for the region of the German Rhine basin over the period 1958 to 2001. Their findings reveal that daily minimum and maximum temperatures have increased, and that in summer, the average amount of rain and the average precipitation intensity on rain days, as well as the greatest five-day total rainfall, have decreased, and the maximum consecutive number of dry days has increased.

Summing up, the assumption that the stable positive trend in German agricultural yields is strongly related to technological development seems well justified. Influences such as changing CO_2 concentration or a climate change signal have not been important factors for past agricultural yield development on the German national level according to the literature cited here. Other yield drivers have been described as present or influential on NUTS 1 (water stress) or NUTS 2 and 3 (radiation, temperature) levels in the past decades.

Although these factors have had an impact on yields in at least some of the regions included in the NUTS 0-level data analyzed here, these signals are not distinguishable in the results of Bayesian updating of aggregate data, possibly due to the aggregation level or because they cannot be related clearly to a distinct hypothesis or point in time. This suggests these factors have contributed to the hypothesis of an overall constant positive trend and increasing variance gaining probability, or have averaged out with other factors driving in opposite directions, or their overall impact has been too weak in comparison with other, more influential drivers.

Moreover, the effect of possible changes in weather variability may be difficult to distinguish in the present analysis with its specific focus on absolute yield variability. Analyzing the development of relative yield variability with the assistance of a Bayesian approach could lead to further insights.[5] This topic of inquiry, however, is beyond the scope of this paper, where absolute variability is discussed because of the economic importance of (absolute) yield losses.

Apart from technological and environmental conditions, policy or regulatory issues can be important drivers for agricultural productivity. As an example, while no environmental or technological reason has been found in the literature to explain the sudden gain of weight of hypothesis no. 5 for cereal yields (and, to a lesser extent, for winter wheat yields) around 1990, two political events can be identified which may have contributed to this tendency toward a hypothesis implying a growing slope of the trend function around 1990. First, productivity increases after the 1989 German reunification may have been due to a wider availability of new machinery, seeds, or management practices in the eastern part of Germany. Second, a reform of European Common Agricultural Policy took place. In order to tackle overproduction of cereals, a set-aside system was proposed in 1988, and a subsidizing system linked to compulsory set-asides was introduced in 1992 (MacSharry reforms). Intuitively, farmers likely set aside their least productive growing areas, thereby increasing average productivity.

On the aggregate level within Germany, it cannot be confirmed which, if any, of these events has caused the rise of hypothesis no. 5. Additional updating carried out using cereal yield data for single western German federal states (NUTS 1 level) has revealed that some of them (Hessen, Lower Saxony, North Rhine-Westphalia, Rhineland-Palatinate) show increases in the weight of hypothesis no. 5, and even periods of dominance of this hypothesis (in the 1990s), while others (Bavaria, Baden-Wuerttemberg, Saarland) do not.[6] Therefore, productivity increases have been present in at least some western federal states during this period, making the hypothesis that the European set-aside system has contributed to the development of increases in agricultural productivity more likely. Of course, this does not exclude the fact that the reunification or other political or environmental aspects may have played a role as well.

A complete analysis of reasons behind cereal productivity development cannot be provided here. Still, this example verifies that the method is able to capture important changes in yield trend. It has also demonstrated that political or managerial signals in past yield development may have been stronger or at least more distinguishable than signals related to weather patterns or climate change.

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[5] The development of the coefficient of variation (CV) over time was examined, calculated for moving windows of yield data of 20, 30, and 40 years. The CV has shown a downside trend over nearly the entire range of yield data used here up to the early 2000s. In the heat wave year 2003, there is a clear upward jump of the CV for all three crop types and all window sizes considered. The low yields of that year were influenced by the extreme weather conditions, and the reaction of the CV in 2003 hints toward the argument that measures of relative variability may be more appropriate for analyzing yield reaction to changes in weather variability.

[6] For updating cereal yield expectations in western German federal countries (NUTS 1 level), again data from the German Federal Statistical Office (www.destatis.de) have been used. Figures documenting the outcomes are included in the supplementary material to this paper, available online at http://www.pik-potsdam.de/members/jkrause/agriculture.

Analyzing the Reliability of the Derived Expectations for the Future

The present assessment is built exclusively on data of the past and model assumptions, whereby all further knowledge on future development is ignored. Thus, it is important to assess how this knowledge relates to the present results.

In a review paper, Tubiello et al. (2007) describe recent research on crop and pasture responses to climate change. Summarizing the various research findings, they state that moderate warming in temperate regions may benefit crop yield, yields tend to increase with higher CO_2 concentration, but the interaction of elevated CO_2, temperature, and precipitation is not well understood beyond the single-plant level. The increased frequency or strength of extreme events is likely to increase production losses, as may pests and diseases. As the authors argue, there is still significant uncertainty about climate change impacts on crop and pasture species, and consequently a potential for negative surprise.

In a recent paper, Long et al. (2006) argue that the fertilization effect of increasing CO_2 concentration has been overestimated in past enclosure studies. Under field conditions, the effect was only half as large as formerly thought and could not be large enough to offset yield reductions through increased temperature and reduced soil moisture.

Ewert et al. (2005) calculate changes in future crop productivity in Europe as affected through changes in climatic conditions, CO_2 concentration, and technology. According to their findings, increases in wheat productivity by 2080 could range from 43% to 163% of today's productivity, depending on the scenario chosen. Although technology is found to be the most important factor for this development (causing increases of 28% to 134%), CO_2 contributes positively (with increases of 15% to 32%), and climate causes slight decreases (2%) or no change, again depending on the scenario chosen. The authors consider present yield trends as the possible maximum for future technology-induced productivity increases.

Constructing a climate scenario for the period 2001 to 2055, Schindler et al. (2007) conclude that drought risk will get worse for northeast and central Germany. On average, plant growth may be limited by drought on 40% of agricultural land.

Overall, while key interactions still are not fully understood, it is not unreasonable to expect German cereal yields to continue growing along a stable trend with increasing variance in the years to come. Some effects related to climate change—e.g., the favorable impact of gradual warming on the development of some crop types or the possible increase in variability through extreme weather events—are in harmony with the tendencies identified here. However, it may become necessary to update these expectations when new insights emerge.

Conclusion

The Bayesian updating procedure produces a consistent result for German winter wheat, corn, and aggregated cereal yields. Specifically, since 1990 at the latest, the hypothesis that the linear trend function for agricultural yields has a stable positive slope dominates, and no changes in this trend are expected for future years. Variance of yield data has been found to increase over time, and future expectations focus on further increases. As the corresponding hypothesis has a weight of more than 99% for the three crop types considered, expectations for the future are stable. Although this general result is confirmed for all crop types analyzed, the point in time where expectation stabilizes varies. For corn yields, the hypothesis of a stable trend with increasing variance always has a weight of more than 95% as of 1983; for winter wheat this is the case as of 1998, and for aggregated cereal yields as of 2002.

These results have been compared to earlier findings on yield development and its causes. While the trend is likely to have been driven mainly by technological development, the reason for increasing variance is less evident. No clear climate change signal can be distinguished to have been a driver. Current knowledge on future development of agricultural yields, including possible effects of climate change, does not contradict the expected future yield development derived here.

As absolute variability of yields has increased in the past and is expected to continue increasing, development of insurance strategies and hedging options against growing yield risks is warranted. It is crucial to investigate how different hedging instruments—e.g., traditional insurances, index-based insurances, and weather derivatives—perform under conditions of growing variance and how they can be adapted to meet this challenge.

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Modeling Agricultural Production Risk and the Adaptation to Climate Change

Robert Finger and Stéphanie Schmid

Abstract

An approach that integrates biophysical simulations in an economic model is used to analyze the impact of climate change on Swiss corn and winter wheat production. Adaptation options such as changes in sowing dates, changes in production intensity, and the adoption of irrigation farming are considered in the model. By carrying out sensitivity analysis with different scenarios, we find farmers' adaptation actions and crop yields to be very sensitive to both climate change and output prices. Moreover, our model results show that simple adaptation measures are sufficient to generate higher and less variable crop yields in the future.

Key words: biophysical modeling, climate change, crop production functions, crop yields, robust estimation, yield variation

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In the coming decades Swiss farmers will face changing climatic conditions, which are characterized by elevated carbon dioxide concentrations, reduced summer rainfalls, and elevated temperatures for the Swiss Plateau region (OcCC, 2005). Furthermore, Swiss agriculture will face changing market conditions due to market liberalization. Both input and output prices are expected to decrease in the next decades. To address these concerns, the objective of this paper is to assess impacts of climate change on the production of Swiss corn (*Zea mays* L.) and winter wheat (*Triticum* L.) under different price development scenarios.

Previous studies that analyze the effects of climate change (CC) on crop production and crop variability are based either on (crop) simulation or regression models. Crop simulation models simulate and compare crop productivity for different climatic conditions (e.g., Torriani et al., 2007b). Regression models use historical climate and agricultural data to outline potential effects of climate change on crop productivity (e.g., Isik and Devadoss, 2006).

Neither approach is sufficient to analyze all aspects of impacts of CC on crop production (Antle and Capalbo, 2001). If the analysis is restricted to crop physiology, such as in crop simulations, farmers' adaptation actions are not taken into account. But sufficient inference requires consideration of farmers' reactions to changes in climate and economic conditions.

This contrasts with the extrapolation of historical farm-level and aggregated data which take into account farmers' historical reactions to changes in climatic and economic conditions. However, the consideration of adaptation in regression models is limited because new, innovative adaptation measures cannot be examined with the extrapolation of historical data. Moreover, historical data are unable to effectively capture future plant-climate interactions, particularly if the crop-weather relationship is restricted to a small number of variables, such as temperature and rainfall. Finally, such models cannot sufficiently integrate expected CO_2 fertilization effects on plants due to low variation in historical CO_2 concentrations (Antle and Capalbo, 2001). In order to overcome these drawbacks, we employ a combination of both approaches—simulation of future crop productivity and regression models.

Existing studies show that CC will have particular influence on yield variation (Mearns, Rosenzweig, and Goldberg, 1996; Tubiello et al., 2000; Southworth et al., 2002; Fuhrer, 2003; Ciais et al., 2005; Torriani et al., 2007b). The analysis of yield variation is restricted to climatic variables such as shifts in annual means and intra-annual distributions of climatic variables. However, these studies do not adequately address adaptation actions of the farmers. In contrast, our approach considers farmers' adaptation actions to CC and is thus better able to model the impact of CC on yield variation. An empirical example using corn and winter wheat, two of the main crops in Switzerland (Torriani et al., 2007b), is chosen to assess and illustrate the impact of CC on both crop yields and yield variability at the eastern Swiss Plateau.

Our model covers no short-term adaptation actions (i.e., tactical decisions) of farmers, but rather adaptation choices with a longer time horizon, i.e., strategic and structural decisions (cf. Risbey et al., 1999). We consider strategic and structural decisions at the field level consisting of changes in production intensity, changes in sowing dates, and the adoption of irrigation farming. Though crop yields are influenced by various factors, our analysis focuses on the crucial inputs of nitrogen fertilizer and irrigation water. Consequently, this investigation is of particular environmental and economic interest because application of both inputs can lead to the degradation of environmental systems (Institute for European Environmental Policy, 2000; Khanna, Isik, and Winter-Nelson, 2000). Moreover, nitrogen fertilizer is a major source of climate-relevant agricultural emissions (Hungate et al., 2003).

Our model is based on an integrated assessment approach that combines a biophysical with an economic model. In contrast to other integrated models (e.g., Antle and Capalbo, 2001), farmers' behavior is simulated using nonlinear programming. The model is divided into three major components: data simulation, estimation of model parameters, and economic analysis.

The data simulation module describes the crop yield simulation process which includes the experimental design that enhances yield variability with respect to application of nitrogen fertilizer and irrigation. Additionally, current and simulated future daily weather data are crucial inputs for the simulation process. The data simulation leads to individual data sets for different climatic scenarios and crops that contain yield and input data. These data sets are used to estimate production and yield variation functions. Subsequently, based on these functions, farmers' adaptation choices are analyzed for different climate and price development scenarios using nonlinear programming. Final assessment is based on a comparison of optimal input levels and the corresponding yield levels, yield variation, and coefficients of variation for these scenarios of climate change and future price development.

Crop Yield Simulation

The analysis is based on yield data generated by the deterministic crop yield simulation model CropSyst (e.g., Stöckle, Donatelli, and Nelson, 2003). This is a process-based, multi-crop, multi-year cropping system simulation model. It simulates above- and below-ground processes of a single land block fragment representing a biophysically homogeneous area. These processes are simulated on a daily time step and comprise the soil water budget, soil-plant nitrogen budget, crop phenology, canopy and root growth, biomass production, crop yield, residue production and decomposition, and soil erosion by water.

In CropSyst, processes are simulated in response to weather, soil characteristics, crop characteristics, and management options. The model is therefore suitable for analyzing the impact of environment and management on crop productivity, and has already been tested for a wide range of environmental conditions (e.g., Donatelli et al., 1997; Stöckle, Donatelli, and Nelson, 2003). Torriani et al. (2007b) provide a model calibration, tests of yield simulation, and a documentation of critical crop parameters of corn and winter wheat for the eastern Swiss Plateau that are used in our yield simulation.

CropSyst requires daily values of maximum and minimum temperature, solar radiation, and maximum and minimum relative humidity. In CropSyst, phenology is determined by thermal time, i.e., a specific development stage is reached when the required daily accumulation of average air temperature above a base temperature and below a cutoff temperature is reached.

To simulate current climate conditions, we use weather data provided by the Swiss Federal Office of Meteorology and Climate for the years 1981 through 2003 from six meteorological stations distributed over the eastern Swiss Plateau ranging from 06°57' to 08°54' longitude (Finger and Schmid, 2007). Compared to an approach with one single location, incorporating observations from six different weather stations significantly broadens the database. For the atmospheric CO_2 concentration input, we use recordings from the years 1981–2003, ranging from 339 ppm to 379 ppm.

Two climate change scenarios are applied to generate crop yields for the coming decades. These climate projections, taken from the Swiss Advisory Body on Climate Change (OcCC, 2005), are based on simulations with two CO_2 emission scenarios, four global climate models, and eight regional climate models. These simulations—with a total of 16 scenario-model combinations on a grid of 50×50 km over the entire European continent—were performed within the scope of the PRUDENCE project (Christensen, Carter, and Giorgi, 2002).

The OcCC climate projections used in this study represent the median of the simulations with the 16 scenario-model combinations for the years 2030 and 2050. Henceforth, these two scenarios are abbreviated as "2030" and "2050." Based on these scenarios, climate anomalies include seasonal changes of temperature and precipitation for northern Switzerland (Table 1).

From today's weather data and the anomalies of temperature and precipitation (Table 1), sets of future weather data are developed using the stochastic weather generator LARS-WG (Semenov et al., 1998). Atmospheric CO_2 concentrations vary randomly within the defined range for each climate scenario, with concentrations ranging from 437 ppm to 475 ppm for the 2030 scenario and from 495 ppm to 561 ppm for the 2050 scenario [Intergovernmental Panel on Climate Change (IPCC), 2000].

For each location and scenario, we assume the same uniform soil type as used by Torriani et al. (2007b) to calibrate the CropSyst model for Switzerland. The soil texture is characterized by 38% clay, 36% silt, and 26% sand. CropSyst assesses the hydraulic properties of the soil according to its texture. Soil depth extends to 1.5 m, and the soil organic matter content is at 2.6% weight in the top soil layer (5 cm) and 2% in lower soil

Table 1. Seasonal Anomalies of Temperature and Precipitation

	Climate Scenario							
	2030				2050			
Description	**Dec.-Feb.**	**March-May**	**June-August**	**Sept.-Nov.**	**Dec.-Feb.**	**March-May**	**June-August**	**Sept.-Nov.**
Temperature	+1.0	+0.9	+1.4	+1.1	+1.8	+1.8	+2.7	+2.1
Precipitation	1.04	1.00	0.91	0.97	1.08	0.99	0.83	0.94

Source: OcCC (2005).
Note: This table reports anomalies of temperature in °C (absolute value) and of precipitation in relative values with respect to the climate of the year 1990.

layers. Soil properties are assumed to be homogeneous over the entire simulated crop area.

The applied management scenarios are uniform on the simulated crop area and include nitrogen (N) fertilization and irrigation. The amount of N applied per year ranges from 0 to 320 kg ha^{-1} for corn and from 0 to 360 kg ha^{-1} for winter wheat. The currently applied amounts of N fertilizer (Walther, Ryser, and Flisch, 2001) are expanded in the simulation in order to cover potential future N fertilization strategies.

For corn (winter wheat), there are three fertilizer applications per year if $N \leq 160$ kg ha^{-1} ($N \leq 180$ kg ha^{-1}) and four fertilizer applications per year if $N > 160$ kg ha^{-1} ($N > 180$ kg ha^{-1}), respectively. For higher N amounts, however, an additional application date is introduced between the second and third dates. In the simulations, fertilizer application dates are defined relative to the sowing date and derived from Dubois et al. (1998) and Walther, Ryser, and Flisch (2001).

To simulate irrigation, we chose the automatic irrigation option of CropSyst. With this option, irrigation is triggered as soon as soil moisture is lower than a specific user-defined value. The degree of soil moisture is expressed as a value between 0 (permanent wilting point) and 1 (field capacity). When soil moisture falls below the previously defined value, water is added to the soil until field capacity is reached. However, there is an upper limit of irrigation water application of 20 mm per irrigation event. To allow for comparison of results, the simulated experimental framework is equal for each climate scenario.

For simulations under the current climate we use sowing dates provided by Dubois, Zihlmann, and Fried (1999) and Torriani et al. (2007b). Temperature increase in the climate change scenarios leads to a shift of the annual temperature pattern, and thus to a shift in the period of optimal crop development (Torriani et al., 2007b). Therefore, sowing dates are placed according to the temperature offset of the climate change scenario (Table 2). Although sowing dates are placed earlier, CC leads to shorter maturity periods. Consequently, shifts in expected (i.e., sample average) dates of maturity are larger than for sowing dates.

For each location and year, one simulation is conducted without application of fertilizer and irrigation. Furthermore, to broaden variability, the amount of fertilizer and the degree of soil moisture that trigger irrigation were varied randomly within the defined range. Depending on the crop and climate scenario, the data sets contain between 527 and 541 observations comprising yield and input data. (Data sets are available from the authors upon request.) A dry matter content of 85% and 90% is assumed for corn and winter wheat yields, respectively.

Table 2. Sowing and Average Maturity Dates for the Assumed Climate Scenarios

		Climate Scenario		
Crop		**Base**	**2030**	**2050**
Corn	Sowing Date	10th May (130)	7th May (127)	4th May (124)
	Expected Day of Maturity	17th September (263)	4th September (250)	28th August (240)
Winter Wheat	Sowing Date	10th October (283)	13th October (286)	16th October (289)
	Expected Day of Maturity	5th August (217)	17th July (208)	18th July (199)

Source: CropSyst simulations.
Note: Values in parentheses are days of year.

The Economic Model

The economic analysis is based on maximization of the certainty equivalent (CE), i.e., a certain level of payoff which provides a decision maker with the same utility as a higher but uncertain level of payoff, and is defined as follows:

(1) $CE = E(\pi) - RP,$

where E is the expectation operator, $E(\pi)$ is the expected quasi-rent π (revenue minus variable costs), and RP is the risk premium, which is the difference between the expected quasi-rent and the certainty equivalent. In our analysis, the risk premium is defined as $RP = \gamma\sigma_\pi$, where σ_π is the standard deviation of the quasi-rent and γ is the coefficient of absolute risk aversion that indicates risk-averse, risk-neutral, or risk-taking behavior if $\gamma > 0$, $\gamma = 0$, or $\gamma < 0$, respectively.

The variability of quasi-rents can be the result of both stochastic yields and stochastic prices. Input and output prices are assumed to be deterministic in the subsequent analysis. Only crop yields are stochastic, with yield variation $\sigma_Y(X)$. Thus, under assumption of price certainty with a constant output price p, the standard deviation of the quasi-rent can be expressed as (cf. Coyle, 1999):

(2) $\sigma_\pi = p\sigma_Y(X).$

An indicator function, I, is used to model farmers' adoption of irrigation farming: $I = 1$ for adoption of an irrigation system, and $I = 0$ for crop farming without irrigation. Farmers are assumed to implement an irrigation system if the certainty equivalent minus adoption costs is higher than the certainty equivalent of crop farming without application of irrigation. Specifically, $I = 1$ if and only if $CE(I = 1) - K > CE(I = 0)$, where K denotes the annual costs of adoption (e.g., the rental costs of the irrigation system). The expected quasi-rent is defined as:

(3) $E(\pi) = pE(Y(X)) - ZX - IK,$

where Z indicates the input prices and $Y(X)$ denotes the functional relationship, i.e., the production function, between output (Y) and inputs (X). Two inputs are considered in the subsequent analysis: nitrogen (N) and irrigation water (W). The decision on adoption of irrigation farming leads to two types of production functions in the model: one with and one without irrigation. This distinction is omitted in this section to ensure clarity.

Yield variation, $\sigma_Y(X)$, is defined here as the absolute difference between observed yields and expected yields:[1]

(4) $\sigma_Y(X) = |Y(X) - E(Y(X)|.$

Therefore, the difference between observed and predicted yield for a single observation i corresponds to the absolute residual of the regression analysis ($|e_i|$):

[1] In our analysis, observed yields are yields simulated with CropSyst, and expected yields are observations on the production function.

(5) $\sigma_{Y_i}(X_i) = |e_i| = |Y_i(X_i) - \hat{Y}_i(X_i)|$.

Substitution of equations (2) and (3) into (1) yields the following final optimization problem:

(6) $\max_{X,I} CE = pE(Y(X)) - ZX - \gamma p\sigma_Y(X) - IK.$

The certainty equivalent is maximized subject to the production function constraint $Y(X)$. The first-order conditions for certainty equivalent maximization are presented in a later section.

Estimation Methodology and Coefficient Estimates

The production function, $Y = f(X)$, is used to estimate the yield responses to nitrogen and irrigation water (cf. Llewelyn and Featherstone, 1997) and is fitted to a square root functional form following Finger and Hediger (2007):

(7) $$Y = \alpha_0 + \alpha_1 N^{0.5} + I\alpha_2 W^{0.5} + \alpha_3 N + I\alpha_4 W + I\alpha_5 (NW)^{0.5},$$

where Y denotes corn yield (kg ha^{-1}), N the amount of nitrogen applied (kg ha^{-1}), and W irrigation water applied in mm. The α_i's are parameters that must satisfy the subsequent conditions in order to ensure decreasing marginal productivity of each input factor: α_1, $\alpha_2 > 0$, and α_3, $\alpha_4 < 0$. Further, if $\alpha_5 > 0$, the two input factors are complementary. They are competitive if $\alpha_5 < 0$, while $\alpha_5 = 0$ indicates independence of the two input factors.

The estimation of model parameters is a two-step procedure. The first step is the estimation of production function coefficients [equation (7)] using robust regression. These estimates are used to calculate robust regression residuals for the entire data set. Subsequently, robust regression residuals are used to estimate yield variation functions in a second step of estimation [equation (5)]. These procedures are described more fully below.

Robust Regression and the Production Function

In this study, robust regression is used to estimate the coefficients of production functions [equation (7)]. This estimation technique was found to increase the accuracy of estimation and to expose the true underlying input-output relationship (Finger and Hediger, 2007).

The main idea of robust regression is to give little weight to outlying observations in order to isolate the true underlying relationship. Outliers are characterized by exceptional yield levels and exceptional input-output relationships, respectively. Hence, they deviate from the relationship described by the majority of the data. The identification of the true relationship and of outliers, respectively, is a nontrivial challenge, particularly if the situation exceeds the simple regression case. We use the reweighted least squares (RLS) regression for the robust estimation. RLS is a weighted least squares regression, which is based on an analysis of least-trimmed squares (LTS) regression residuals that assigns zero weights to observations identified as outliers (see Rousseeuw and Leroy, 1987, for details). An observation is identified as an outlier if the standardized LTS residual exceeds the cutoff value of 2.5 (Hubert, Rousseeuw, and van Aelst, 2004).

The estimation of coefficients and related residuals with ordinary least squares (OLS) regression can be inefficient if extreme yield events (i.e., outliers) are analyzed. One outlier can be sufficient to move the coefficient estimates arbitrarily far away from the actual underlying values (Rousseeuw and Leroy, 1987; Hubert, Rousseeuw, and van Aelst, 2004). Thus, any analyses based on regression residuals derived by OLS estimation are inefficient and can produce misleading results.

In contrast, robust regression such as RLS enables efficient estimation in the presence of outliers. Additionally, to correct for heteroskedasticity, feasible generalized

Table 3. Coefficient Estimates: Production Function for Corn and Winter Wheat (equation 7)

	Climate Scenario					
	Base		2030		2050	
Description	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**
PANEL A. Corn						
Intercept	6,601.92***	162.13	6,972.65***	180.68	7,053.14***	165.17
$N^{0.5}$	313.09***	16.34	347.61***	19.79	309.87***	16.36
$W^{0.5}$	67.14***	4.17	59.65***	4.69	71.59***	5.50
N	10.54***	8.15	11.00***	9.38	9.59***	7.60
W	2.50**	2.17	0.93	1.09	1.02	1.19
$(NW)^{0.5}$	0.36	0.45	1.04	1.55	3.52***	4.92
Adjusted R^2	0.73		0.84		0.84	
PANEL B. Winter Wheat						
Intercept	4,582.36***	67.37	4,894.40***	80.81	5,142.07***	81.35
$N^{0.5}$	161.23***	9.34	178.41***	11.93	151.34***	9.64
$W^{0.5}$	25.48	1.18	70.17***	3.73	68.30***	3.38
N	5.24***	5.43	5.97***	7.16	5.18***	5.90
W	0.86	0.56	2.94**	2.19	3.47**	2.36
$(NW)^{0.5}$	0.51	0.59	0.36	0.48	0.54	0.67
Adjusted R^2	0.39		0.47		0.37	

Note: Double and triple asterisks (*) denote statistical significance at the 5% and 1% levels, respectively.

least squares (FGLS) regression is applied (see Johnston and DiNardo, 1997, for details). Hence, weights are generated with respect to both outliers and heteroskedasticity in the final estimation of production functions. The estimation is conducted with the ROBUSTREG and MODEL procedures of the SAS statistical package (SAS Institute, Inc., 2004).

Coefficient Estimates for the Production Functions

Coefficient estimates of the corn and winter wheat production functions for the assumed climate scenarios are presented in Table 3. It shows that coefficient estimates have the correct (expected) sign. The intercept, i.e., the yield where neither nitrogen nor irrigation is applied, shows an increase from the base scenario to the 2050 scenario for both crops. This is because of more favorable climatic conditions for crop growth. In particular, an increased CO_2 concentration leads to higher yield levels (Fuhrer, 2003). Further, these yield increases are the result of applied shifts in sowing days, as this is a powerful adaptation option to avoid negative effects of climate change (cf. Southworth et al., 2002; Torriani et al., 2007b).

The analysis of yields where neither irrigation nor nitrogen fertilization takes place is purely hypothetical. Both winter wheat and corn farm management without any input use are nonexistent in Switzerland. Therefore, conclusions about the impact of climate change on yield levels can be drawn if and only if optimal input levels and corresponding optimal yield levels are calculated (such as given in a subsequent section below). The coefficient estimates presented here are used as input in the economic model.

Table 3 shows a constant increase of the interaction parameter $(NW)^{0.5}$ from the base to the 2050 scenario for corn.

Thus, independency of nitrogen fertilizer and irrigation water in the base and 2030 scenarios shifts to significant complementary interaction in the 2050 scenario. The interaction is important, as nitrogen is taken up in a water solution. In the first two scenarios, nitrogen uptake is sufficiently ensured by precipitation. In the latter scenario, which is characterized by lower amounts of summer rainfall (Table 1), optimal nitrogen uptake in corn production is only ensured if irrigation takes place. Therefore, climate change is expected to increase the application of nitrogen fertilizer in the presence of irrigation, but to decrease nitrogen application if no irrigation is available.

However, as observed in Table 3, this is not the case for winter wheat. The interaction parameter $(NW)^{0.5}$ is not affected by CC. It remains low and is not significantly different from zero for all climate scenarios. Winter wheat is less vulnerable to increased temperature and decreased summer rainfall than spring sown crops such as corn. This finding is in agreement with the results reported by Torriani et al. (2007b) who noted that irrigation will become more important for spring than for winter crops in Switzerland.

Yield Variation Function

Observations which are identified as outliers are not taken into account for the final estimation of production function coefficients. Yet, these observations are of particular interest for the estimation of yield variation because they increase yield variation. Therefore, residuals are calculated for the entire data set, including the observations identified as outliers. The inclusion of outliers in the remaining analysis is possible if and only if no typing, copying, or measuring errors other than exceptional climatic events are the source of the identified outliers, as proved by Finger and Hediger (2007) using the same data sets.

Yield variance is estimated using regression residuals [equation (5)] and is determined, among other factors such as weather and soil, by input use. This relationship is modeled using a square root function for corn. Irrigation water (W) is only an element of yield variation functions for irrigation farming ($I = 1$):

$$(8)\quad \sigma_Y(X) = \beta_0 + I\beta_1 W^{0.5} + \beta_2 N^{0.5}.$$

Shifts in the intercept, β_0, capture effects of changes in weather conditions on yield variation across different climate scenarios; β_1 and β_2 quantify the influence of irrigation and nitrogen application on yield variation. An input is risk decreasing if $\beta_i < 0$, and risk increasing if $\beta_i > 0$.

For winter wheat, a quadratic specification was found to be most appropriate:

$$(9)\quad \sigma_Y(X) = \beta_0 + I\beta_1 W + \beta_2 N^2 + \beta_3 N.$$

Interpretation of coefficients β_0 and β_1 remains the same as in equation (8). The influence of nitrogen on yield variation was found to have a quadratic shape for winter wheat, first decreasing, then increasing yield variation [coefficients β_2 and β_3 in equation (9)].

The yield variation functions are estimated using the MODEL procedure of the SAS statistical package and FGLS regression to correct for heteroskedasticity. In contrast to other studies that focus on heteroskedasticity correction (Just and Pope, 1979) and take simultaneous equation biases into account (Isik and Khanna, 2003), our estimation approach is oriented toward efficient estimation in the presence of extreme events. Given that such events are more likely to occur with changing climate (e.g., Fuhrer et al., 2006), this property is of particular interest.

Coefficient Estimates for the Yield Variation Functions

Table 4 reports final coefficient estimates for the yield variation functions for corn and winter wheat [equations (8) and (9)]. For both crops, the intercept coefficient β_0 (i.e., yield variation solely determined by

Table 4. Coefficient Estimates: Yield Variation Function for Corn and Winter Wheat

	Climate Scenario					
	Base		2030		2050	
Description	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
PANEL A. Corn (equation 8)						
Intercept	409.03***	14.78	381.75***	18.33	468.51***	19.52
$N^{0.5}$	38.98***	10.78	39.21***	11.82	39.82***	11.26
$W^{0.5}$	−8.13**	2.41	−12.75***	5.32	−20.29***	8.19
Adjusted R^2	0.19		0.24		0.27	
PANEL B. Winter Wheat (equation 9)						
Intercept	789.23***	23.11	680.50***	22.21	728.55***	23.60
W	−0.50	1.63	−0.41	1.50	−0.45	1.62
N^2	0.004**	2.37	0.006***	3.97	0.009***	5.75
N	−2.19***	3.85	−2.51***	4.97	−3.38***	6.69
Adjusted R^2	0.07		0.05		0.08	

Note: Double and triple asterisks (*) denote statistical significance at the 5% and 1% levels, respectively.

weather and soil conditions) decreases from the base to the 2030 scenario and increases in the 2050 scenario. Thus, if neither irrigation nor nitrogen fertilizer application were to take place, yield variation would increase from the 2030 to the 2050 scenario.

For corn, irrigation, ceteris paribus, causes a decrease ($\beta_2 < 0$) and nitrogen fertilizer causes an increase ($\beta_1 > 0$) in yield variation. The propensity of irrigation to reduce corn yield variation ($|\beta_2|$) continuously increases along our climate change scenarios. Higher temperature and lower summer rainfall cause irrigation to be a more risk-decreasing activity than it is currently.

In contrast, the coefficient β_1, the propensity of nitrogen fertilizer to increase yield variation, is nearly constant under different climate conditions. We expect no impact of climate change on the relationship of yield variation and nitrogen for corn production.

For winter wheat, nitrogen first causes a decrease, then an increase in yield variation. Irrigation causes a decrease of the latter. In contrast to the results for corn, the relationship between input use and yield variation is not affected by CC for both nitrogen and irrigation inputs. However, conclusions about the impact of climate change on the yield variation can be drawn if and only if optimal input levels and the corresponding yield variations are calculated (such as presented in the section below).

Optimal Input Use, Yield, Yield Variation, and Adoption Rates

Predictions about the influence of climate change on input use, yield levels, and yield variability require modeling of farmers' behavior. To this end, the certainty equivalent is maximized as described earlier. Derived optimal input levels provide the highest certainty equivalents per hectare. Input prices (Z) are restricted to variable costs. Thus, considering nitrogen fertilizer (N) and irrigation (W) only, ZX is defined as the variable nitrogen costs (nitrogen applied × nitrogen price) plus the variable irrigation costs (irrigation water applied × irrigation water price). Other costs are assumed constant and thus irrelevant for the certainty equivalent-maximizing input combination.

Table 5. Price Development Scenarios (in CHF)

Price Scenario	Corn kg^{-1}	Wheat kg^{-1}	Nitrogen kg^{-1}	Irrigation (mm per ha)
Current	0.396	0.570	1.33	0.6
P_{EU}	0.185	0.182	0.91	0.6
1.5 × P_{EU}	0.278	0.273	0.91	0.6
2 × P_{EU}	0.370	0.364	0.91	0.6

The first-order conditions for optimal input use [equation (6)] are expressed as follows:

$$(10)\quad \partial f(x_i^*)/\partial x_i - z_i/p - \gamma \partial \sigma_Y(X)/\partial x_i = 0 \quad \forall\, i,$$

where z_i denotes the price and x_i^* the optimal level of input *i*. For $\gamma \neq 0$, the respective propensity of inputs to increase and decrease yield variation, $\partial\sigma_Y(X)/\partial x_i$, affects optimal input use. The optimal level of factor use for an input that increases yield variation is smaller for a risk-averse than for a risk-neutral agent, and vice versa. Equation (10) is solved for both irrigation and non-irrigation farming independently.

Price Development Scenarios

Current Swiss agricultural output and input prices are much higher than in other European countries. Due to market liberalization, Swiss agriculture will face diminishing output-input price ratios in crop production down to levels of, for instance, the European Union (EU). The differences between current (referring to 2006) Swiss and EU prices are much smaller for inputs such as nitrogen fertilizer than for outputs such as corn and wheat. Because detailed price forecasts for the periods of interest are impossible to calculate, and in order to show the sensitivity of adaptation processes to both climate change and price development, we assume three price development scenarios for 2030 and 2050—ranging from current EU prices (P_{EU}) to 1.5 × P_{EU} and 2 × P_{EU}.

Price assumptions are presented in Table 5 and are documented in Finger and Schmid (2007). Current Swiss prices are applied for the base scenario. Moreover, our numerical analysis is restricted to one example of constant (i.e., independent from the level of certainty equivalents) absolute risk aversion with $\gamma = 0.5$.

Model Results

First-order conditions [equation (10)] are solved for both crops taking into account the three price development scenarios (Table 5). For the sake of brevity, not all results are presented in detail. For one price development scenario (P_{EU}), Table 6 presents optimal factor inputs, certainty equivalents, optimal yield, and optimal yield variation for corn and winter wheat. Results are reported for both irrigation and non-irrigation farming. Differences in input levels, certainty equivalents, yields, and yield variation between irrigation and non-irrigation farming are also provided. All results are within the range of the data.

As shown by Table 6, the assumed combination of price development and climate change scenarios has only small effects on optimal use of nitrogen fertilizer for corn. In contrast, the optimal amount of applied irrigation water more than doubles from the base and the 2030 scenarios to the 2050 scenario. Due to reduced output prices, future levels of certainty equivalents are lower than currently. Yield levels increase by up to 20% from the base to the 2050 scenario for irrigation farming ($I = 1$). In contrast, optimal levels of corn yields decline from the 2030 to the 2050 scenario for

Table 6. Optimal Input Levels, Certainty Equivalents, Yields, and Yield Variation for Corn and Winter Wheat

Climate Scenario	Nitrogen ($kg\ ha^{-1}$)	Irrigation Water (mm)	Certainty Equivalents (per ha)	Yield ($kg\ ha^{-1}$)	Yield Variation ($kg\ ha^{-1}$)
PANEL A. Corn					
▸ I = 1 (irrigation)					
Base	114.10	87.48	3,286.20	9,189	749
2030	112.48	85.20	1,632.79	9,995	680
2050	137.93	208.49	1,685.66	10,788	643
▸ I = 0 (non-irrigation)					
Base	111.50	0	3,147.22	8,732	821
2030	106.16	0	1,567.24	9,387	786
2050	99.84	0	1,529.50	9,192	866
▸ Diff. between I = 1 and I = 0					
Base	2.60	87.48	138.98	457	-72
2030	6.32	85.20	65.55	608	-106
2050	38.09	208.49	156.16	1,596	223
Panel B. Winter Wheat					
▸ I = 1 (irrigation)					
Base	138.59	90.01	3,019.59	5,976	520
2030	75.03	30.87	1,007.01	6,274	515
2050	71.33	30.92	1,023.44	6,348	519
▸ I = 0 (non-irrigation)					
Base	131.72	0	2,934.92	5,743	573
2030	76.58	0	973.16	5,999	525
2050	68.93	0	986.67	6,041	538
▸ Diff. between I = 1 and I = 0					
Base	6.87	90.01	84.67	233	-53
2030	-1.55	30.87	33.85	275	-10
2050	2.40	30.92	36.77	307	-19

Note: The price development scenario reported here is P_{EU}.

non-irrigation farming. Corn yield variation decreases from the base to the 2050 scenario for irrigation farming but increases for non-irrigation farming.

For winter wheat, optimal amounts of nitrogen and irrigation water are smaller for the future scenarios compared with the base scenario mainly because of the reduced output-input price ratio. Both climate change and irrigation farming have only small impacts on yield variation of winter wheat. Therefore, differences between irrigation and non-irrigation farming are much smaller for winter wheat than for corn. In particular, the yield gap between irrigation and non-irrigation farming—i.e., the expected yield increase due to application of irrigation farming—is at maximum 307 kg ha^{-1} for winter wheat but 1,596 kg ha^{-1} for corn (2050 scenario, Table 6).

Adoption of irrigation farming is triggered by differences of certainty equivalents between irrigation and non-irrigation farming in our model. For both crops, differences of certainty equivalents, $CE(I = 1) - CE(I = 0)$, decrease from the base to the 2030 scenario due to the decline of output prices (Table 6). For corn, this difference increases considerably in the 2050 scenario. Even though the output price is lower, CC leads to a higher profitability of irrigation in corn farming. This contrasts with the results for winter wheat, where the profitability of irrigation remains low in the 2050 scenario.

Results of the remaining price development scenarios can be summarized as follows. Higher output prices cause higher input use and thus higher yield levels and higher levels of certainty equivalents. Furthermore, this leads to larger certainty equivalent differences between irrigation and non-irrigation farming for both crops. Thus, an increase of output prices, ceteris paribus, causes higher profitability of irrigation farming.

Adoption of Irrigation Farming

Farmers are assumed to adopt irrigation farming ($I = 1$) if and only if $CE(I = 1) - K > CE(I = 0)$, where K denotes the annual adoption costs per hectare (e.g., for renting of equipment). Adoption costs are modeled stochastically to reflect heterogeneous adoption costs for farmers due, for example, to differences in farm size, access to irrigation water, and infrastructure endowments (Kulshreshtha and Brown, 1993).

One hundred thousand draws are made from a normal distribution ($\mu = 200$, $\sigma = 40$). This results in simulated costs, expressed in certainty equivalents, which range from 20 to 385 units with an inter-quartile range between 173 and 226. While this distribution of costs is not representative, it avoids corner solutions compared with a single value for adoption costs. Hence, this approach is more suitable to highlight the sensitivity of the model. Comparison between the scenarios is ensured by applying identical distributions of costs for each scenario. Every simulated observation adopts irrigation farming if the certainty equivalent

Table 7. Adoption Rates of Irrigation Farming for Corn (in %)

Climate Scenario	Price Scenario		
	P_{EU}	$1.5 \times P_{EU}$	$2 \times P_{EU}$
Base	6.45	6.45	6.45
2030	0.05	5.95	74.52
2050	13.75	100.00	100.00

difference between irrigation and non-irrigation farming (see Table 6) is larger than the simulated costs.

Simulated adoption rates are smaller than 1% for winter wheat. Irrespective of the price development scenarios, the assumed CC scenarios do not lead to adoption of irrigation farming in winter wheat production. This is because shifts in maturity stages avoid heat stress in summer (Table 2), and reductions of relevant spring rainfall are small in the assumed climate change scenarios (Table 1). These findings are consistent with the results of Torriani et al. (2007b) who found only marginal benefits of irrigation in winter wheat farming on the eastern Swiss Plateau for current and future climatic conditions.

In contrast, the adoption rate in the base scenario for corn is 6.5%. As shown in Table 7, higher prices generally lead to higher adoption rates. As a consequence, all farmers switch to irrigation farming in 2050 for the $1.5 \times P_{EU}$ and $2 \times P_{EU}$ price development scenarios in our model. Assuming P_{EU}, however, the highest adoption rate is 13.75% for the 2050 scenario. Specifically, even in 2050, the adoption of irrigation farming will be relatively small if Swiss farmers face current EU prices.

To obtain final results, the adoption rates are combined with the results for input use, yield level, yield variation, and certainty equivalents. For instance, the final result for yields (Y^*) is calculated as follows: $Y^* = \textit{adoption rate} \times Y^*(I = 1) + (1 - \textit{adoption rate}) \times Y^*(I = 0)$. For farmers who adopt irrigation farming, certainty equivalents are reduced by the average adoption costs revealed in the respective simulated sample.

Final model results for yield levels, yield variation, and coefficients of variation are illustrated in Figure 1. It shows increasing yields and decreasing yield variation for corn and winter wheat production in the future. Although corn yield variation increases for two scenarios (P_{EU} in 2050, and 1.5 × P_{EU} in 2030), the coefficients of variation (i.e., the ratio of yield variation and yield level) for all price development scenarios are unambiguously smaller than in the base scenario. Moreover, Figure 1 shows that higher output prices lead to smaller coefficients of variation for both corn and winter wheat. Because positive effects of CC on yield production cannot offset reduced output prices, the future certainty equivalents decrease for all but the 2 × P_{EU} price development scenario for corn (not shown).

Discussion and Conclusions

Approaches of earlier studies analyzing the impact of climate change on crop production were not able to incorporate both future climate-plant interactions and adaptation measures simultaneously. To overcome this drawback, we use a modeling approach that combines predicted climate-plant relationships (crop simulation modeling) and an economic model that focuses on strategic adaptation.

We find beneficial effects of climate change if adaptation measures such as changes in sowing dates, changes in production intensity, and implementation of irrigation systems are taken into account. For the time horizon considered in this analysis (2030–2050), we expect Swiss corn and winter wheat yields to increase above current levels.

Using a regression modeling approach, Flückiger and Rieder (1997) projected decreasing corn and increasing winter wheat yields in Switzerland. Their projections for winter wheat are consistent with the findings of our analysis because the adaptation options considered here do not significantly change the impact of climate change on winter wheat production. The contrasting findings for corn yield projections are due to the adaptation measures that are taken into account in our analysis but are not considered by Flückiger and Rieder.

Yield variation in Switzerland is projected to increase for corn and to decrease for winter wheat according to the analysis of Torriani et al. (2007b), which is restricted to potential crop yields and employs a crop simulation approach. The latter result supports our findings. However, the increase of corn yield variation is inconsistent with our results because economic incentives for farmers' adaptation in general, and production intensity adjustment in particular, are not taken into account by Torriani et al.

Our results further indicate that adaptation actions, and thus crop yield development, are determined by both future climate and future crop prices. This finding is particularly important for Switzerland because changes in crop prices due to market liberalization are expected to be large.

Our approach of modeling impacts of climate change on crop production and production risk is valuable for future research because it enables the simultaneous analysis of climate change and price scenarios. In particular, adaptation measures at the farm level (e.g., changes in crop rotation patterns) should be further integrated into such a modeling approach.

In order to validate our results, further soil types and additional climate change, price development, and risk-aversion scenarios should be considered. Additional climate change scenarios should emphasize the probability of future extreme climatic events such as droughts. The procedure proposed here for estimation of model parameters is suitable for the incorporation of such extreme climatic events. Using robust

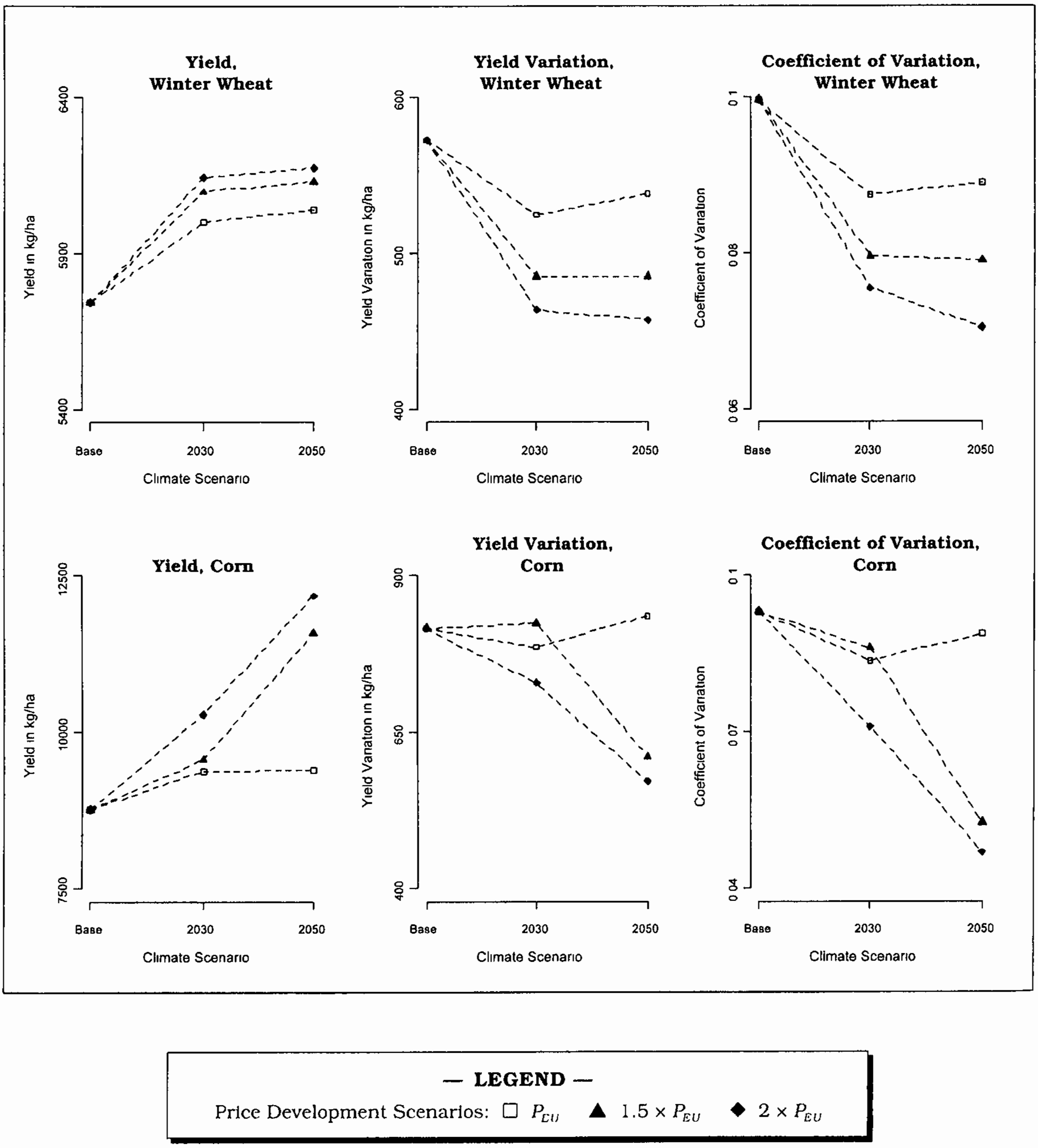

Figure 1. Final Model Estimates for Yield, Yield Variation, and Coefficient of Variation for Winter Wheat and Corn

regression for production function estimation ensures efficient estimation of model parameters in the presence of outliers (e.g., observations caused by extreme climatic events).

Our case study shows that simple adaptation measures at the field level—such as changes in sowing dates, changes in production intensity, and adoption of irrigation farming—are sufficient to generate positive effects of climate change for corn and winter wheat production at the eastern Swiss Plateau. Taking into account that further adaptation measures such as breeding of new varieties and financial instruments such as weather derivates were found to be valuable adaptation strategies for Swiss crop production (Torriani et al., 2007a,b), the latter is expected to benefit from climate change.

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Revisiting the Demand for Agricultural Insurance: The Case of Spain

Alberto Garrido and David Zilberman

Abstract

This paper seeks to characterize the factors that explain crop insurance participation. A stylized model of insurance demand, with a simple setup of one crop, CARA preferences, yield insurance, and pdfs for revenue and yield with moment-generating functions, provides a number of hypotheses about the incentives to contract crop insurance. In the empirical model, we use the actual insurance records of 41,660 Spanish farmers and 12 years of data to estimate six probit models for the insuring versus non-insuring choice, based on individual loss ratios and the dispersion of indemnities, together with idiosyncratic and geographical variables. Results suggest that adverse selection is not a major source of inefficiency in the Spanish insurance system, nor is it the primary motivation to contract crop insurance. Premium subsidies are the leading factor that increases the probability of using insurance. Conclusions are applicable to very diverse farms in Spain.

Key words: agricultural insurance, econometric models, insurance demand models, Spain

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The literature provides quite contradictory views about agricultural insurance. Among the studies questioning the benefits of agricultural insurance are Hazell, Pomareda, and Valdés (1986); Chambers (1989); Hueth and Furtan (1994); Cafiero et al. (2005); and Wright (2006). In contrast, Mishra (1996) and Burgaz and Pérez-Morales (1996) offer more positive assessments. Yet, most of the available evaluations are based on a very limited number of experiences and countries, and focus primarily on publicly provided insurance. Many world countries, both developed and developing, presently have agricultural insurance systems or have gone through processes of development, crises, and revitalization. The European Union (EU) is considering shifting a portion of the income support mechanisms toward safety nets and risk management instruments, including agricultural insurance (European Commission, 2005).

Conventional wisdom assumes agricultural insurance is vulnerable to serious problems of asymmetric information (Chambers, 1989; Just and Pope, 2002). In the EU member states, the private sector provides basic coverages for a very limited number of hazards; consequently, many of the risks and hazards to which farmers are exposed cannot be insured by private insurance companies. Some EU countries—including Spain, Austria, France, Greece, and Italy—have developed comprehensive insurance policies as a means to provide safety nets for farmers. In the last 10 years, the United States, Spain, and Canada, among others, have expanded their insurance systems in terms of insured risks, coverages, and premium subsidies.

More recently, Italy, Austria, and France have renewed insurance programs with government support (European Commission, 2006).

Figure 1 (borrowed from Garrido and Bielza, 2008) helps to identify three groups of countries in the EU with respect to agricultural insurance. The group of Mediterranean countries (except Greece, not shown because of lack of information), depicted in the upper right-hand side, intensely subsidize the premia, and premia are relatively large with respect to total agricultural output. At the other extreme, premia of the countries of Germany, Denmark, France, Ireland, and Sweden are relatively small, and subsidies are small or zero. Total premia are also relatively small compared to the value of farm production. The size of the circle represents the ratio of total premium and total agricultural production. Data show that penetration rates are greater in countries where insurance is less subsidized, though coverages are broader in the Mediterranean countries (Garrido and Bielza, 2008).

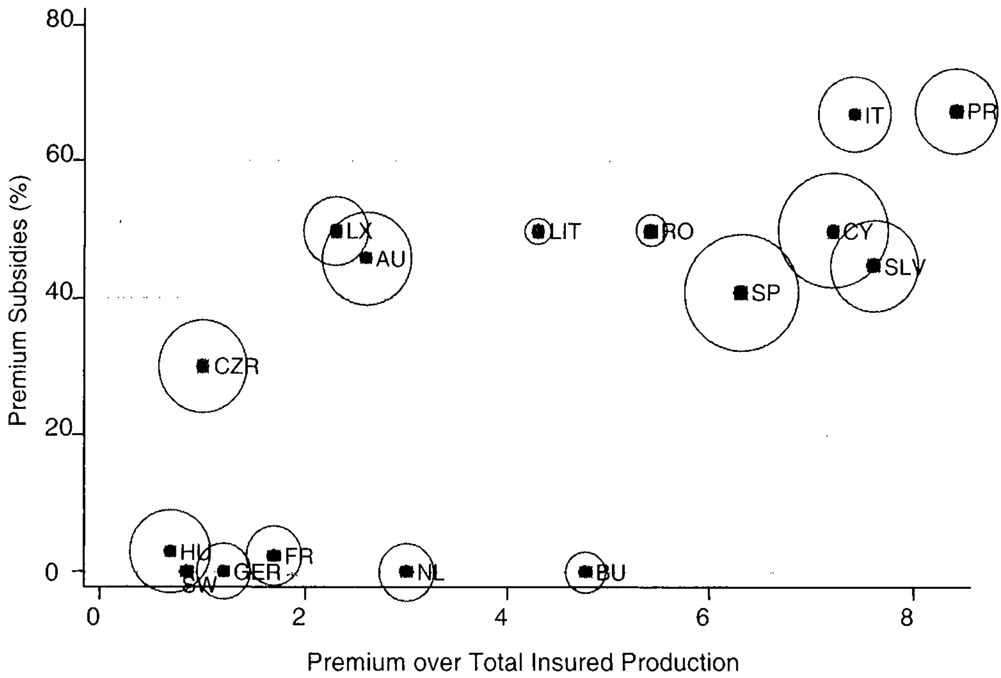
Despite the importance of insurance in many countries in terms of insured acreage, total liabilities, and premium subsidies, very little is known about non-U.S. insurance experiences, with the exceptions of Canada and India. Most policy reviews of other experiences are very superficial [European Commission (EC), 2001; Organization for Economic Cooperation and Development (OECD), 2000]. The Spanish case is especially striking because it offers a rich experience in developing new and innovative agricultural insurance, which has been expanding during the last 25 years.

Canada, Spain, and the United States are among the OECD countries with more developed agricultural insurance policies. In the last decade, these three countries have increased the budget devoted to premium subsidization, as well as the percentages of farmers and surface with some coverage. As rough measures, these countries spend in subsidizing insurance policies an equivalent of 1% to 2% of their total agricultural output. In response to this significant budget allocation, approximately 50% to 60% of eligible farmers purchase at least one insurance policy. On average, the United States spends about US$25 per insured hectare in insurance subsidies, Spain €25, and Canada Can$50.

This paper focuses on the demand for agricultural insurance in Spain. Although the history of agricultural insurance in Spain dates back to the beginning of the 20th century, it remained fairly unimportant and underwent various waves of decline and resurgence until 1978. This year saw the passage of the Agricultural Insurance Act, which set the stage for a continuous growth of agricultural insurance in Spain.

The Spanish system is based on a mixed public/private model, in which farmers' unions and associations also play a crucial role. [Interested readers can find a complete description of the Spanish insurance system in OECD (2000) and EC (2006) reports.] The system has evolved in the last 20 years to offer a wide menu of products for a broader range of crops and animal production. Over the period 1980–2004, loss ratios for all policies, experimental policies, and viable policies were 99.56%, 114.31%, and 82.98%, respectively, indicating that the system has grown following sound actuarial criteria (Agroseguro, 2004). Total liability in 2006 surpassed €10 billion, representing between 25% and 30% of the total agricultural output.

Spain has followed a traditional approach to define insurable risks and establish loss adjustment procedures, fitting with the model of Multiple-Peril Crop Insurance. In recent years, the system has expanded to provide yield insurance, based on individual or zonal records, for many crops including cereal and winter crops, olive trees, and a number of other fruit crops. Two kinds of parametric insurance have been used experimentally with varying success.



Data Sources: European Commission (2006), Eurostat, Garrido and Bielza (2008), and own fieldwork.
Note: Size of circle represents % of total premium over total agricultural output; series lengths vary with countries.

Figure 1. Insurance Policies Across EU Member States (subsidies as a percentage of premium and premium as a percentage of insured production)

The failed attempt (which very few farmers purchased) was a potato revenue insurance, based on a price index, offered in seasons 2003 and 2004 (Bielza, Garrido, and Sumpsi, 2007). The more successful example is a "drought" insurance available to range livestock growers, which is based on vegetation indices produced from satellite images.

This paper seeks to assess farmers' demand for insurance in Spain and identify the main factors explaining farmers' participation in insurance. The novelty of the approach is that it uses farmers' actual insurance outcomes and other actuarial variables as the main explanatory factors for insurance participation. Another breakthrough of our analysis is the variety of crops, insurance policies, and farming conditions included in the sample, which is comprised of more than 41,660 farmers and 12 years of insurance records.

The remainder of the paper is structured as follows. After reviewing the literature on insurance demand, we then develop an analytic framework to model the incentives to purchase crop insurance. This simple model shows the impact of policy and insurance parameters as well as risk preferences on farmers' insurance choices. The econometric approach to estimate the insurance demand models is then discussed, followed by a description of the data sources and documentation of variables. Next, we report and discuss the econometric results. The following section is then devoted to probability estimates of insurance uptaking for reasonable ranges of the most influential explanatory variables.

The paper's most salient conclusions are summarized in the final section.

Factors Driving Farmers' Demand for Insurance

Farmers purchase insurance polices because (*a*) expected benefits are positive, (*b*) they gain from asymmetric information, and (*c*) they are risk averse (Just, Calvin, and Quiggin, 1999). The bulk of the literature on agricultural insurance has focused on the first two of these hypotheses, which have been tested under alternative assumptions about item (*c*).

Insurance subsidization, though important in absolute and relative terms, is not the only means used by governments to support agricultural insurance. Agencies directly or indirectly promote research and support continuous innovation, offering a broad menu of insurance options for field crops, fruits and vegetables, and livestock farmers. Some countries provide reinsurance services, underwriting all or part of outstanding risks. On the demand side, farmers respond by changing the crops they insure, the type of policy, or the coverage. In Spain, some insurance policies are purchased by 100% of eligible farmers (banana or tomato in the Canary Islands) and some others by less than 4%, including olive trees or revenue insurance for potato in the years it was offered.

Asymmetric information implies that insuree and insurer possess different information about productive risks and the insuree's behavior. Asymmetric information is thought to provide incentives for moral hazard and adverse selection. Quiggin, Karagiannis, and Stanton (1993) argue that very often it is not possible to empirically distinguish between moral hazard and adverse selection, however different they may be in theoretical terms.

Consider the case of a farmer who defers his planting date to learn more about soil-moisture and decide whether it is in his interest to purchase drought insurance. This type of behavior is illustrative of both moral hazard and adverse selection. It exhibits adverse selection because insurance is purchased only if lower yield is expected. It reflects moral hazard because the decision to defer planting is influenced by the existence of yield insurance. Moschini and Hennessy (2001) review in detail the problems related to asymmetric information. What this wealth of literature, entirely based on U.S. cases and data, seems to suggest is that there is disagreement about whether or not asymmetric information poses incentives to increase production, and how premium subsidies actually affect farmers' insurance strategies.

Ramaswami (1993) distinguishes two kinds of insurance effects: *moral hazard* effects and *risk reduction* effects. The first encourages reductions of input use and, by means of the second, the insuree would seek greater expected revenue. Yet, there is some ambiguity with regard to moral hazard effects, because increased production inputs also can be risk-augmenting. In general, it is thought that fertilizers are risk-augmenting inputs, and pesticides risk-reduction inputs. However, insurance policies include a number of provisions and features that are meant to reduce moral hazard.

While Horowitz and Lichtenberg (1993) found no evidence of moral hazard among U.S. maize growers, Wu (1999) reported very weak evidence among this group of growers. The list of those researchers who report evidence of moral hazard includes Quiggin, Karagiannis, and Stanton (1993) with U.S. grain producers; Smith and Goodwin (1996) analyzing U.S. wheat producers; Babcock and Hennessy (1996) with simulation models; Coble et al. (1996) with Kansas farms; Serra, Goodwin, and Featherstone (2003) with Kansas growers; and Mishra, Nimon, and El Osta (2005) with U.S. wheat producers. None of these studies examine more than 1,600 farms, or look at crops other than wheat, maize, and soybeans.

Fighting adverse selection is paramount to being able to offer specific insurance policies to relatively homogeneous groups of farmers. For this, insurers must rely on objectively discriminatory elements to group agents under homogeneous risk levels. Adverse selection indicates the absence of discrimination elements based on different levels of risk exposure and the imbalance of premia and indemnities. Evidence of adverse selection was found by Skees and Reed (1986) with U.S. soybean and maize growers; Goodwin (1994) among Kansas farms; Quiggin, Karagiannis, and Stanton (1993) and Just, Calvin, and Quiggin (1999) with U.S. growers; Ker and McGowan (2000) among insurance firms in the case of wheat producers in Texas; and by Makki and Somwaru (2001) with corn producers from Iowa, using the largest data set (6,000 farms) among those reviewed here.

The evidence in favor of severe asymmetric information problems is dubious and mostly based on a limited number of U.S. insurance policies (MCPI and APH), though Makki and Somwaru (2001) report strong evidence for adverse selection in the presence of four types of policies including revenue insurance. The literature suggests that farmers seem to be compelled to purchase insurance because they are attracted by the expected results, which are also dependent on the level of subsidies (Just, Calvin, and Quiggin, 1999). As shown by Makki and Somwaru (2001), high-risk U.S. farmers are more likely to purchase revenue insurance and higher coverage levels, and low-risk farmers tend to be overcharged.

A controversial issue about the role of subsidies in the demand for insurance has not yet been settled in the literature. Goodwin, Vandeveer, and Deal (2004) document demand elasticities for insurance between –0.24 and –0.20. Serra, Goodwin, and Featherstone (2003) show that it has become less elastic in the United States as farmers have turned to broader coverages, favored by the increase of premium subsidies through the Agricultural Risk Protection Act of 2000.

None of the above studies use actual insurance outcomes, such as individual loss ratios, indemnities, or expected returns from insurance. Even Makki and Somwaru (2001), who employ the largest and most insurance-diverse data set, evaluate measures of expected indemnity for Iowa corn growers as a proxy for actual indemnities. Just, Calvin, and Quiggin (1999) rely on the comparison between stated yield percentiles and insurance premia, but do not include actual indemnities. Among the major drawbacks of the previous works is the fact that crop failures or low yields are not indemnifiable in all cases. Hence, in order to evaluate the demand for insurance, one must include in the analysis what farmers actually get or may reasonably expect from their premia, and compare this with the cost. This is best analyzed by using farmers' actual insurance results, instead of inferred ones.

A Stylized Model of Insurance Participation

The most general formulation of the revenue risk of one crop, when both yield and price are stochastic, is $\tilde{R} = \tilde{p} \times \tilde{y}$. Assume $\tilde{p} \in [\underline{p}, \bar{p}]$ (with $\underline{p}$ and $\bar{p}$ being the respective minimum and maximum price) and $\tilde{y} \in [\underline{y}, \bar{y}]$ (with $\underline{y}$ and $\bar{y}$ being the respective minimum and maximum yield) have known probability distribution functions, $g(p)$ and $f(y)$. Following Glen, Leemis, and Drew (2004), the probability distribution function (pdf) of $\tilde{R}$, $h(R)$, has a closed form as long as independence between $\tilde{p}$ and $\tilde{y}$ holds and has defined supports, as follows:

$$(1)\quad h(R) = \int_{R/\bar{p}}^{\bar{y}} g\left(\frac{R}{y}\right) f(y)\,\frac{1}{y}\,dy.$$

With yield insurance, revenue is given by:

$$(2)\quad \tilde{R}_i = \begin{cases} \tilde{p} \times \tilde{y} & \text{if } \tilde{y} > y_e, \\ p_e \times (y_e - \tilde{y}) + \tilde{p} \times \tilde{y} & \text{if } \tilde{y} \le y_e, \end{cases}$$

where y_e and p_e are the trigger yield and price for evaluating the indemnity. Profit is given by $\tilde{\pi}_i = \tilde{R}_i - c - P_n + s$, with c representing the crop's cost; P_n is the net premium; and s is an agricultural policy subsidy that takes the form of a direct aid. Insurance net premium, as paid by the farmer, results from $P_n = (1 + \delta)(1 - \tau)P_f$, where δ is the loading factor, τ is the insurance subsidy, and P_f the fair premium, evaluated as follows:

$$(3)\quad P_f = p_e \int_{\underline{y}}^{y_e} (y_e - y) f(y)\, dy.$$

Computing P_f is far from trivial, and in fact is not defined in the case of all pdfs[1] [see Appendix A for the case where $f(y)$ follows a gamma distribution]. In the absence of insurance, profit is calculated as $\tilde{\pi} = \tilde{R} - c + s$.

To compare whether insuring is utility-augmenting, an expected utility model can be formulated using a revenue pdf like the one defined by (1) and a premium as defined by (3). Analytical complexity can be kept to reasonable levels if farmers' preferences are modeled with an exponential utility function, exhibiting constant absolute risk aversion (CARA) preferences, $U(\pi) = 1 - e^{-r\pi}$. Farmers would purchase insurance if they expect utility gains, which under the expected utility hypothesis implies that $EU(\pi_i) > EU(\pi)$. Expected utility in the case of insurance is given by:

$$(4)\quad EU(\pi_i) = \int_{\underline{y}}^{y_e} \left(1 - e^{-r[p_e(y_e - y) - P_n - c + s]}\right) f(y)\, dy + \int_{\underline{yp}}^{\overline{py}} \left(1 - e^{-r[R - P_n - c + s]}\right) h(R)\, dR.$$

In (4), the indemnity can be separated from the crop revenue, because $f(y)$ and $h(R)$ are different stochastic variables.

[1] If $f(y)$ follows a beta, then obtaining the premium requires evaluating a hypergeometric 2F1 function; if it is gamma, an incomplete gamma function; and if it is a lognormal or normal, one needs to evaluate an error function.

Under no insurance, expected utility is given by:

$$(5)\quad EU(\pi) = \int_{\underline{yp}}^{\overline{py}} \left(1 - e^{-r[R - c + s]}\right) h(R)\, dR.$$

There are two possible strategies to compare the expected utilities of insurance versus no insurance, both taking advantage of the moment-generating function of the distribution functions, as in Collender and Zilberman (1985). One, which relies on the assumption of independence between $\tilde{y}$ and $\tilde{p}$, is to use the result of Glen, Leemis, and Drew (2004), evaluate the integral to obtain $h(R)$ using equation (1), and get a closed form of $EU(\pi_i)$ and $EU(\pi)$. However, this strategy is applicable to a very limited number of cases, because the combination of pdfs for $\tilde{y}$ and $\tilde{p}$ which ensure that function (1) can be integrated is limited to lognormal-lognormal, and beta-beta, and independence between both must be assumed. Furthermore, even if the integral in (1) can be solved, the solution generally will be cumbersome mathematical expressions which will prevent the posterior analysis of the model.

The alternative strategy is more restricting, using CARA preferences, but perhaps more insightful. It is based on the assumption that $\tilde{R}$ follows a continuous distribution function which has a moment-generating function. Obvious candidates are gamma, chi-squared, or normal distributions. For a wide range of pdfs for $\tilde{y}$ and $\tilde{p}$—including beta, gamma, lognormal, and normal—a gamma distribution fits statistically well for the resulting $\tilde{R}$.[2]

In Appendix B, we show that if $\tilde{y}$ and $\tilde{R}$ follow distribution functions with moment-generating functions, then $EU(\pi_i) - EU(\pi) > 0$ if and only if:

$$(6)\quad \left[\gamma_{y_e} - e^{-r(R_e + \beta)} LIMGF_y(rp_e;\, y_e)\right] + \left[e^{-r\beta'} MGF_R(-r)\left(1 - e^{rP_n}\right)\right] > 0,$$

[2] Simulation work using @Risk yielded this conclusion. Results can be obtained from the authors upon request.

where γ_{y_e} is the probability of $y < y_e$; $R_e = p_e y_e$; $\beta = -P_n - c + s$; and $\beta' = -c + s$. $LIMGF_y(rp_e;\, y_e)$ denotes the lower incomplete moment-generating function of $\tilde{y}$ of order rp_e and upper bound of y_e (see Appendix B); and $MGF_R(-r)$ is the moment-generating function of $\tilde{R}$ of order $-r$. The first bracketed term in (6) is the expected utility resulting from the insurance indemnity scheme, whereas the second term, which is negative due to the premium, is the difference between the expected utility with and without insurance resulting from stochastic revenue $\tilde{R}$. Note, one of the consequences of assuming CARA preferences is that wealth does not affect the decision to insure, as shown in (6).

Although condition (6) holds only for any pair of random variables ($\tilde{y}$ and $\tilde{R}$), with pdfs with MGFs, to gain some intuition we focus on the particular case of $\tilde{y}$ and $\tilde{R}$ following two gamma distributions, with parameters (λ_R, α_R) and (λ_y, α_y).[3] In Appendix C, we show that condition (6) can be transformed to:

$$(7)\quad \gamma_{y_e} e^{-r(P_n-\beta')} > e^{-rR_e} MGF_y(rp_e;\, y_e) \times RGF\big(\alpha_y,\, (\lambda_y - rp_e)y_e\big) + MGF_R(-r)\,(1 - e^{-rP_n}),$$

where $RGF(\cdot)$ is a regularized gamma function (whose domain is [0, 1]). Note that condition (7) has similar formulations if either $\tilde{y}$ or $\tilde{R}$ are normal, gamma, chi-squared, exponential, or uniform among continuous distributions; or discrete uniform, Bernoulli, binomial, negative binomial, or Poisson among discrete distributions.[4] From equation (7), if $P_n - \beta' > 0$, a necessary but not sufficient condition for $EU(\pi_i) - EU(\pi) > 0$ to hold is (see proof in Appendix C):

$$(8)\quad EU(R - P_n) + EU(I) > EU(R),$$

where I indicates indemnity ($\tilde{I} = p_e(y_e - \tilde{y})$). Condition (8) is intuitively clear: insurance is purchased if, after paying the premium, the farmer may be compensated with the utility gain resulting from the indemnity. Note, however, that only condition (7) is necessary and requires that $P_n - \beta' > 0$. If the per hectare subsidy, s, is sufficiently high, or the premium is intensively subsidized, then it may be the case that $P_n - \beta' = P_n + c - s < 0$. Should this be the case, condition (7) would not be a necessary condition, so equation (8) must hold to ensure that insurance is purchased. Therefore, if the premium is inexpensive relative to other costs, either because of subsidies or because risk is low, and the direct subsidy is large, then insurance may be purchased even if inequality (8) is reversed. Furthermore, if $P_n - \beta' < 0$, then the exponent of the left-hand-side term in (7) switches from negative to positive. Hence, the larger the subsidies, the greater the incentives to purchase insurance.

Factors Affecting Insurance Participation

Now let's assume there exists a premium P^* that makes insuring and not insuring equally attractive. From (6), if we make $P_n = P^*$ so that (6)'s inequality is cancelled, we obtain:

$$(9)\quad P^* = \frac{1}{r}\log\left[\frac{\gamma_{y_e} e^{r(-c+s)} + MGF_R(-r)}{LIMGF_y(rp_e;\, y_e)e^{-rR_e} + MGF_R(-r)}\right].$$

Therefore, only if $P_n < P^*$ is insurance contracted, which is another way of expressing condition (7) applying to any combination of pdfs for $\tilde{y}$ or $\tilde{R}$ with moment-generating functions. Note, however, that a necessary condition for $P_n < P^*$ is that the bracketed term in (9) be

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[3] Mean equal to α/λ; variance equal to α/λ^2; and moment-generating function of order t equal to $1/(1 - t(1/\lambda))^{\alpha}$, for $t < \lambda$. The gamma distribution also nests chi-squared and exponential distributions, and is related to the normal distribution, because if X is a gamma (α, λ), then $\mathrm{Lim}_{\alpha\to\infty} X = Y$, with Y being a normal distribution (α/λ, α/λ^2).

[4] One advantage of using functions with MGFs is that one can always find an analytic expression for the lower incomplete moment-generating functions, and bring the model to more analytic results.

greater than 1. Solution P^* incorporates all relevant parameters, including risk aversion, agricultural policies, insurance parameters, and the idiosyncratic yields and revenue risks. If we assume that $\tilde{y}$ and $\tilde{R}$ follow gamma distributions, there are eight parameters capturing each of these effects. Denoting $P^* = H(r, s, y_e, p_e, \alpha_y, \lambda_y, \alpha_R, \lambda_R)$ as the general formulation (9), we now investigate the effects of some of the key parameters on P^*.[5] Throughout the following presentation, the bracketed term in (9) is denoted by T, with $Num(T)$ and $Dem(T)$ denoting T's numerator and denominator.

Direct Payment or Premium Subsidies (*s*)

Parameter s represents a per hectare direct payment. It is straightforward to show that:

$$(10) \quad \frac{\partial P^*}{\partial s} = \frac{\gamma_{y_e} e^{\beta'}}{Num(T)} > 0.$$

This means that if direct subsidies increase or crop costs diminish, P^* increases and incentives to insure will also increase.

Moment-Generating Function of R

$MGF_R(-r)$ is always positive and depends on the parameters of the distribution of revenue (λ_R, α_R), which in turn depend on the combined effects of price risk, yield risk, and their correlation, and on any farm policy affecting the distribution of output prices. If R follows a gamma distribution, an increase of α_R will increase $MGF_R(-r)$; the opposite occurs with an increase in λ_R. Furthermore, if $\tilde{R}$ experiences an increase of mean-preserving spread, $MGF_R(-r)$ likewise increases for any r. It is straightforward to show that:

$$(11) \quad \frac{\partial P^*}{\partial MGF_R(-r)} > 0\ (<0) \quad \text{if } T > 1\ (<1).$$

Therefore, if revenue instability increases, P^* goes up and insurance would likely be more appealing. In general, for the same yield distribution, $MGF_R(-r)$ will grow if prices experience an increase of mean-preserving spread.[6] Consequently, larger market volatility would be followed by more incentives to purchase yield insurance. Note that result (11) is largely undetermined because it is impossible to ascertain whether any change in prices, yields, and their correlation, or any policy parameter (like reduced border protection via dismantling of tariffs) will either reduce or increase $MGF_R(-r)$. However, if revenue instability rises, result (11) will prevail and farmers' willingness to pay for insurance will grow.

Changes in the Trigger Yield (y_e) *and Price* (p_e)

The way expected utility expressions are defined by (4) and (5) implies that if either y_e or p_e increases, then P^* will increase as well. A more interesting analysis is to evaluate the effect of an increase in either trigger price or yield, maintaining constant their product ($R_e = y_e \times p_e$). Starting with the simpler case of a change in the trigger price, p_e, in Appendix D we show that:

$$(12) \quad \left.\frac{\partial P^*}{\partial p_e}\right|_{R_e = \bar{R}_e} < 0.$$

Similarly, an increase of y_e, maintaining R_e constant, also yields the following result if:

$$(13) \quad \left.\frac{\partial P^*}{\partial y_e}\right|_{R_e = \bar{R}_e} > 0.$$

Thus, farmers would always prefer an increase of the trigger y_e to an increase of p_e, keeping R_e constant. Obviously, an increase in y_e would be followed by a larger increase in the premium than would result from an increase in p_e.

[5] While our analysis cannot predict when P^* will be greater than P_a, or even when P^* will be greater than 0 ($T > 1$), it is meant to determine when P^* will augment or diminish.

[6] This has been checked numerically.

Risk-Aversion Coefficient

The risk-aversion coefficient, r, shows up in all terms in expression (9). Whether a larger r implies more willingness to purchase insurance is dependent on more factors than found in the previous analyses. The most direct way to investigate the effect of an increase of r is to start from the identity that equals insuring and non-insuring solving for $P^*(r)$ and take derivatives with respect to r in:

$$(14) \quad \gamma_{y_c} - e^{-r(R_c+\beta'-P^*)} LIMGF_y(rp_e; y_e) + 1 - e^{-r(\beta'-P^*)} MGF_R(-r) \equiv 1 - e^{-r(\beta')} MGF_R(-r).$$

From (14), we find that $\partial P^*/\partial r > 0$ if:

$$(15) \quad e^{-r(R_c-P^*)}\left[(R_e+\beta'-P^*)LIMGF_y(rp_e; y_e) - \frac{\partial LIMGF_y(rp_e; y_e)}{\partial r}\right] > MGF_R(-r)\left[\beta'-(\beta'-P^*)e^{rP^*}\right] + \frac{\partial MGF_R(-r)}{\partial r}(e^{rP^*}-1),$$

where the two partial derivatives with respect to r are always positive. The intuition of (15) is the following. If $\beta' < 0$, then $-c + s - P^* < 0$; thus, purchasing insurance increases the costs. Further, for the LHS in (15) to be positive, it must be the case that $R_c - \beta' - P^* > 0$. Otherwise condition (15) does not hold, and then $\partial P^*/\partial r < 0$. Note that even if $R_c - \beta' - P^* > 0$, condition (15) may not hold. More risk aversion would be followed by increasing willingness to pay for insurance if, as condition (15) expresses, the disutility resulting from the uncertainty of the indemnity scheme grows less with r than the increasing disutility resulting from the uncertainty of revenue R, net of the premium. In an extreme case of very high yield trigger, y_c, and very expensive premium, more risk aversion would clearly be followed by less incentives to insure. Bielza, Garrido, and Sumpsi (2006) show that farmers with less risk aversion may benefit more from heavily subsidized insurance compared to their more risk-averse counterparts.

Empirical Models

The simplest and most general insurance participation model that our database permits estimating is a binary choice model. Thus, the decision to contract any type of insurance is the behavior we will be analyzing with our econometric models.

As the theoretical model indicates, farmers would more likely purchase insurance if direct payments and premium subsidies are higher. Also, product price volatility induces more insurance participation incentives, keeping constant the yield distribution. In general, we expect that farmers who grow nonperishable products will be less inclined to purchase insurance, because revenue is more stable with storable products. By contrast, as they are entitled in the EU to direct payments, field crops have this added incentive to being insured. Concerning the role of yield risk, the theoretical model does not offer a direct interpretation because the parameters of the yield distribution appear in all terms in equation (9). What this equation makes clear is that the variability of the indemnity scheme is a crucial factor in determining whether insuring augments utility. Our empirical analysis emphasizes the importance of the observed or inferred indemnity schemes as a critical factor explaining farmers' observed insurance strategies.

We assume farmer i will purchase at least one insurance policy in year t if:

$$(16) \quad \Pr(Insur_{it} = 1 \mid \mathbf{X}_t^c, \mathbf{Z}) = \Pr(\alpha\mathbf{Z} + \beta\mathbf{X}_t^c + \varepsilon_{it} > 0),$$

where two sets of variables ($\mathbf{Z}$, $\mathbf{X}_t^c$) are defined as follows. First, there is a vector of variables $\mathbf{Z}$ that capture specific conditions affecting farmers' decisions. These refer to non-idiosyncratic elements such as general climatic features and other geographical characteristics. The other vector of variables, $\mathbf{X}_i^c$, includes those intrinsically idiosyncratic elements. As some of these originate from farmers' past insurance experience, we assume their records of actuarial results will influence farmers' decisions. Note that in our simple theoretical formulation where $\tilde{R}$ follows a gamma distribution and agents exhibit CARA preferences, the risk-aversion coefficient interacts with the revenue's distribution parameters, as shown in three of the four terms in T [equation (9)].

Our empirical approach is meant to explain the probability of contracting insurance under the assumption that all farmers exhibit a certain level of risk aversion ($r_i > 0 \ \forall \ i$), but is guided by common factors stemming from fixed agricultural conditions, and the expectations farmers can build from their personal past insurance records and the *comarca*'s (equivalent to U.S. counties) data. These include expectations about the indemnity scheme, the types of insurance policies contracted in the past, the expected probability of crop failures, and premium subsidies.

Data Sources and Documentation

The econometric analysis uses data from the Spanish agricultural insurance system (ENESA). Our database includes records of individual farms from seven agriculturally diverse comarcas. The complete database includes all 41,660 farmers who contracted crop insurance at least once during the period 1998–2004, and a complete characterization of each farmer's insurance strategy, paid premiums, premium subsidies, and collected indemnities during 1993–2004.[7]

Table 1 summarizes the main descriptive elements of each comarca. The database includes a diverse set of crop risks, natural conditions, and kinds of insurance policies. For cereals, farmers can choose among three coverage levels, ranging from basic coverage including hailstorm and fire risks to individual yield risks. Fruit growers can choose between two coverage levels. From each farmer and year, records include the following variables: (*a*) whether the farmer purchased any insurance (binary); (*b*) crops insured, including surface (ha), expected yield (kg/ha), total liability (€), paid premiums (€), premium subsidies (€), and the kind of coverage; and (*c*) indemnities (€) received by crop, coverage, and year.

Table 1 reports the counts of the dichotomous variable *Insur*, which takes a value of 1 if the farmer contracted at least one insurance policy in the corresponding year, and 0 otherwise for the period 1999–2004. Since the longest record each farmer can build for 2004 results from the experience over the 11-year period 1993–2003, we estimate equation (16) for 2004 and for 2003 (as a robustness check).

In addition to the controls of the comarcas, which indirectly allow for checking the impact of direct farm subsidies, there are six idiosyncratic variables included in $\mathbf{X}_i^c$, which are grouped into two categories. The first includes three variables computed from individual farmers' actuarial results ($LRat_{it}$, $LRat\_in_{it}$, and Var_{it}). The second category includes insurance policy details ($PLoss_{it}$, $RelPrem_{it}$, and $RelSubs_{it}$). Below, we first define these variables and then comment on their meanings.

- $LRat_{it}$ (continuous, > 0): The loss ratio evaluated for each individual farmer up to year $t-1$ (farmer i, comarca j, crop k, year t):

$$(17)\ LRat_{it} = \frac{\sum_{t_0}^{t-1}\sum_{k} Ind_{ikt}}{\sum_{t_0}^{t-1}\sum_{k} Pmium_{ikt}} \quad \text{if } Pmium_{ikt} > 0,$$

where Ind_{ikt} is the indemnity (€) and $Pmium_{ikt}$ is the premium paid (€), net of subsidies, for crop k in year t. $LRat_{it}$ provides an idea of

[7] Farmers whose last record is in 1998 are not considered in this analysis. For those considered, we use the entire records from 1993–2004.

Table 1. Description of the Study Comarcas and Insurance Data

Name of Comarca	Autonomous Community	Main Insured Crops	No. of Farmers	No. of Years When *Insur* = 1 Between 1998 and 2004: Mean (Std. Dev.)	Percentile 5%	Median	Percentile 95%
Mancha	Castilla-La Mancha	Vineyards, vegetables, cereals	8,526	4.659 (2.071)	1	5	7
Campina	Andalusia	Cereals, citrus, cotton, olive, sunflower	4,151	4.231 (1.929)	1	4	7
Segria	Catalonia	Fruits, vineyards, cereals	5,099	5.046 (2.003)	2	6	7
Guadalentin	Murcia	Vegetables, greenhouse crops, grapes, fruits	1,286	4.122 (2.019)	1	4	7
Campos	Cast-Leon	Cereals, sugar beet, leguminosae	3,672	4.774 (1.985)	2	5	7
Albaida	C. Valenciana	Fruits, grapes, vineyards, citrus, vegetables	1,442	5.440 (1.739)	2	6	7
Jucar	C. Valenciana	Fruits, citrus, vegetables	17,484	4.920 (1.893)	2	5	7
Total			41,660	4.794 (1.975)	2	5	7

Source: Data derived from the Spanish agricultural insurance system (ENESA).

the actual expected benefits in terms of collected indemnities for one euro spent in contracting insurance.

■ $LRat\_in_{it}$ (continuous, > 0): The inferred loss ratio resulting from purchasing insurance, computed with the following formula (farmer i belonging to comarca j, crop k, year t):

$$(18)\quad LRat\_in_{it} = Insur_{it}\frac{\sum_k (Liab_{ikt}LRat_{kjt})}{\sum_k Liab_{ikt}} + (1 - Insur_{it})\frac{\sum_k (TIns_{ik}LRat_{kjt})}{\sum_k TIns_{ik}}$$

$$\text{if } Ind_{ikt} = 0 \;\; \forall\, k, t;$$

$$(19)\quad Exp\_ben\_in_{ijt} = Exp\_ben_{ijt} \quad \text{if } Ind_{ikt} \neq 0 \;\; \text{for any } k, t,$$

where

$$LRat_{kjt} = \frac{\sum_{t_0}^{t-1}\sum_i Ind_{ijkt}}{\sum_{t_0}^{t-1}\sum_i Pmium_{ijkt}},$$

and represents the loss ratio of crop k in comarca j; $Liab_{ikt}$ denotes total liability (€) of the insured crop by farmer i; $TIns_{ik}$ is defined by

$$TIns_{ik} = \sum_{t=1993}^{t=2003} Ins\_crop_{ikt},$$

where $Ins\_crop_{ikt} = 1$ if crop k was insured in year t.

■ Var_{it} (continuous, ≥ 0): A dimensionless measurement of the expected variability of the loss ratios, evaluated as follows:

$$(20)\quad Var_{it} = \sum_{t_0}^{t}\beta_t\Big[Insur_{it}(LRat_{it} - \overline{LRat_i})^2 + (1 - Insur_{it})(LRat_{jt} - \overline{LRat_j})^2\Big],$$

where β_t is a weighing factor with

$$\sum_{t_0}^{t}\beta_t = 1 \;\; \text{and} \;\; \beta_{t_1} > \beta_{t_0} \text{ if } t_1 > t_0,$$

and $LRat_{jt}$ is the loss ratio of comarca j up to year t.

■ $PLoss_{it}$ (continuous, ≥ 0): The expected probability of obtaining an indemnity for farmer i's relevant crops. It has been evaluated using formula (18), where instead of $LRat_{kjt}$ we substituted the proportion of farmers who contracted the same policy as did farmer i and received an indemnity up to year $t-1$.

- *RelPrem*$_i$ (continuous, ≥ 0): The average ratio of total paid premium over total liability of farmer i during the period 1998–2004.

- *RelSubs*$_i$ (continuous, ≥ 0): The average ratio of total premium over total paid premium of farmer i during the period 1998–2004.

$LRat_{it}$ is just the loss ratio of farmer i accumulated up to year $t-1$. If, for any given year t, $LRat_{it}$ is greater than 1, this means the farmer collected more indemnities up to year $t-1$ than the total premium paid up to $t-1$. Note, premium subsidies significantly increase the loss ratios because the denominator is the sum of all premiums, net of subsidies. $LRat_{it}$ is zero for farmers who did not receive an indemnity up to year t; however, $LRat_{it} = 0$ does not imply that the expected benefit of purchasing insurance is also zero. Hence, as an alternative formulation, we use the inferred loss ratio, $LRat\_in_{it}$, which is based on a weighted average of the comarca's loss ratios of the crops the farmers have purchased [formulated by expressions (18) and (19)]. Neither $LRat_{it}$ nor $LRat\_in_{it}$ are perfect indicators of the expected returns of purchasing insurance, but our hypothesis is that they may be sufficient to explain farmers' insurance strategies. Alternative demand models are estimated with the actual or inferred loss ratios as robustness checks.

Var_{it} provides a measurement of the relative dispersion of the loss ratios. For Var_{it}, we are assuming that if the farmer did not purchase any policy in year t, an equivalent measurement of the dispersion of payoffs is provided by his comarca. Note also, the inclusion of β_t ensures that more weight is placed on the most recent years up to t. In this way we introduce a slight degree of memory in the construction of variances, following the same approach used by Chavas and Holt (1990). Note, however, that $LRat_{it}$ (or $LRat\_in_{it}$, for that matter) and the variable Var_{it} provide a completely different description of the insurance payoff. While $LRat_{it}$ provides a raw return of the money spent in purchasing insurance, Var_{it} captures the relative dispersion of the payoffs. $LRat_{it}$ and Var_{it} are positively but nonlinearly correlated ($\rho = 0.24$ and Spearman= 0.50, both with $p < 0.01$).[8] Accordingly, with result (8), we expect that larger values of $LRat_{it}$ and Var_{it} increase the probability of contracting crop insurance, because $EU(\pi_i)$ increases with larger indemnities and less frequent occurrence of the worst results as long as $U(\cdot)$ is concave.

Finally, $PLoss_{it}$, $RelPrem_i$, and $RelSubs_i$ provide three complementary aspects of farmers' insuring strategies. The first captures the probability of suffering losses that are indemnifiable, for those crops and policies relevant to each farmer. Although they are clearly connected, $PLoss_i$ differs from γ_{y_e}. Specifically, $PLoss_i$ is evaluated from the comarca's probability of crop failure whereas γ_{y_e} is a genuine idiosyncratic probability of receiving an indemnity. $RelPrem_i$ captures the relative magnitude of the insured risks with respect to total liability. Broader coverages and larger crop risks imply greater relative premia with respect to total liability. According to result (13), the option to increase the coverage by means of a larger yield threshold, y_e, will generally be followed by more incentives to purchase any type of insurance, provided that $\overline{R}$ is kept constant. However, since a larger coverage rarely is compensated by a reduction of p_e, $\overline{R}$ is generally not constant. In our data set, a larger relative premium indicates broader coverage or larger risk.

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[8] A quadratic regression of *Var* against *LRat*, $LRat^2$, and comarcas' controls yields an adjusted R^2 of 0.13, with a positive and significant coefficient of *LRat* and a negative and significant coefficient for $LRat^2$. Results of this regression are available from the authors upon request.

Table 2. Basic Statistics of the Relevant Variables (n = 41,660, year = 2004)

Variable	Mean	Std. Dev.	Percentile 5%	Median	Percentile 95%
$LRat_{it}$	0.594	0.801	0.000	0.298	2.257
$LRat\_in_{it}$	0.898	0.741	0.031	0.776	2.270
Var_{it}	0.021	0.050	0.000	0.007	0.075
$RelSubs_i$	0.220	0.123	0.046	0.208	0.430
$RelPrem_i$	0.080	0.046	0.012	0.077	0.159
$PLoss_i$	0.216	0.122	0.025	0.193	0.422

Source: Data derived from the Spanish agricultural insurance system (ENESA).

$RelSubs_i$ captures the role of the premium subsidies, and is unambiguously signed by terms of result (10).

A final note regarding the time frame of variables within $\mathbf{X}_i^e$ may clarify our approach. The idiosyncratic variables $\mathbf{X}_i^e$ ($LRat_{it}$ or $LRat\_in_{it}$, Var_{it}, $PLoss_{it}$, $RelPrem_i$, and $RelSubs_i$) have different time perspectives. Those with the time subscript t are evaluated up to year $t-1$, as farmers would ponder the value of contracting insurance in year t, taking into account their previous results. The assumption we make is that farmers are guided by their own personal insurance experience or their comarca's results up to year $t-1$. By contrast, relative premium ($RelPrem_i$) and relative subsidies ($RelSubs_i$) are idiosyncratic too, but do not vary with time, because subsidies depend on the type of farm and relative premium depends on the specific crop's risks, which in turn depend on the climate characteristics.

Probit models will be estimated for years 2003 and 2004, for the complete database using $LRat\_in_{it}$ and $LRat_{it}$, and for the subset of farmers whose $LRat_{it} > 0$, i.e., for farmers who at least received an indemnity in one year over the entire period 1993–2003. In Table 2 we report the basic statistics of all idiosyncratic variables pertaining to the largest database and year 2004.

Insurance Demand Models

Table 3 presents the probit models for these three specifications ($LRat\_in$, $LRat$, and $LRat$ using only farmers for whom $LRat > 0$), for the years 2003 and 2004. The binary and dependent variable in each of the models is $Insur_{it}$. The 2004 run has more observations than 2003 because there are 259 farmers who became insurees in 2004 for the first time during 1999–2004, but were in the 1993–98 records. All runs have reasonably good sensitivity (correct classifications of real ones and zeros) and specificity indicators (real ones and zeros correctly classified). The six models predict at least 85.6% of the real ones, although the worst prediction of zeros is 52.5%. McFadden's R^2 ranges from 0.241 to 0.428

All estimated coefficients are significant (at 99% significance levels), except for $LRat$ which is not significant in the last regression (year 2004). In addition, the sign of $LRat$ changes across equations, whereas $LRat\_in$ values are all negative. These results indicate the loss ratio has an ambiguous influence on farmers' decision to purchase insurance. If loss ratios are indicators of adverse selection, our results show that the association with farmers' insurance demand is at best doubtful.

The comarcas' controls are all significant and consistent across equations (*Mancha* is the omitted comarca, but its effect is picked up in the intercept). Since the set of comarcas is diverse in the proportion of farmers who grow crops entitled to direct payments, we can use the controls as a source of evidence for the role of CAP subsidies on insurance participation [see equation (10)].

Table 3. Probit Models of Insurance Demand (dependent variable = $Insur_{it}$)

Item	Inferred $LRat\_in_{it}$		Actual $LRat_{it}$		Actual $LRat_{it} > 0$	
	2003	**2004**	**2003**	**2004**	**2003**	**2004**
$LRat\_in_{it}$	-0.087	0.022				
	(0.009)	(0.010)				
$LRat_{it}$			-0.085	-0.137	0.177	-0.005[†]
			(0.009)	(0.010)	(0.013)	(0.013)
Var_{it}	2.573	1.917	2.697	2.671	2.353	2.967
	(0.193)	(0.168)	(0.199)	(0.181)	(0.241)	(0.223)
$RelSubs_i$	8.201	6.968	8.306	7.077	11.064	8.533
	(0.193)	(0.168)	(0.096)	(0.081)	(0.147)	(0.113)
$PLoss_i$	-0.212	-0.612	-0.268	-0.334	-0.751	-0.787
	(0.097)	(0.104)	(0.096)	(0.081)	(0.147)	(0.113)
$RelPrem_i$	-8.203	-8.289	-8.079	-8.458	-10.113	-10.518
	(0.229)	(0.215)	(0.228)	(0.216)	(0.325)	(0.292)
Campiña	-0.153	-0.555	-0.166	-0.494	-0.741	-0.962
	(0.032)	(0.032)	(0.032)	(0.032)	(0.055)	(0.052)
Segrià	-0.346	-0.472	-0.372	-0.445	-0.858	-0.747
	(0.029)	(0.028)	(0.029)	(0.027)	(0.040)	(0.035)
Guadalentin	-0.573	-0.657	-0.578	-0.653	-0.830	-0.896
	(0.045)	(0.043)	(0.045)	(0.043)	(0.069)	(0.061)
Campos	-0.304	-0.460	-0.327	-0.440	-0.464	-0.610
	(0.033)	(0.032)	(0.033)	(0.032)	(0.057)	(0.053)
Abaida	0.112	-0.231	0.090	-0.233	-0.416	-0.472
	(0.052)	(0.046)	(0.052)	(0.046)	(0.077)	(0.063)
Jucar	0.195	-0.096	0.175	-0.082	-0.268	-0.406
	(0.023)	(0.024)	(0.023)	(0.023)	(0.039)	(0.039)
Intercept	-0.174	0.066	-0.206	0.066	-0.596	0.065
	(0.029)	(0.029)	(0.029)	(0.029)	(0.063)	(0.059)
Sensitivity $Pr(+\|D)$[a]	0.889	0.858	0.890	0.856	0.926	0.901
Specificity $Pr(-\|{\sim}D)$[a]	0.533	0.525	0.535	0.530	0.640	0.592
Positive Predictive Value $Pr(D\|+)$[a]	0.831	0.794	0.832	0.795	0.887	0.847
Negative Predictive Value $Pr({\sim}D\|-)$[a]	0.649	0.635	0.653	0.633	0.738	0.705
McFadden's R^2	0.293	0.241	0.293	0.241	0.428	0.336
No. of Observations	41,341	41,660	41,341	41,660	25,301	26,098

Notes: All coefficients are asymptotically significant at $p < 0.01$ (except †); values in parentheses are standard deviations.
[a] In $Pr(+|D)$, + means classified as 1, D indicates true 1; in $Pr(-|{\sim}D)$, − means classified as 0, ${\sim}D$ indicates true 0.

Our results are ambiguous. Of the six comarca controls reported in Table 3, those two with the highest and lowest probability of contracting insurance are, respectively, the pairs *Jucar-Albaida* and *Segrià-Guadalentin.* Farmers in these two pairs of comarcas primarily grow and contract crop insurance for fruitcrops and vegetables (see Table 1). The middle group is formed by comarcas *Campos-Campiña*, whose farmers primarily grow field crops, most of which are entitled to CAP per hectare subsidies. Consequently, our results do not confirm the hypothesis that direct payments generally induce farmers to purchase insurance. Other factors seem to override the effect of per hectare direct subsidies.

The remaining coefficients—*Var*, *RelSubs*, *PLoss*, and *RelPrem*—are all significant and have consistent signs and magnitudes across specifications. *Var* is a measurement of dispersion of the indemnities and, together with *LRat*, accounts for each farmer's received or expected indemnities. A larger *Var* indicates that indemnities are larger but less frequent. Our models show that a larger *Var* is followed by a higher probability of purchasing insurance. Since the values of *Var* and *LRat* are of the same order of magnitude, the comparison of the coefficients of these two variables reveals that *Var* is far more important than the loss ratios (be they represented by *LRat* or by *LRat_in*).

RelSubs captures the role of subsidies with respect to insurance premium and, as expected, is highly significant and positive. As shown by Table 2, premium subsidies vary between 5% and 43% of the commercial premium for 90% of the farmers. *PLoss* represents the expected probability of obtaining an indemnity for the crops and policies that are relevant to the farmers. Its negative coefficient is somewhat unintuitive (Table 3), as one would expect farmers to be more inclined to contract insurance when the probability of obtaining an indemnity is higher. Yet what we find is just the opposite. It is not possible to test whether farmers simply refuse to grow the crop whose probability of suffering damage is higher, or if they do grow the crop but refuse to insure it. It is clear that farmers insure less if their comarca's probability of experiencing a loss for their relevant crop is higher. We suspect this is because farmers refuse to grow crops that are very vulnerable to frequent hazards, and these are perceived to be higher when the proportion of farmers in a comarca who report crop failures is higher. Another explanation is that, consistent with the effect of a larger *Var*, farmers may not feel motivated to contract crop insurance when crop failure is more frequent. In this case, indemnities must be small—because if they were large, insurance would neither be offered nor affordable.

The last variable, $RelPrem_i$, is the farmer's average ratio of the paid premium over total liability. Its negative and highly significant sign in all model runs (Table 3) indicates farmers are more likely to insure when premia are lower, because either risk or coverage is lower. Of course, $RelPrem_i$ is closely related to the price of insurance, so a higher premium would be associated with lower insurance demand. This variable stands against $RelSubs_i$, although it appears that the relative subsidies have a more powerful effect on farmers' probability of contracting insurance than $RelPrem_i$.

As a robustness check, we also ran two more probit models with a subsample of farmers that included only those who at least once during the 1993–2004 period received an indemnity (totaling 26,098 farmers in 2004). This group was again subdivided into two segments, the first with farmers whose loss ratio was greater than one ($LRat_i > 1$), and the second with loss ratios smaller than one ($LRat_i < 1$).

Table 4 reports the results, including only the six key variables and omitting the intercept and the comarca dummies. The findings do not contradict those reported for the entire data set in Table 3. Measures of goodness of fit and the models' predicting potential are slightly better. Likewise, the option to insure is better predicted (sensitivity above 88.6%) than the option not to insure (specificity above 58.6%). All coefficients are asymptotically significant ($p < 0.01$). The coefficient of the loss ratio ($LRat_i$) is negative for farmers whose loss ratio is greater than one, and positive for those with $LRat_i < 1$. These results do not support the hypothesis that adverse selection may be a strong motivation to contract crop insurance. Note also the difference in the coefficient of *PLoss* between both equations. Farmers whose loss ratio is high seem more responsive to the probability of suffering crop failures, thus less eager to contract insurance if *PLoss* is high.

Table 4. Probit Models of Insurance Demand (dependent variable = $Insur_{it}$) Differentiating $LRat > 1$ and $LRat < 1$: Subsample of 26,098 Farmers in 2004

	Only if $LRat_{it} > 0$ and $LRat_{it} > 1$		Only if $LRat_{it} > 0$ and $LRat_{it} < 1$	
Item	**Coefficient**	**Std. Dev.**	**Coefficient**	**Std. Dev.**
$LRat_{it}$	-0.044	0.021	0.215	0.048
Var_{it}	2.488	0.306	3.397	0.334
$RelSubs_i$	8.118	0.306	8.789	0.143
$PLoss_i$	-1.762	0.271	-0.152	0.143
$RelPrem_i$	-8.126	0.496	-12.080	0.366
Sensitivity Pr(+ | *D*) [a]	0.886		0.912	
Specificity Pr(− | ~*D*) [a]	0.586		0.599	
Positive Predictive Value Pr(*D* | +) [a]	0.830		0.857	
Negative Predictive Value Pr(~*D* | −) [a]	0.694		0.720	
McFadden's R^2	0.307		0.358	
No. of Observations	9,084		17,014	

Notes: Comarca dummies and intercept not reported; all coefficients are asymptotically significant at $p > 0.01$.
[a] In Pr(+ | *D*), + means classified as 1, *D* indicates true 1; in Pr(− | ~*D*), − means classified as 0, ~*D* indicates true 0.

Predicting Probabilities of Contracting Insurance

Using the 2004 probit models of *LRat* and *LRat* > 0 (columns 4 and 6 in Table 3), we estimated the probabilities of insurance uptaking for various parameterizations of the explanatory variables. The results are presented in graph format, with the probability of contracting insurance along the vertical axis, and the relevant parameter in the horizontal axis, keeping the remainder of the variables at their means unless noted. All graphs consist of two panels, with model *LRat* (fourth column in Table 3) shown in the left panel, and the model with *LRat* > 0 (sixth column) shown in the right panel.

Figure 2 shows how the indemnities' dispersion, captured by *Var*, affects the probability of purchasing insurance. Each panel plots two levels of *LRat* (in the right-hand panel they are overlapped). The models predict that with *Var* > 0.4, most farmers would decide to purchase insurance, and that variations of *LRat* barely affect the impact of *Var*.

Figure 3 displays the impact of premium subsidies, plotting one curve for each comarca. The order of the comarcas is illustrative of the interaction between different crops' risks and premium subsidies. The graphs show that farmers purchasing insurance for extensive crops are more demanding of premium subsidies than those growing fruits and vegetables. The differentiated effects of subsidies by comarcas are larger in the right-hand panel than in the left-hand panel. Focusing on the bottom comarca, *Guadalentin*, the chance that a farmer in this comarca contracts insurance is about 25% when the premium is subsidized at 20% and all farmers are considered (left panel). This probability grows to 50% for farmers who have received an indemnity ($LRat_i > 0$). This means that farmers who have never received an indemnity need on average larger subsidies to make the choice to contract insurance.

There is a direct policy implication connected with this finding. Since the probability of receiving an indemnity grows with the number of years of insurance experience, larger premium subsidies are needed to attract farmers at early stages of

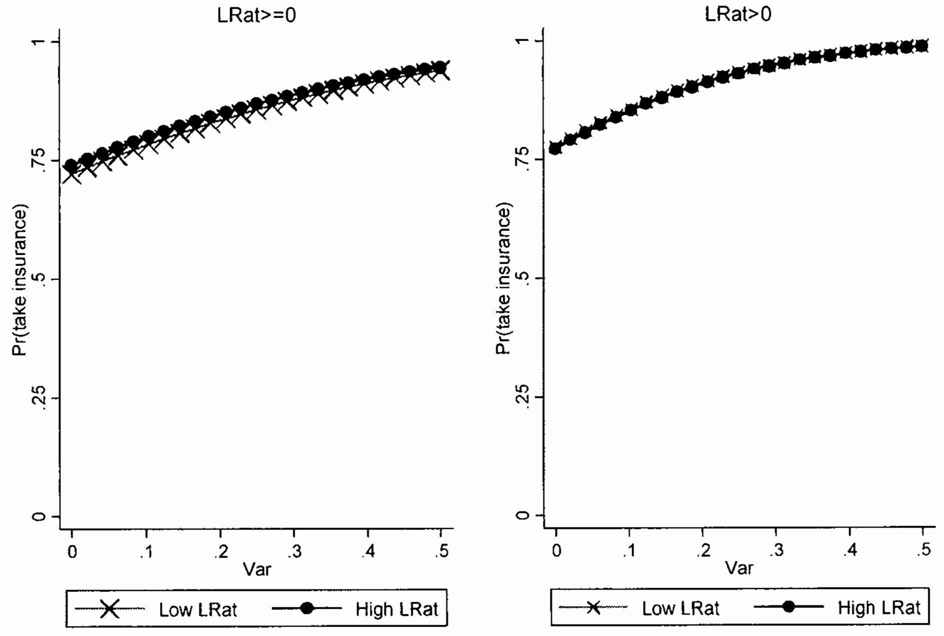

Figure 2. Probability of Contracting Insurance for Different Values of *Var* (models: *LRat* and *LRat* > 0, year 2004)

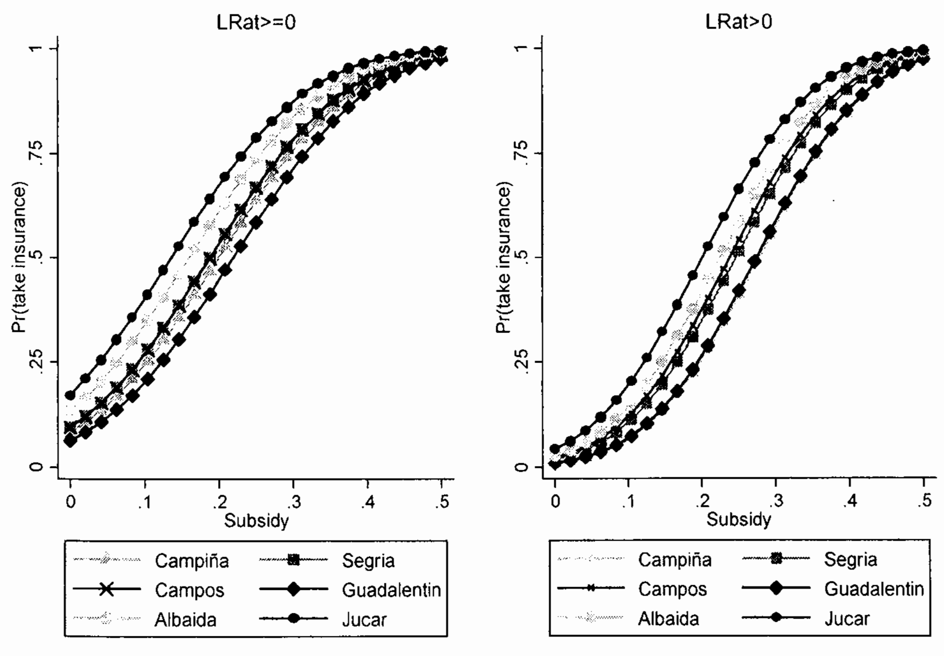

Figure 3. Probability of Contracting Insurance for Different Values of Relative Subsidies (*RelSubs*) (models: *LRat* and *LRat* > 0, year 2004)

the implementation of agricultural insurance programs. Once farmers accumulate sufficient insurance practice and experience, their subsidies might be lowered without causing significant losses in insurance participation rates.

Figures 4 and 5 plot the effects of the variables *PLoss* and *RelPrem*. The effect of *PLoss* is significant as attested by the regression results, but the rather flat slopes show that the probabilities of contracting insurance do not vary dramatically with changes of expected probability of experiencing crop failures. In general, 10% of additional probability of loss is followed by a 3% to 5% lesser probability of contracting insurance. By contrast, the relative price of premium (*RelPrem*) is more marked, as depicted by the slopes in Figure 5. Slopes, though, are steeper in the right-hand panel, which includes only farmers with *LRat* > 0. This finding implies that farmers with *LRat* = 0 (no indemnities in their records) are less sensitive to increases in the price of the premium. Their willingness to contract larger coverages or insure more risk-prone crops is slightly greater than for those who have received an indemnity at least once.

Summary and Conclusions

This paper began by introducing a simplified model to analyze the incentives for farmers to contract crop insurance. Our model assumes just one crop, yield insurance, CARA preferences, and density functions that have moment-generating functions. Comparative static results show the impact of premium subsidies, direct payments, yield profile, risk aversion, and insurance parameters on farmers' probability of purchasing insurance. Except for premium subsidies, product price volatility, and direct payments, which clearly stimulate purchasing insurance, the other parameters do not offer unambiguous results. Risk aversion is thought to be the primary motivation for contracting insurance. But insurance policies rarely provide coverage to all hazards, and are sold as contracts of adhesion, with numerous provisions, rules of conduct, duties, and obligations required for coverage. The complexity of farming decisions under uncertainty prevents obtaining clear-cut results about which parameters play unambiguous effects in favor or against contracting crop insurance. This also applies to the coefficient of risk aversion.

Using the theoretical framework as guidance, we analyzed the demand for agricultural insurance by employing a new empirical approach that takes into account farmers' actual insurance results. The complete records of all 41,660 farmers within seven Spanish comarcas and with 12 years of data allowed us to compute two measures of individual loss ratios and instability of the indemnities and other key idiosyncratic variables affecting farmers' decision to contract insurance policies. Results show that these two variables, describing the observed economic returns from insurance and its variability, together with premium subsidies, insurable risks, and other idiosyncratic factors, explain insurance participation across widely different agricultural conditions.

All models and specifications reveal that the variability of insurance returns (variance of the indemnity schemes) has more influence than loss ratios, whose level has a very small effect on farmers' insurance participation. Premium subsidies are associated with larger probabilities of insurance, but stand opposed to two other factors. In general, insurance policies involving a large premium in relation to total liability are not attractive to farmers. The model also provides clear evidence that larger expected probabilities of crop failure are not followed by more frequent insurance participation.

Based on these findings, farmers are not eager to insure against frequent events of low intensity. In general, insuring against these risks is expensive because expected losses and loss adjustment costs are higher.

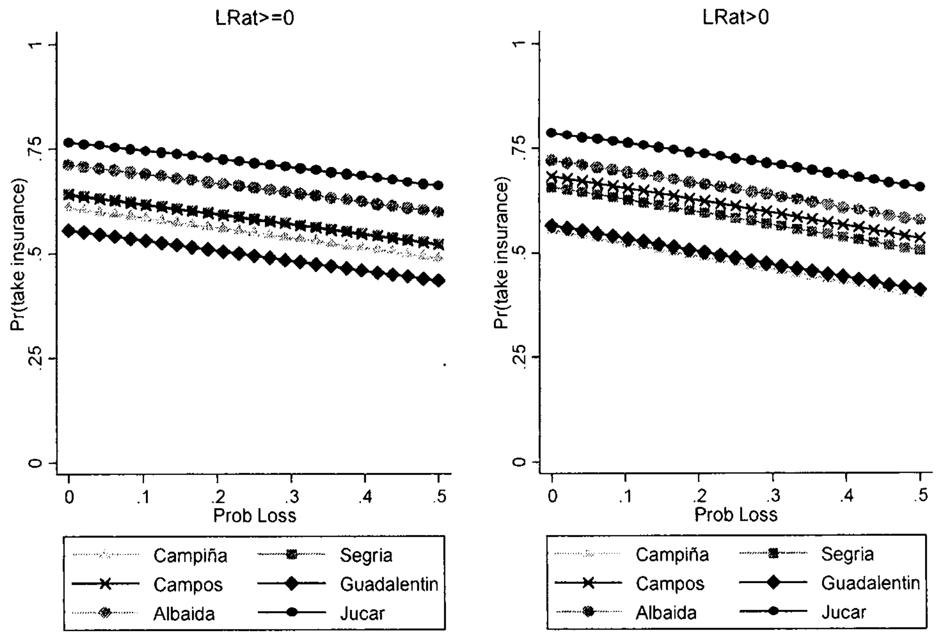

Figure 4. Probability of Contracting Insurance for Different Values of Expected Loss (*PLoss*) (models: *LRat* and *LRat* > 0, year 2004)

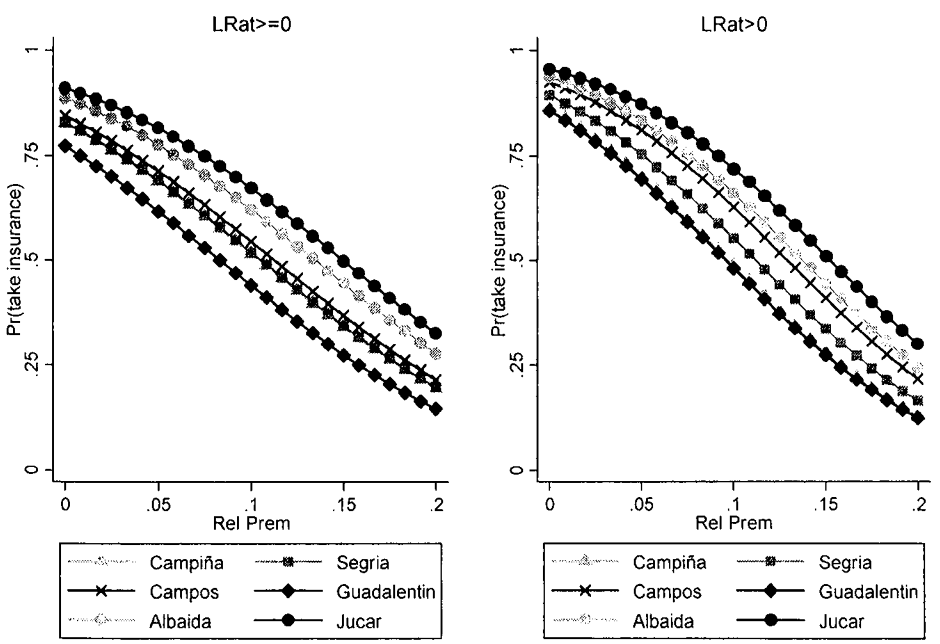

Figure 5. Probability of Contracting Insurance for Different Values of Relative Premium (*RelPrem*) (models: *LRat* and *LRat* > 0, year 2004)

This effect fits within the conceptual notion of self-revealing mechanisms which Innes (2003) claims are necessary to ensure that policies providing compensations for catastrophes and hazards are efficient.

Offering publicly provided or subsidized insurance is a self-reinforcing means to reduce ex post compensation programs, because farmers seem to avoid purchasing insurance when the sources of crop failures are frequent but unimportant. If entitlement to relief and compensation programs is conditioned on contracting crop insurance, then the government can indirectly reduce the number of beneficiaries of ad hoc relief programs by promoting crop insurance. Spain, France, and the Netherlands have already introduced this type of conditional mechanism (Garrido and Bielza, 2008).

Two further policy implications can be drawn from this study. First, adverse selection is not the primary factor explaining insurance participation among Spanish farmers. This is the first study in the literature that uses actual indemnities for a large and diverse set of farmers, with 12 years of individual insurance records. As high loss ratios are generally associated with adverse selection, the weak and ambiguous connection found in this study between insurance participation and loss ratios should question the prevailing negative view that all publicly funded insurance is vulnerable to adverse selection (Chambers, 1989; Wright, 2006).

Second, it seems that agricultural insurance needs premium subsidies to take off and expand the coverages farmers can insure against in order to increase participation rates. Our models have shown that premium subsidies are perhaps the most influential factor in tilting the balance toward the decision to purchase an insurance policy. But we also found that farmers who have experienced indemnified crop failures require smaller premium subsidies to contract crop insurance. Thus, as insurance becomes a more common practice, the probability of experiencing an indemnity grows, and correspondingly, a lowering of the level of subsidies that farmers may need to insure. The prevailing view that farm insurance cannot go beyond very basic coverages without premium subsidies is unmistakably confirmed in this study. In the long term, expecting low but nonzero probabilities of obtaining indemnities is a powerful motivation to contract crop insurance. Clearly, when expectations are realized in actual indemnities, farmers are more likely to maintain their insurance practices, even though loss ratios may be far below one.

The analyses carried out here represent a small portion of the issues that our database makes available for examination. We have completely omitted promising analyses of the farmers' choice of coverage and more crop-specific insuring strategies. Furthermore, formal tests for adverse selection could be implemented using the same database, which would perhaps change our view of contemporary agricultural insurance policies applied in the European Union.

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Appendix A: Evaluation of Fair Premium for Yield Insurance

Fair premium is evaluated as follows:

$$\begin{aligned} P_f &= p_e \int_{\underline{y}}^{y_e} (y_e - y) f(y)\, dy \\ &= p_e y_e \int_{\underline{y}}^{y_e} f(y)\, dy - p_e \int_{\underline{y}}^{y_e} y f(y)\, dy \\ &= p_e y_e \gamma_{y_e} - p_e \int_{\underline{y}}^{y_e} y f(y)\, dy, \end{aligned}$$

where γ_{y_e} is the probability of yield being below the threshold ($y < y_e$). If $f(y)$ follows a gamma distribution with parameters (λ, α), then:

$$\begin{aligned} P_f &= R_e \gamma_{y_e} - p_e \int_{\underline{y}}^{y_e} \frac{\lambda^\alpha}{\Gamma(\alpha)} y^\alpha e^{-\lambda y}\, dy \\ &= R_e \gamma_{y_e} - p_e \frac{\lambda^\alpha}{\Gamma(\alpha)} \Big[-y^{\alpha+1} E_{-\alpha}(\lambda y) \Big]_{\underline{y}}^{y_e}, \end{aligned}$$

where $E_{-\alpha}(\lambda y)$ is an exponential integral function. Since $E_n(z) = z^{n-1}\Gamma(1 - n, z)$, then:

$$\begin{aligned} P_f &= R_e \gamma_{y_e} - p_e \frac{\lambda^\alpha}{\Gamma(\alpha)} \\ &\quad \times \Big[-y^{\alpha+1} (\lambda y)^{-\alpha-1} \Gamma(1+\alpha, \lambda y) \Big]_{\underline{y}}^{y_e}, \end{aligned}$$

$$P_f = R_e\gamma_{y_e} - p_e \frac{\lambda^{\alpha}}{\Gamma(\alpha)}$$

$$\times\left\{\left[-y_e^{\alpha+1}(\lambda y_e)^{-\alpha-1}\Gamma(1+\alpha, \lambda y_e)\right] - \left[-\underline{y}^{\alpha+1}(\lambda \underline{y})^{-\alpha-1}\Gamma(1+\alpha, \lambda \underline{y})\right]\right\},$$

$$P_f = R_e\gamma_{y_e} + \frac{p_e}{\lambda}\left[\frac{\Gamma(1+\alpha, \lambda y_e) - \Gamma(1+\alpha, \lambda \underline{y})}{\Gamma(\alpha)}\right],$$

where $\Gamma(1+\alpha, \lambda y_e) - \Gamma(1+\alpha, \lambda \underline{y}) < 0$.

Appendix B: Conditions for Insurance Being Utility-Augmenting

We start by defining $EU(\pi_I)$, and then establish the conditions for $EU(\pi_I) - EU(\pi) > 0$:

(A1) $\mathrm{EU}(\pi_I) =$

$$\int_{\underline{y}}^{y_e}\left(1 - e^{-r[p_e(y_e-y)-P_n-c+s]}\right)f(y)\,dy + \int_{\underline{yp}}^{\overline{py}}\left(1 - e^{-r[R-P_n-c+s]}\right)h(R)\,dR$$

$$= \gamma_{y_e} - e^{-r(R_e+\beta)}LIMGF_y(rp_e;\, y_e) + 1 - e^{-r\beta}MGF_R(-r),$$

where γ_{y_e} is the probability of $y < y_e$; $\beta = -P_n - c + s$; and $R_e = p_e y_e$. With $LIMGF_y(rp_e;\, y_e)$ we denote a portion of a complete moment-generating function of variable y of order rp_e, defined only on the limited interval $[\underline{y}, y_e]$, specified as follows:

(A2) $$LIMGF_{y_e}(rp_e;\, y_e) = \int_{\underline{y}}^{y_e} e^{ryp_e} f(y)\,dy.$$

The second part of $EU(\pi_I)$ uses the same notation, where $MGF_R(-r)$ denotes a standard moment-generating function:

(A3) $$MGF_R(-r) = \int_{\underline{yp}}^{\overline{py}} e^{-rR}h(R)\,dR.$$

The EU under the case of no insurance is defined as:

(A4) $$EU(\pi) = \int_{\underline{yp}}^{\overline{py}}\left(1 - e^{-r[R-c+s]}\right)h(R)\,dR = 1 - e^{-r\beta'}MGF_R(-r),$$

with $\beta' = -c + s$.

Therefore, $EU(\pi_I) - EU(\pi) > 0$ holds if and only if:

(A5) $$\gamma_{y_e} - e^{-r(R_e+\beta)}LIMGF_y(rp_e;\, y_e) + e^{-r\beta'}MGF_R(-r)(1 - e^{rP_n}) > 0.$$

Appendix C: Conditions for Insurance Being Utility-Augmenting with Gamma PDFs for Revenue and Yield

If $\tilde{y}$ and $\tilde{R}$ follow gamma distributions with parameters (λ_R, α_R) and (λ_y, α_y), then:

$$LIMGF_y(rp_e;\, y_e) = \int_0^{y_e} \frac{\lambda_y^{\alpha_y} e^{ryp_e} y^{\alpha_y-1} e^{-y\lambda_y}}{\Gamma(\alpha_y)}\,dy$$

$$= \frac{\lambda_y^{\alpha_y}}{\Gamma(\alpha_y)}\int_0^{y_e} e^{y(rp_e-\lambda_y)} y^{\alpha_y-1}\,dy$$

$$= \frac{\lambda_y^{\alpha_y}}{\Gamma(\alpha_y)}\left[-y^{\alpha_y}[-y(rp_e-\lambda_y)]^{-\alpha_y} \times \Gamma\left(\alpha_y, (\lambda_y - rp_e)y\right)\right]_0^{y_e}$$

$$= \frac{\lambda_y^{\alpha_y}}{\Gamma(\alpha_y)}\left[-[(\lambda_y - rp_e)]^{-\alpha_y} \times \Gamma\left(\alpha_y, (\lambda_y - rp_e)y_e\right) - \Gamma(\alpha_y, 0)\right],$$

where function $\Gamma(\alpha_y, y_e(\lambda_y - rp_e))$ is an incomplete gamma function [with property $\Gamma(\alpha_y, 0) = \Gamma(\alpha_y)$]. Further algebra leads to:

$$LIMGF_y(rp_e;\, y_e) = MGF_y(rp_e)\left[-\frac{\Gamma\left(\alpha_y, (\lambda_y - rp_e)y_e\right)}{\Gamma(\alpha_y)} + 1\right] = MGF_y(rp_e)\left[P\left(\alpha_y, (\lambda_y - rp_e)y_e\right)\right],$$

where $P(\cdot)$ is a regularized gamma function, and takes values $P(\alpha_y, 0) = 0$ and $P(\alpha_y, \infty) = 1$. With the above results, (A5) can be expressed as:

(A6) $$\gamma_{y_e} > e^{-r\beta'}\Big\{e^{r(P_n-R_e)}MGF_y(rp_e;\, y_e) \times P\big(\alpha_y,\, (\lambda_y - rp_e)y_e\big) + MGF_R(-r)(e^{rP_n} - 1)\Big\}.$$

Reordering terms and taking logarithms gives:

(A7) $$\gamma_{y_e} e^{-r(P_n-\beta')} > e^{-rR_e}MGF_y(rp_e;\, y_e) \times P\big(\alpha_y,\, (\lambda_y - rp_e)y_e\big) + MGF_R(-r)(1 - e^{-rP_n}),$$

(A8) $$-r(P_n - \beta') > \log\left[\frac{e^{-rR_e}MGF_y(rp_e;\, y_e) \times P\big(\alpha_y,\, (\lambda_y - rp_e)y_e\big) + MGF_R(-r)(1 - e^{-rP_n})}{\gamma_{y_e}}\right].$$

If $c > s$, then $\beta' < 0$, the left-hand side of (A8) is always negative. Therefore, a necessary but not sufficient condition for $EU(\pi_i) - EU(\pi) > 0$ is that the term within the log of the right-hand side be less than 1, so:

(A9) $$\gamma_{y_e} > e^{-rR_e}MGF_y(rp_e;\, y_e) \times P\big(\alpha_y,\, (\lambda_y - rp_e)y_e\big) + MGF_R(-r)(1 - e^{-rP_n}).$$

Further algebra allows us to obtain the sought necessary condition:

(A10) $$EU(R - P_n) + EU(Im) > EU(R),$$

where Im is indemnity ($Im = p_e(y_e - y)$).

Appendix D: Comparative Statics of Increases of Yield and Price Parameters Insurance

Beginning in text equation (9), we take a partial derivative of P^* with respect to p_e, keeping R_e constant:

(A11) $$\left.\frac{\partial P^*}{\partial p_e}\right|_{R_e=\bar{R}} = \frac{-\big(MGF_R(-r) + \gamma_{y_e}e^{r\beta'}\big) \times \left(e^{-rR_e}\frac{\partial LIMGF_y(rp_e;\, y_e)}{\partial p_e}\right)}{r\big[LIMGF_y(rp_e;\, y_e)e^{-rR_e} + MGF_R(-r)\big]}.$$

So the sign of (A11) is negative if $LIMGF_{y_e}(rp_e;\, y_e)$ grows with p_e, which in fact it does after valuating the function numerically. Both $LIMGF_{y_e}(rp_e;\, y_e)$ and $MGF_R(-r)$ are always positive. This proves text equation (12).

Text result (13) is more cumbersome to prove because y_e shows up in $LIMGF_{y_e}(rp_e;\, y_e)$ and in γ_{y_e}. Taking partial derivatives of P^* with respect to p_e, and keeping R_e constant, we have:

(A12) $$\left.\frac{\partial P^*}{\partial y_e}\right|_{R_e=\bar{R}} = \frac{\left\{\frac{\partial \gamma_{y_e}}{\partial y_e}e^{r\beta'} + \frac{\partial LIMGF_y(rp_e;\, y_e)}{\partial y_e} \times \left[(-e^{-rp_e} - 1)MGF_R(-r) - \gamma_{y_e}e^{r\beta'}\right]\right\}}{r\big[LIMGF_y(rp_e;\, y_e)e^{-rR_e} + MGF_R(-r)\big]},$$

which is positive if

$$\frac{\partial LIMGF_y(rp_e;\, y_e)}{\partial y_e} < 0,$$

which in fact it is, because

$$LIMGF_y(rp_e;\, y_e) = MGF_y(rp_e)\big[P\big(\alpha_y,\, (\lambda_y - rp_e)y_e\big)\big],$$

and

$$\frac{\partial P(\cdot)}{\partial y_e} < 0;$$

$P(\cdot)$ is the regularized gamma function.

Hedging with Weather Derivatives to Cope with Climate Variability and Change in Grain Maize Production

Daniele Simone Torriani, Pierluigi Calanca, Martin Beniston, and Jürg Fuhrer

Abstract

The effectiveness of hedging drought risks with weather derivatives was investigated for rain-fed grain maize production in Switzerland under current (1981–2003) and projected future (2070–2100) climatic conditions. Depending on location, hedging reduced the value-at-risk (VaR) measure to a variable degree, although with a considerable basis risk, but hedging may provide a valid risk transfer since loading of 90% to 240% of the fair premium can be paid to obtain a hedged situation with improved outcomes relative to the reference. However, the fair premium of a specific contract may vary by a factor of two to four over the 70-year period considered, which represents a substantial uncertainty for both the farmer and the institution writing the contract.

Key words: climate risks, climatic change, drought, hedging, maize production, weather derivatives

Current climatic conditions in central Europe are favorable to crop production. Yet, projections of future climate (Fuhrer et al., 2006; Beniston and Diaz, 2004) characterized by changes in the hydrology of alpine basins (Jasper et al., 2004) and more frequent droughts (Calanca, 2007), together with the continuing rise of human water demand (Shiklomanov, 2000), emphasize the need to minimize agricultural water use as part of optimal resource allocation [Food and Agriculture Organization (FAO), 2002], and to improve risk management to cope with increasing weather risks. Recent severe weather events, such as during the summer of 2003 (Schär et al., 2004) with estimated losses in the agricultural sector of around 12 billion US$ in Europe (SwissRe, 2004) and 500 million Swiss Francs (CHF) in Switzerland alone (Keller and Fuhrer, 2004), clearly demonstrate the importance of extremes in climate.

Risk management involving hedging with relatively new financial instruments, the so-called weather derivatives (Hull, 2002; Jewson and Brix, 2005; Zeng, 2000), could be envisaged in Europe. Conceptually, any weather variable can be indexed (Agarwal, 2002). Contracts based on precipitation have been described in the literature (Agarwal, 2002; Martin, Barnett, and Coble, 2001; Skees et al., 2001; Vedenov and Barnett, 2004), but more frequently temperature-based indices have been used (van Asseldonk, 2003; Leggio and Lien, 2002; Oetomo and Stevenson, 2005; Richards, Manfredo, and Sanders, 2004; Taylor and Buizza, 2004, 2006; Turvey, Weersink, and Chiang, 2006; Zeng, 2000).

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The aim of this exploratory study for grain maize (*Zea mays* L.) production in Switzerland was to evaluate the effectiveness of weather derivatives in hedging against risks associated with increasing precipitation shortage. Our approach was to compare a reference situation of conventional rain-fed cultivation, which reflects the current Swiss standard, with the alternative scenario represented by rain-fed management backed up by weather derivatives. The comparison was applied to the current climatic situation (1981–2003) and, for the first time, to future conditions using a scenario for climate by 2070–2100.

The climate change (CC) scenario was extrapolated from results of a regional climate model (HIRHAM4) based on the IPCC A2 emission scenario (Nakicenovic and Swart, 2000). The efficiency of the two strategies was compared with a concept similar to the value-at-risk metric (Artzner et al., 1999) broadly used among finance practitioners. Based on a simple concept, it offers the opportunity to summarize the risk of a portfolio to just one number.

From a statistical point of view, this approach is a quantile analysis of the distribution of profits simulated with a Monte Carlo (MC) chain translating the weather variables into stochastic distributions for maize yield and associated economic returns. This allows handling the mean-variance framework for risk analysis in the situation where production costs are correlated with crop yields, and the distribution of both the variables and the profits are skewed, not Gaussian, and censored at critical thresholds. For this study, specific locations in Switzerland were selected, but to broaden the scope a sensitivity analysis was performed by varying mean and variability of the initial probability space for seasonal precipitation sum.

The limitation in the availability of yield or weather time series often constrains the application of regression fitting to calculate the loss function, and correlations between yield and weather variables may be too weak (even if significant) for hedging purposes. As an alternative, in this study we adopted a novel approach. The loss function was determined using a stochastic yield model with a minimum set of parameters required (Torriani et al., 2007a).

Methods and Data

Production Costs

Costs for maize production were estimated with the methodology described by Lips and Ammann (2006) with census data for representative Swiss farms covering the years 1975 through 2004 (FAT, 2002) (Table 1). Variable costs associated with machinery and cleaning/drying dominate over fixed costs generated by interest/rent or administration. A fixed grain price of 450 CHF t^{-1} was used since reference prices vary each year based on projected production, expected quality of crop, and decisions concerning custom taxes and import policy. However, over the past five years, the price varied only by +/–5% (SwissGranum, available online at http://swissgranum.ch).

Profits

A Monte Carlo chain was used to develop profits with or without hedging. A sample of $n = 300 \times 10^3$ was drawn from the gamma probability density function (PDF) of seasonal rainfall. This function was chosen on the basis of results of statistical tests comparing different forms of the function. The large sample size was necessary to achieve a precision (i.e., minimum variability) of 0.01 t ha^{-1} (Torriani et al., 2007a). The distribution of profit B (CHF ha^{-1}) for grain maize production without hedging was calculated as:

(1) $B = Yp_m - c(Y)$,

with grain yield Y (t ha^{-1}) sold at a price p_m (CHF t^{-1}), and the cost function $c(\cdot)$ (CHF ha^{-1}) as the first-degree polynomial

Table 1. Summary of Costs and Revenues (in CHF) for Different Yield Levels

	Level of Grain Yield (t ha^{-1})				
Description	**7.5**	**8.5**	**9.5**	**10.5**	**11.5**
Costs ha^{-1}:					
Seeds	272	272	272	272	272
Fertilizer	249	249	249	249	249
Plant Protection	217	217	217	217	217
Cleaning & Drying	805	912	1,019	1,127	1,234
Hail Insurance	61	69	77	85	93
Other Direct Costs	7	7	7	7	7
Labor Costs	764	764	764	764	764
Machinery Costs	1,345	1,359	1,368	1,368	1,368
Land Value	718	718	718	718	718
Interest Rate Costs	38	40	43	46	49
Other Indirect Costs	728	728	728	728	728
Income:					
Grain Price t^{-1}	450	450	450	450	450
Producer Benefits	3,375	3,825	4,275	4,725	5,175
Other Benefits	41	41	41	41	41
Direct Payments	1,600	1,600	1,600	1,600	1,600
Profit ha^{-1}	−187	130	453	785	1,116

Data Source: Lips and Ammann (2006), Agroscope ART Taenikon, Switzerland.

($21.15Y + 3{,}471$, $R^2 = 0.94$, RMSE = 7.84 CHF ha^{-1}) providing costs depending on the yield level (see Table 1). Profit with hedging B_{wd} (CHF ha^{-1}) was calculated from profit for conventional production (B) and considering a number of weather derivatives h (contracts ha^{-1}) with a premium of c_{wd} (CHF contract^{-1}) and a payoff P (CHF contract^{-1}). The producer would pay a constant amount hc_{wd} to the writer for an indemnity of hP. Analytically, this can be expressed as:

(2) $B_{wd} = B - hc_{wd} + hP.$

Here, the contract was tailored to one hectare, and thus $h = 1$.

The effectiveness of hedging was evaluated on the basis of a quantile-based risk measure of the profit distribution (Hull, 2002), i.e., the value-at-risk (VaR) measure, as an alternative to the abstract risk preference and utility functions (i.e., Martin, Barnett, and Coble, 2001). The notation θ-VaR was used, where θ is the confidence level for the corresponding α-quantile; thus, $\theta = (1 - \alpha)$. Accordingly, the 95-VaR refers to a probability of PR{$B \leq$ 95-VaR} = 5%. Although 95-VaR is commonly used, it may be too precise given a typical 10% error in measuring harvested yield. Consequently, in the present analysis, we also considered the 90-VaR. A second parameter defining VaR is the duration in days over which the risk is evaluated. Maize harvest occurs once a year, and therefore only year-to-year variations were considered. Thus a single year was the smallest discrete step of our analysis.

Results of the monetary balance were placed in mean-variance plots for a sensitivity analysis performed by changing (*a*) mean rainfall from zero to 600 mm, and (*b*) the second moment of the distribution from zero to 250 mm. Production costs, yield levels, and profits were adjusted for each condition.

Pricing

The premium was calculated as the unconditional expectation (E) of payoff and discounted at the risk-free rate ($d = e^{-rt}$), with an interest rate r_t usually taken as equal to the risk-free interest rate (Hull, 2002). The payoff distribution was simulated with Monte Carlo methods from the rainfall distribution, as described in Torriani et al. (2007a). Pricing a weather option is a typical case of incomplete market where the classical Black-Scholes-Merton approach cannot be replicated (Black and Scholes, 1973; Merton, 1973). Hence, in this case, the statistical measure of risk was taken.

Direct comparison is conventionally done after converting the future value into the net present value by discounting at $d = e^{-rt}$. The option is purchased at date t_1 and cashed at maturity date $t_2 > t_1$, separated by t (years). The rainfall index x is defined as the integration of the daily precipitation (mm) [see equation (13)]. The put payoff function $p(\cdot)$ pays an amount D (CHF mm^{-1}) for each mm of cumulated rainfall below a strike K (mm), following Jewson and Brix (2005):

(3) $p(x; D, K) = \max\big(0, D(K - x)\big).$

As an example, if $K = 200$ mm, $D = 100$ mm, then for an index value of $x = 150$ mm at the end of the accumulation period (at maturity) the put will pay $5{,}000 d_t$, or 4,925 CHF for $r = 0.02$ and $T = 0.75$. The option value v then becomes:

(4) $v(x, t; D, K, r_t) = e^{-rt} E\big[p(x; D, K)\big].$

One contract costs v (CHF contract^{-1}), and in the long term a farmer can expect (in a probabilistic context) to receive back the same amount discounted at d_t. The risk-free rate is approximated at 2% from the historic LIBOR rate for the nine-month maturity duration over the years 1997–2005 (LIBOR, 2006). As noted previously, grain prices can be assumed constant and price volatility equal to zero (and covariance between grain prices and indemnities), thus not affecting the pricing procedure (Davis, 2001). We assumed no transaction costs outside the interest rates on capital.

Structured Product

The payoff function of the standard put is linear, but sometimes it is more interesting to obtain nonlinear payoffs that better fit the hedging purposes and reduce the basis risk (Berg and Schmitz, 2007). The goal is to create a synthetic put with a concave payoff function mirroring the loss function $l(x)$ [see equation (9)]. Here we considered a structure of standard puts with equal tick size and equally spaced strikes. The latter assumption aims at imitating existing markets since the advantage is to rationalize the process of writing standard instruments that can be used for multiple purposes among industrial sectors, thereby possibly attracting more liquidity in the weather market. But this assumption is not primordial since trading strategies seeking to replicate synthetic options are possible. The structured product payoff function s is then:

(5) $s(x, m, w; D, K) = \sum_{i=1}^{m} w_i p(x; D, K_i).$

For a general case where w_i is the weight of the put options to be purchased at each strike K_i and separated by an offset O (mm), for m components of the structures, the parameters are found with:

(6) $m = 1 + floor\left(\dfrac{K_m - K_{i=1}}{O}\right).$

Details on the "floor" function can be found in the Matlab documentation at (http://www.mathworks.com/access/helpdesk/help/techdoc/matlab.shtml). The quantity of options that need to be purchased at each strike is equal to the slope $l(x)$ minus the quantity purchased until then for higher strikes, with the initial condition of $K_m = 1$. Hence, we solved iteratively beginning from the second topmost strike:

(7) $w_i = \dfrac{d}{dx} l(K_i) - \sum_{j=i-1}^{m} s_j.$

A final assumption was that w_1, i.e., the weight for the put with the smaller strike, is equal to the difference between the sum of all quantities purchased until then and the slope at the intercept:

$$(8)\quad w_i = \frac{d}{dx} l(O) - \sum_{j=2}^{m} s_j .$$

Loss Function

Ideally, the loss function representing a relationship between yield and the underlying variable should be parameterized for each location and corresponding climatology. Here we used a single function parameterized with the results of the stochastic model sensitivity analysis obtained by changing the shape of the rainfall distribution α (–) and the scale parameter β (mm) with their moment estimators according to Torriani et al. (2007b). The explicit form of the loss function was similar to that of the water stress model in Torriani et al. (2007a). It allows an easy differentiation necessary to calculate the weights of the structured product in equations (7) and (8):

$$(9)\quad l(x, ET_{pot}; k) = \tanh\left(k \frac{x}{ET_{pot}(x)} \right).$$

Potential evapotranspiration (ET_{pot}) was used as a function of rainfall (Calanca, 2004; Torriani et al., 2007a), and k (CHF) as a specific fitting parameter.

Yield Model

The stochastic model to determine the yield probability density functions and the loss function was constructed following the work of Monteith (1977). Yield (Y) is described as the product of radiation use efficiency ε_{pot}, which is a crop-specific parameter, global radiation I (W m^{-2}), and a series of limiting factors η_i:

$$(10)\quad Y = \varepsilon_{pot} I \prod_i \eta_i .$$

The normalized limiting factors η_i considered here are water stress η_w (–) and vapor pressure deficit (VPD) limitation η_t (–), the latter representing the indirect effect of temperature on yield (Torriani et al., 2007a). A deterministic crop growth model, CropSyst (Stöckle, Donatelli, and Nelson, 2003), as described in Torriani et al. (2007a), was used to determine the relationships of the stochastic yield model. Mean VPD was extended between 0 and 25 hPa to reflect drier and wetter atmospheric conditions. Rainfall was reduced over a range of 0 to –60%. Simulations were performed for a single soil type with 38% clay, 36% silt, 26% sand, and 2.6% soil organic matter, characterized by a good water-retention capacity.

The increase in CO_2 concentration positively affects productivity through effects on canopy resistance to water vapor transfer and carbon assimilation (cf. Fuhrer, 2003), but the magnitude of the CO_2 stimulation of yield is debated, especially for C4 crops like maize (Tubiello, Soussana, and Howden, 2007). Therefore, the VaR analysis was performed without considering increased CO_2 in the climate change (CC) scenario.

Meteorological Data

The baseline for 1981–2003 consisted of the observed meteorological data provided by the Swiss Federal Office of Meteorology and Climate (MeteoSwiss). The weather stations at Magadino (MAG: 46° 10′ N, 8° 53′ E, 197 m above sea level), Schaffhausen (SHA: 47° 41′ N, 8° 37′ E, 437 m), and Waedenswil (WAE: 47° 13′ N, 8° 41′ E, 463 m) were used to represent lower altitudes, with MAG also representing the region south of the Alps.

The effectiveness of a hedging strategy may be limited by the uncertainty associated with spatial heterogeneity of rainfall, referred to as the basis risk. If a site is located distant from the weather station where the reference index was measured, the amount of rainfall may differ substantially from the reference quantity, and the correlation between loss and reference index may decline. We used a simple quantification of the spatial heterogeneity for rainfall by comparing the correlation coefficient for the payoff of the structured product between a reference station (Zurich) and different nearby weather stations to determine the change in correlation as a function of distance from the reference station.

The locations of Beznau (BEZ: 47°34′ N, 8°14′ E, 327 m), Kloten (KLO: 47°29′ N, 8°32′ E, 436 m), Leibstadt (LEI: 47°36′ N, 8°11′ E, 341 m), and Reckenholz (REH: 47°26′ N, 8°31′ E, 443 m), situated along a north-south axis, were chosen for this evaluation of the spatial heterogeneity of rainfall. Application of the hedging strategy was carried out for WAE, MAG, and SHA located in direct proximity to the meteorological station.

Climate Change Scenario

The stochastic modeling framework was based on the rainfall index x as the independent variable, with radiation and air vapor pressure deficit (*VPD*) as the dependent variables. Linear covariance between weather variables was assumed, and a stochastic error was added as a normal term $N(0, \sigma^2)$ with zero mean and a suitable standard deviation σ_I and σ_{VPD} for radiation and VPD, respectively, reflecting the observed spread of the indices:

(11) $\langle I \rangle \approx D_I(\langle x \rangle) + N(0, \sigma_I^2)$,

(12) $\langle VPD \rangle \approx D_{VPD}(\langle x \rangle) + N(0, \sigma_{VPD}^2)$.

Here, $D(\cdot)$ is the deterministic linear term for the corresponding variable. The parameterization of the climatic model required records of precipitation (mm), mean temperature (°C), *VPD* (hPa), and global radiation (W m^{-2}) corrected for data inconsistency, but without performing homogenization (Allen et al., 1998).

The rainfall index x is defined as the integration of the daily precipitation P (mm) over the accumulation period including the first (t_1) to the last ($t_2 > t_1$) day considered:

(13) $\langle x \rangle = \sum_{i=t_1}^{t_2} P_i$.

The operator $\langle ... \rangle$ means that integration over the accumulation period was used for rainfall, and averaging was used for the other variables. The chronological limits t_1 and t_2 were kept constant each year, although in reality they should reflect crop phenology as a function of thermal time (growing degree-days, °C-days). Phenological dates were determined through simulations with CropSyst (see above). The t_1 limit was set at 400 °C-days after the sowing date [10 May, or the day of the year (DOY) 130], i.e., shortly before the beginning of the flowering phase and nearest to the start or end of a month to obtain a full month's accumulation. The t_2 limit corresponds to the completion of maturity at 1,250 °C-days, which is a crop-specific parameter and was previously calibrated with observations. The time of maturity varies from year to year by up to 1–2 months depending on region and variety, but here we employed a mean DOY of 273.

The positive temperature trend in the CC situation was considered by inducing a shift by –30 days in the sowing date (Torriani et al., 2007a, b). Specifically, the moment estimator used to adapt the rainfall gamma PDF for CC conditions accounted for this shift in growing season, but parameters for both the deterministic and stochastic terms were not updated in spite of a possible change in the relationships between weather variables.

The CC scenario referred to the years 2071–2093. It was derived from the observed baseline (1981–2003) by shifting the observations as described in Torriani et al. (2007b) and included changes in the inter-annual variability along with shifts in mean monthly values. CC anomalies were extrapolated from the regional model HIRHAM4 (Christensen et al., 1998). Initial and boundary conditions for running the regional model were extracted from the atmospheric circulation model HadAM3H (Pope et al., 2000) and were driven with the output of the ocean-atmosphere coupled global climate model HadCM3 (Johns et al., 2003). The A2 emission scenario (Nakicenovic and Swart,

2000) was considered as representing an upper limit for emission projections.

Results

The hedging contract covers a precipitation range useful to ensure the production from zero up to a mean yield level in Switzerland of about 10 t ha^{-1}. Grain yield reaches a maximum value at around 400 mm and then starts to decline due to limiting radiation and temperature associated with unfavorable wet conditions (Figure 1). This resulted in a maximum liability and thus a maximum payoff of the structured product of 4,630 CHF $contract^{-1}$.

The parameterization of the loss function was performed by fitting (13) to data from the Monte Carlo model with the least squares method (a = 4,833 CHF $contract^{-1}$, c = 0.004851 mm^{-1}, R^2 = 0.98, RMSE = 225 CHF). The optimum weight ω_i for each option necessary to build the structured product was obtained iteratively by solving equation (7) and was used to fit the inverse image of the loss function (Figure 2). It resulted in a total of 23 options between 100 and 400 mm, with the weight for the option at strike 350 mm equal to zero—i.e., this strike is not required (Table 2).

The basis risk associated with the spatial heterogeneity of rainfall was evaluated in terms of differences in seasonal rainfall and differences in the payoff between the reference site and the target locations (Figure 3). The correlation for rainfall showed a proportional decay that remained above an R^2 of 0.7 (with $p < 0.05$ in all cases) for distances of up to 40 km. The R^2 for the payoff was slightly lower, yet above 0.6 for a distance up to 15 km (data not shown), and the basis risk in absolute terms remained below 500 CHF $contract^{-1}$ for distances up to 15 km, with a mean of 200 CHF $contract^{-1}$, but the maximum difference could reach 1,400 CHF $contract^{-1}$ for distances exceeding 15 km. These results need to be analyzed further by considering possible spatial anisotropies, and with an improved spatial interpolation procedure.

The results of the sensitivity analysis are shown in Figure 4 where the standard deviation (sd) of precipitation is related to the mean (m), with isolines indicating the premium for each combination of sd(⟨x⟩) and m(⟨x⟩). The isolines indicate the increase in premium with decreasing m(⟨x⟩) and/or increasing sd(⟨x⟩). The location of the data indicates that the fair premium increased from the baseline climate to CC conditions from 210 to 620 CHF ha^{-1} for MAG and from 160 to 783 CHF ha^{-1} for SHA. At WAE, the fair premium was nearly zero due to the mean rainfall level above the upper put strike, i.e., the weather derivative is usually "out-of-the-money."

A similar analysis was performed for 95-VaR (Figure 5). The comparison between the situations with or without hedging showed that hedging was effective in reducing the 95-VaR gradient along the rainfall variability axis, which may be expected from this type of instrument. MAG, located south of the Alps, and SHA, north of the Alps, are both characterized by climates which favor water stress conditions in maize (Torriani et al., 2007a), and thus the system is sensitive to rainfall variability.

The difference in 95-VaR and 90-VaR with or without hedging was compared for two sites using the baseline climate and CC scenarios. The 95-VaR would be the same for one year over 20. The 90-VaR was included as an option due to the fact that yield losses usually cannot be estimated with less than an error of 10% (Aldrich, Scott, and Leng, 1982), although it can be questioned that the 90-VaR can be interpreted as the amount of money a farmer can lose one year out of 10. Under CC conditions, the conventional 95-VaR dropped by 130% at MAG and by 160% at SHA relative to the situation with hedging (Table 3).

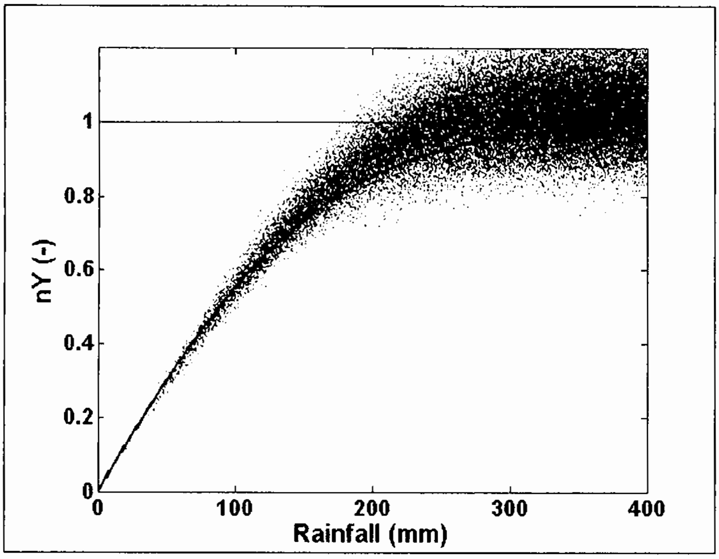
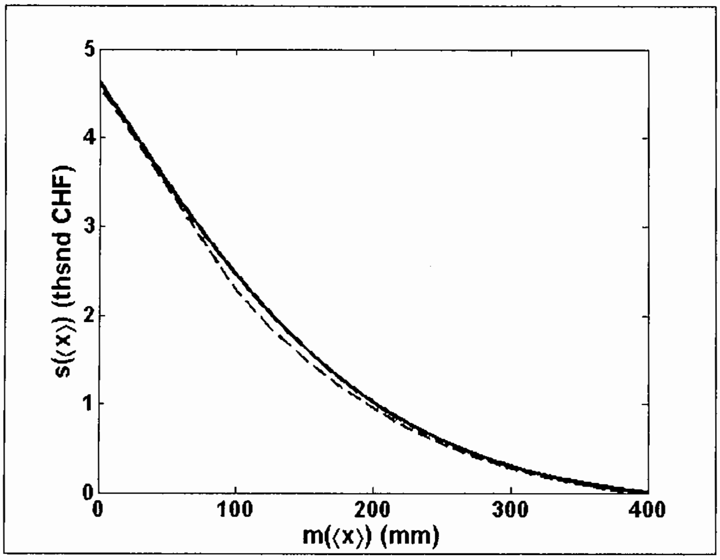


Figure 1. Normalized Loss Function [full curve] and Results of the Stochastic Yield Model for the Sensitivity Analysis

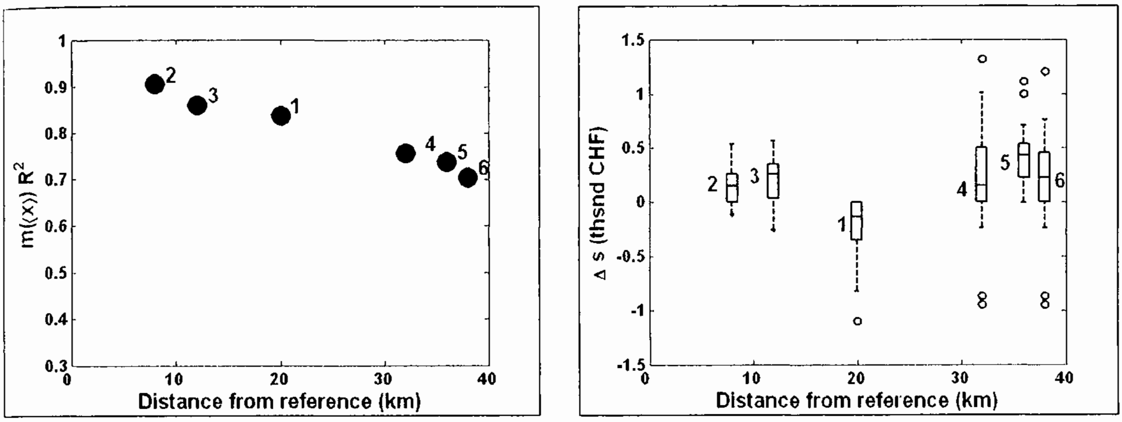


Note: m(⟨x⟩) = mean rainfall.

Figure 2. Inverse Image of the Loss Function [solid line] and the Payoff for the Structured Product, *s*(⟨x⟩) [dashed line]

Table 2. Weights of Each Put Structuring the Product

	Strike Level (mm)												
	100	125	150	175	200	225	250	275	300	325	350	375	400
w_i	6	2	2	2	2	2	1	1	1	1	0	2	1

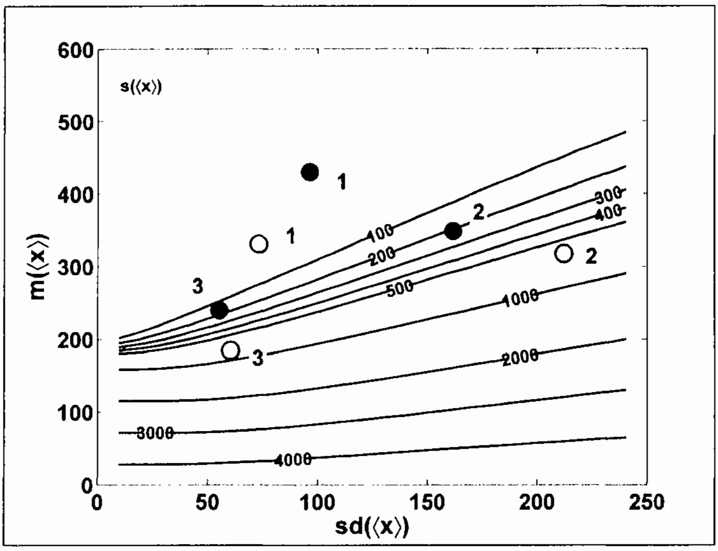


Notes: 1 = WAE, 2 = REH, 3 = KLO, 4 = BEZ, 5 = SHA, and 6 = LEI. In box plots, whiskers extend to 1.5 × the quartile range, the box represents the upper/lower quartile and median, circles represent outliers.

Figure 3. Change in R^2 for Rainfall [left] and Absolute Difference in Payoffs *s* (reference station) [right] as a Function of Distance from the Reference Station (Zurich, SMA) for 1981–2003

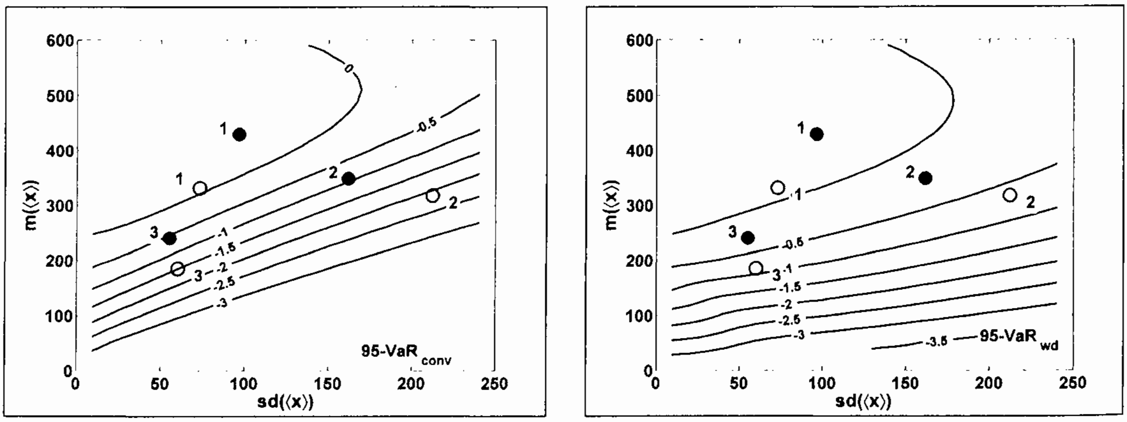
For both locations, the results show that hedging remained effective even if the premiums under CC conditions increased. In contrast, at WAE, hedging was not effective since there was negligible yield reduction due to water stress (about 5%; Torriani et al., 2007a) and due to little rainfall variability in both the baseline and CC scenarios (data not shown). For soils with a lower water retention capacity than assumed here, the risk for water stress would be higher, therefore possibly justifying hedging. Nevertheless, the pricing of the structured product may be difficult. A further limitation of weather options for the WAE location is a premium, which is lower than 10 CHF contract^{-1} due to its "out-of-the-money" situation (when the seasonal rainfall is less than 430 mm) (see Figure 4).

The difference between conventional and hedged VaR can be used to determine by how much a premium can be increased above the fair premium before reaching the risk level of the conventional management, thereby possibly providing a simple quantification of how much a farmer would be willing to pay for hedging and, conversely, how much a financial institution may charge to cover its investments. At MAG, the fair premium can be loaded up to 240% before bringing the situation near the conventional one, whereas at SHA the fair premium can increase by 93%. The smaller potential at SHA is caused by lower mean profits expected for producing maize (baseline: 260 CHF ha^{-1}) in contrast to the slightly higher grain yield and gains at MAG (baseline: 420 CHF ha^{-1}).



Notes: 1 = WAE, 2 = MAG, 3 = SHA. Note the changing spacing between isolines for values below 1,000 CHF; m((x)) is mean rainfall and sd((x)) is standard deviation.

Figure 4. Sensitivity Analysis for Premium of the Structured Product (CHF contract^{-1}) in Relation to the Mean Rainfall Level and Standard Deviation for the Baseline [full circles] and CC Scenario [empty circles]



Notes: 1 = WAE, 2 = MAG, 3 = SHA; m((x)) is mean rainfall and sd((x)) is standard deviation.

Figure 5. Sensitivity Analysis for 95-VaR Value (1,000s CHF ha^{-1}) for the Conventional [left] and Hedged [right] Management with Rainfall Statistics for Baseline [full circles] and CC Conditions [empty circles]

Table 3. Fair Premium and VaR (rounded to 10) for Baseline and CC Scenarios

Weather Station	Premium (CHF Contract^{-1})	95-VaR$_{conv}$ (CHF ha^{-1})	95-VaR$_{wd}$ (CHF ha^{-1})	90-VaR$_{conv}$ (CHF ha^{-1})	90-VaR$_{wd}$ (CHF ha^{-1})
Baseline Scenario:					
MAG	210	−920	−200	−460	−70
SHA	160	−570	−260	−370	−160
CC Scenario:					
MAG	620	−2,130	−640	−1,580	−500
SHA	780	−1,500	−840	−1,230	−740

Discussion and Conclusions

Weather derivatives are effective instruments for hedging against the risk associated with weather variability under today's climate and may become even more attractive under projected future climates characterized by increased frequencies of extreme weather [Intergovernmental Panel on Climate Change (IPCC), 2007]. There is growing evidence that, as a result of global climate change, some of the most severe weather events such as summer heat waves, windstorms, and heavy precipitation could become more frequent in Europe over the next 50 to 100 years (Fuhrer et al., 2006). This increases the risk of yield losses of important agricultural crops (Torriani et al., 2007a, b), although considerable uncertainties exist with respect to the extent of the projected changes in climate at the global, regional, and local scales.

Due to these uncertainties attached to climate scenarios and, in particular, a strong bias in precipitation scenarios for the European alpine region (Fuhrer et al., 2006), application of weather derivatives for hedging against drought risks in crop production would require continuous re-equilibration and recalculation of the premiums. Depending on local conditions, the fair premium of a specific contract for hedging against weather risks in grain maize production may vary by a factor of two to four over the 70-year period considered. This represents a substantial uncertainty for both the producer (farmer) and the institution underwriting the contract.

One objective of this work was to calculate the premium of the contract with the statistical measure of risk (fair premium), implying that there is no loading for the costs and risks endorsed by the financial institution writing the contract. This presents an unrealistic situation, except if a government supports the hedging strategy and covers the risk exposure and expenses. Nevertheless, our findings reveal that even considering premiums which are 100% or higher than the fair premium, hedging remains attractive for maize producers when compared with the conventional management, both for baseline and climate change assumptions, thus allowing the financial institution to cover its expenses and eventually the uncertainties related to climate change.

In this study, we used a modeling approach to determine weather-yield relationships instead of employing traditional regression methods based on observed data. The advantage is that the relationship can be applied to locations for which historical meteorological or yield data are incomplete, or where correlations between rainfall and observed grain yield are inadequate for hedging purposes (even if significant). We used a novel approach to create a simple statistical yield model based on functional relationships between weather variables and yield derived with a deterministic crop model (Stöckle, Donatelli, and Nelson, 2003). The latter was calibrated and tested against observed data from Swiss locations with highly satisfactory results

(Torriani et al., 2007b). Nevertheless, uncertainty related to yield simulations remains an important component of the overall uncertainty in projections of future crop loss risks, as discussed by Torriani et al. (2007a). Moreover, the basis risk resulting from the spatial heterogeneity of the precipitation-based index requires further analysis; solutions exist to improve the spatial representation of the index through extrapolation techniques, spatial mapping through teledetection, or by using ad hoc indices created from aggregation of multiple weather variables (Vedenov and Barnett, 2004).

Integrated economic studies at the farm level and not limited to maize production may offer further opportunities for the application of risk transfer based on capital markets to the benefit of both the society optimizing its investments (Skees, 1999, 2002; Miranda and Glauber, 1997) and the rural sector facing fundamental socioeconomic and technical adaptations. Risk transfer is one strategy to increase the probability that the agricultural production chain can be secured and to safeguard the production of real, tangible agricultural commodities that for many reasons can drop or rise in quantity and quality, but cannot be replaced solely by monetary values.

Application of weather derivatives may be influenced by the availability of seasonal weather forecasts. Their usefulness has been assessed in Europe for winter crop management (Cantelaube and Terres, 2005), but specific studies focusing on forecasting seasonal precipitation dynamics are still scarce. In areas where seasonal weather forecasting represents a valid support to both crop management and financial decisions (Meinke and Stone, 2005), pricing corrections could be considered (Jewson and Brix, 2005). Projections of adverse weather and unsuitable soil conditions during the time of sowing can lead the farmer to change plans, and in extreme situations even force a switch to an alternative crop with the consequence that hedging would be obsolete.

Mechanisms for redeeming the contingent claim can be included in the specifications, but then it is necessary to reconsider weather and seasonal forecasting to recalculate conditional expectation of premiums (Agarwal, 2002). These last issues were not considered here because solutions are specific to regions, countries, and industries, where strong territorial presence of insurance and governmental services will motivate more sophisticated contracts including redemption clauses, while application in remote areas will encourage simplicity (Skees et al., 2001).

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Portfolio Effects and the Willingness to Pay for Weather Insurances

Oliver Musshoff, Norbert Hirschauer, and Martin Odening

Abstract

Since the mid-1990s, agricultural economists have discussed the relevance of index-based insurances, also called "weather derivatives," as hedging instruments for volumetric risks in agriculture. Motivated by the question of how weather derivatives should be priced for agricultural firms, this paper describes an extended risk-programming model which can be used to determine farmers' willingness to pay (demand function) for weather derivatives. The model considers both the derivative's farm-specific risk-reduction capacity and the individual farmer's risk acceptance. Applying it to the exemplary case of a Brandenburg farm reveals that even a highly standardized contract which is based on the accumulated rainfall at the capital's meteorological station in Berlin-Tempelhof generates a relevant willingness to pay. Our findings suggest that a potential underwriter could even add a loading on the actuarially fair price which exceeds the level of traditional insurances. Since transaction costs are low compared to insurance contracts, this finding indicates there may be a relevant trading potential.

Key words: production program planning under risk, rainfall risk, weather derivatives, willingness to pay

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In the recent past, weather derivatives have been increasingly discussed as a novel instrument to hedge production risks in agriculture (e.g., Richards, Manfredo, and Sanders, 2004; Berg and Schmitz, 2007; Turvey, 2005; Odening, Musshoff, and Xu, 2007). They are also frequently referred to as index-based weather insurances. Unlike conventional (yield or) damage-related insurances, the hedge from weather derivatives results from payments tied to weather variables (temperature, rainfall, etc.) that are measured objectively at a specified location. Weather derivatives avoid the moral hazard and adverse selection problems associated with conventional insurances.

Though promising applications of weather derivatives in agriculture exist, it is difficult at present to assess the relevance of weather markets for agribusiness in the future. One reason is the problem related to the pricing of weather derivatives. Since weather cannot be traded, it is not possible to construct a riskless hedge portfolio. Two implications follow from this fact: first, standard no-arbitrage arguments are invalid (Richards, Manfredo, and Sanders, 2004), and second, the risk that remains for the holder of the weather derivative (the basis risk) must be taken into account.

Evaluation of the basis risk requires knowledge about the individual risk preferences. Cao and Wei (1999) and Richards, Manfredo, and Sanders (2004) suggested applying consumption-based capital asset pricing for that purpose (cf. Lucas, 1978). This modeling framework makes it possible to determine the equilibrium price of a weather derivative assuming a representative investor and a liquid secondary market for the derivative. A somewhat less ambitious approach is to calculate the willingness to pay (WTP) for weather derivatives.

The objective here is not to fix a market price ex ante, but to determine a boundary for the price from the viewpoint of an individual buyer—a farmer. In this context, Xu, Odening, and Musshoff (2007) used an indifference pricing model to identify the minimum sales price and maximum purchase price for a weather derivative that is traded over the counter. If the minimum sales price is below the maximum purchase price, there is a trading potential.

The calculation of the WTP is closely related to the hedging effectiveness of the weather insurance since the volatility of the production revenues enters the utility function of the decision maker. The effectiveness of a hedging instrument can be understood very generally as its capacity to reduce the volatility (variability) of some objective value (e.g., the total gross margin) at a constant expectation value.

Various studies on weather derivatives indicate that the basis risk which remains despite the use of weather derivatives can be rather high in agriculture. The causes of a high basis risk are the geographical distance between the location of production and the reference weather station (geographical basis risk) as well as a low correlation between the weather index and the success of the production even at the location of production (production basis risk or local basis risk).

Berg and Schmitz (2007), for example, examined a weather derivative tailored for a potato producer in Lower Saxony and found a hedging effectiveness of approximately 40%. Odening, Musshoff, and Xu (2007) found an effectiveness of approximately 33% for a weather derivative specifically geared for a wheat producer in Brandenburg. Using a downside-risk measure, which is not directly comparable to the variance, Vedenov and Barnett (2004) likewise report a low risk-reduction potential for weather derivatives explicitly designated for the operating conditions of maize, soybeans, or cotton producers in the USA.

One might be tempted to conclude from a low hedging effectiveness that the farmers' potential demand would be low. Yet, such an interpretation would disregard the difference between *effectiveness* and *efficiency*. The potential demand for a weather derivative results from the ratio of its costs and its benefits (i.e., its performance or hedging effectiveness). Derivatives which are based on simple indices and which display low effectiveness lead to a lower WTP on the part of farmers. However, as a result of their lower transaction costs, they can also be provided at lower prices. We cannot, therefore, a priori conclude that weather derivatives with a low hedging effectiveness are "inapplicable" or that they do not have a trading potential. On the contrary, at a low price, weather derivatives with low hedging effectiveness can represent very efficient hedging instruments for farmers.

The objective of this paper is to analyze whether a high basis risk is in fact detrimental to the demand for weather derivatives in agriculture. We assume the perspective of an underwriter who is interested in assessing the WTP, and thus the potential demand of farmers in terms of price-quantity combinations. When determining WTP, empirical information regarding the potential buyers must be taken into account. This includes the farmer's individual risk tolerance and the farm-specific risk-reduction potential of the weather derivative.

We describe an extended risk-programming approach which can be used to determine the amount of derivatives a rational farmer would purchase at various prices (theoretical demand). An exemplary cash crop farm in northeast Germany is used for illustration purposes. This farm is assumed to have the opportunity to hedge weather risks through a standardized rainfall put option. In contrast to many previous, comparative-static approaches (with/without derivative comparisons) which attempted to find an optimal weather derivative, we consider a derivative with a very simple standard design.

We have two reasons for this choice. First, there is no a priori specified production program to which we could fit the derivative because we allow for a dynamic adjustment of the production program after the innovative hedging instrument "weather derivative" has been made available to the farmer. Second, given associated transaction costs, it is implausible that an underwriter will customize weather indexes for single farms. In addition to the determination of the demand for derivatives at various prices, we also specify the optimum (or maximum turnover) price from the viewpoint of a monopolistic underwriter.

Hence, our contribution is twofold from a methodological perspective. First, we explicitly take into account portfolio effects which might have a significant impact on WTP (Brockett et al., 2006). Specifically, the whole farm rather than a single production activity is considered. This is accomplished within a risk-programming framework.

Second, the well-known problem of eliciting individual risk attitudes is tackled. On the one hand, knowledge about the risk attitude of decision makers is necessary in order to calculate risk premiums; on the other hand, such information is rarely available. To overcome this difficulty, risk-aversion coefficients are usually either parameterized or taken from the literature. Both procedures are rather unsatisfactory. Here we circumvent the problem by using implicit information on the risk attitude which is revealed in the realized farm production program.

A Demand-Oriented Evaluation of Weather Derivatives

The Model for a Farm-Specific Evaluation of Weather Derivatives

The starting point for the evaluation procedure suggested here is a risk-programming approach used to determine the farmer's optimum production program under risk:

$$(1) \quad \max_{x_{t^*}^j} E(TGM_{t^*}) = \sum_{j=1}^{J} E(GM_{t^*}^j) x_{t^*}^j$$

$$\text{s.t.:} \quad \sum_{j=1}^{J} a_{t^*}^{i,j} x_{t^*}^j \le b_{t^*}^i \quad \text{for } i = 1, 2, \ldots, I,$$

$$\sqrt{\sum_{j=1}^{J} (x_{t^*}^j \sigma^j)^2 + 2 \sum_{j=1}^{J} \sum_{k<j}^{J} x_{t^*}^j \times \sigma^j x_{t^*}^k \sigma^k \rho^{j,k}} \le \overline{S}_{t^*},$$

$$x_{t^*}^j \ge 0.$$

The objective function coefficients $E(GM_{t^*}^j)$ designate the expected gross margins per unit of production activity j for the target year t^*. The activity levels $x_{t^*}^j$ which lead to the maximum objective function value are determined while taking the restrictions into account. The right-hand-side values $b_{t^*}^i$ designate these restrictions for the target year, and $a_{t^*}^{i,j}$ designate the capacity requirements per unit of activity. The additional restriction $\overline{S}_{t^*}$ denotes the maximum permissible standard deviation of the total gross margin. If the single gross margins or error terms are normally distributed, the standard deviation of a production program's total gross margin can be calculated using the weights (levels) of the individual activities $x_{t^*}^j$, the correlation coefficients $\rho^{j,k}$, and the standard deviations σ^j and σ^k. By maximizing the expected total gross margin $E(TGM_{t^*})$ for different upper limits of the standard deviation $\overline{S}_{t^*}$, the farm-specific risk efficiency line can be determined.[1]

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[1] In the remainder of this paper, the time index t will not be used when it is possible to exclude it without generating confusion.

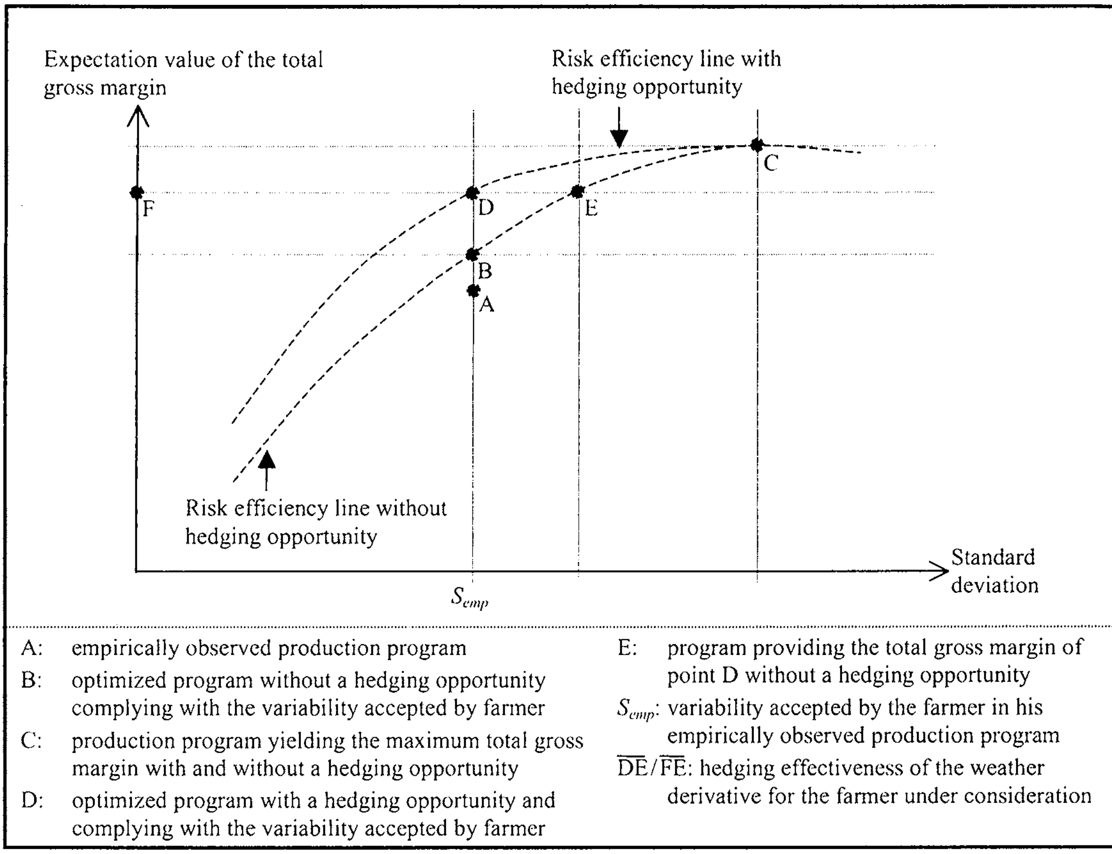

Figure 1. Risk Efficiency Line with and without a Hedging Opportunity

We now include the weather derivative to be evaluated (or, more precisely, the "purchase of this weather derivative") in the set of possible activities of the optimization model, together with the classic production activities. For a given derivative price (which is parameterized later), we then repeatedly solve the optimization problem for different standard deviation restriction levels. Farm-specific risk efficiency lines are thereby generated for varying derivative prices.

Figure 1 depicts a stylized version of a risk efficiency line with and without a hedging opportunity. In this illustration, we presuppose a derivative price at which it would be rational for a (risk-averse) farmer to purchase a certain amount of weather derivatives. At prohibitively high derivative prices, the production function with a derivative coincides with the production function without a derivative. Figuratively speaking, the risk efficiency line with a hedging opportunity is to the left above the production function without a hedging opportunity. It should be noted that the production programs yielding the maximum total gross margin with and without hedging opportunity are identical (point C) if the weather derivative has a positive loading.

The greater the area between the risk efficiency line with and without a hedging instrument, the higher the "quality" of the derivative understood as its farm-specific risk-reduction potential. A simple measure for this farm-specific performance would be the ratio between the area below the risk efficiency line with a hedging opportunity and the area below the risk efficiency line without a hedging opportunity. The farm-specific risk-reduction potential depends on two components: first, the level of the (negative) correlation between the future payoff of the derivative and the gross margins of the classic production activities, and second, the costs of the derivative.

However, the actual usefulness of the hedging instrument for the individual decision maker considered here can be assessed only after taking his individual risk attitude into consideration. Due to well-known problems of empirically estimating consistent risk attitudes, Musshoff and Hirschauer (2007, p. 22) suggest optimizing program decisions within an expected value-variance (EV) approach and reverting to the concept of second-degree stochastic dominance (SSD) in the context of the optimization of production programs: "... neither trying to elicit nor knowing the individual farmers' risk attitudes and risk premiums, we concern ourselves only with second degree stochastically dominant solutions, i.e., with the more limited attempt to find out whether expected payoff could be increased without increasing the empirically observed variance." The latter refers to the risk tolerance which is implicitly expressed by the production program selected empirically by the farmer. The optimization model described in (1) employs this approach to evaluate weather derivatives.

Point A of Figure 1 indicates the empirically observed production program of a bounded rational farmer. A comparison of the optimized production program without a hedging opportunity (point B) with the optimized production program with a hedging opportunity (point D) shows how much the expected total gross margin can be increased after introducing the weather derivative—without increasing the farmer's risk.

For two reasons, the proposed risk-programming approach identifies only a lower limit of the benefit derived from a weather derivative. First, we determine the potential increase of the total gross margin given the standard deviation of the total gross margin accepted by the farmer. In other words, since SSD is implicitly used, the distance $\overline{DB}$ can be interpreted as the lower limit of the additional benefit which can be obtained by a rational farmer by using the weather derivative.

Second, we underestimate the benefit for the farmer because we resort to an EV approach. At first glance, the assumption of a normal distribution for the total gross margin seems plausible in the context of portfolio optimization due to the central limit theorem. However, the plausibility of a normally distributed total gross margin decreases with increasing hedging effectiveness. Weather derivatives in the form of options cause a systematic reduction of a distribution's left-hand-side probabilities (and thus a right-skewed distribution). Assuming nonetheless a normal distribution, one underestimates the hedging effectiveness since the total variability is misinterpreted as a symmetric deviation from the mean.

In brief, we can summarize that the *area* between the two risk efficiency lines describes the general capacity of the hedging instrument to reduce risk on a specific farm. By contrast, the (minimum) additional benefit of the hedging instrument for an individual farmer can be deduced by an SSD-based comparison of two *points* on the two production functions.

Specification of the Weather Derivative Considered

Grain farmers in northeast Germany are heavily exposed to rainfall risk. However, no hedging instruments have been offered in Germany until now to insure farmers against drought-related volume risks. To illustrate our evaluation procedure, we therefore hypothetically presuppose in the following that an underwriter has offered rainfall derivatives. More precisely, we exemplarily use a put rainfall option whose payoff F_T is defined as follows:

(2) $F_T = \max(\bar{I} - I_T, 0)V.$

The underwriter presumably chooses the cumulative rainfall measured at the Berlin-Tempelhof weather station between April 1 and June 30, 2006, as weather index I_T. The farmer can purchase the option on July 1, 2005. On June 30, 2006, i.e., at its maturity of $T = 1$ year, the option provides an "insurance payment" for the farmer if the measured rainfall index I_T falls short of the strike level $\bar{I} = 151.6\,\text{mm}$.[2] The tick size V defines a monetary value of €1 per mm shortfall of the strike level.

The actuarially fair premium is determined on the basis of the actuarial standard procedure (cf., e.g., Jewson and Brix, 2005, p. 135), i.e., using the burn analysis (historical simulation). In other words, based on the weather records at the reference weather station in Berlin-Tempelhof between 1980 and 2005, we calculate the payoff of the contract which would have been produced if the weather derivative had been available during that period of time. Using the risk-free interest rate (here 5% p.a.), we find a fair premium of €16.85 per option contract.

The price at which the underwriter offers the weather derivative results from the actuarially fair premium plus a loading for his transaction costs, risk premium, and requested profit. If we unrealistically assumed that the derivative price equaled the fair premium, the activity "purchase of the weather derivative" would generate an expected gross margin $E(GM^D)$ of zero for the farmer. With the more realistic assumption of a positive loading, the expected gross margin of this activity is simply the negatively signed loading. At a derivative price of €20, for instance, we could thus say that the "insurance effect" costs the farmer only (20 – 16.85 =) €3.15 per contract.

[2] We assume the strike level is chosen corresponding to the average three-month rainfall in April/May/June from 1980 to 2005.

Collecting and Evaluating Farm-Specific Data

Before we can analyze the impact of the above-described weather derivative for a specific farm business by using the risk-programming approach, we must quantify the restrictions that are in force on this farm. In addition to capacity limitations and crop rotation restrictions, this includes the empirically observed standard deviation which is used in the risk-programming model as an upper bound, thus limiting the search to the set of SSD solutions. Furthermore, the expectation value and the variability of the single gross margins of the different activities must be quantified statistically. This includes, in addition to the "classical" production activities, the activity of "purchasing a weather derivative."

The crop farm showcased here is situated approximately 40 km west of the reference weather station in Berlin-Tempelhof. With an approximate acreage of 700 ha and four employees (including the manager), its main crops are winter and summer wheat, winter rye, winter and summer barley, winter canola, corn, non-food canola, and set-aside land. In addition to the factor endowment (workers and land), information is collected regarding the crop rotation restrictions, the expected number of available fieldwork days and hours during the critical working time periods, and the number of working hours required for the single activities during these critical periods of time. To determine the variability of the total gross margin accepted by the farmer, the empirical production program for the production period 2005/06 was also captured.

At the assumed time of production planning (fall 2005), the single gross margins GM_i^J to be obtained in the target year (after the harvest in 2006) were not known. The single gross margins from 1980 through to the planning date in 2005 represent the database for the quantitative assessment of the uncertainty.[3] We carry out a linear time-series analysis in order to identify the ARIMA(p, d, q) model which best fits the single gross margin time series (cf. Box and Jenkins, 1976).

According to the time-series analysis, all single gross margins follow first-order autoregressive [AR(1)] processes with normally distributed error terms. With an AR(1) process, the future value of the random variable results from an expected value $E(GM_{t^*}^j)$ plus an error term $\chi_{t^*}^j$. The former is commensurate with a constant α_0^j plus the preceding observation value $GM_{t^*-1}^j$ weighted with a factor α_1^j (cf. Pindyck and Rubinfeld, 1998, p. 535):

$$(3) \quad GM_{t^*}^j = E(GM_{t^*}^j) + \chi_{t^*}^j = \alpha_0^j + \alpha_1^j GM_{t^*-1}^j + \chi_{t^*}^j,$$

with $|\alpha_1^j| < 1$.

The expected value of the single gross margins as well as the standard deviation and the correlation of the error terms are fed into the optimization model. The gross margin of the activity "purchasing a weather derivative" is represented in our risk-programming model as a normal distribution. To determine the distribution parameters, we use the would-be payoffs from 1980 to 2005, i.e., the payoffs that would have been realized if the weather derivative had existed during that period.

Using the format of a classical optimization tableau, Table 1 summarizes the information obtained from the time-series analysis and from the data regarding the restrictions and factor requirements. In the tableau, we have printed an expected value of zero for the gross margin of the activity (purchasing a) "weather derivative." Knowing this is equivalent to the unrealistic assumption that the underwriter takes no loading on the fair premium, we use this value as a placeholder. It denotes the starting point of variant calculations which parameterize the loading in order to determine the price-quantity combinations (price-dependent contract volume) demanded by a rational farmer.

We furthermore show the standard deviation of € 100,493 which the farmer implicitly accepted with his own 2005 program as an upper bound for the permissible variability. This value will also be parameterized. And finally, with regard to the correlation matrix, it should be noted that the correlation between the single gross margins of the crop activities (with the exception of corn) is clearly positive, whereas the correlation with the "insurance payment" of the weather derivative is negative.

Findings

Including weather derivatives in his portfolio enables the farmer to diversify his actual production activities to a lesser extent—i.e., the farmer can increase the weight of the more profitable (and at the same time riskier) activities in his program without increasing the variability of the total gross margin. Table 2 shows the corresponding findings produced by the variant calculations of the risk-programming model. The expected total gross margin (columns 2–6) and the hedging effectiveness (columns 7–10) are depicted depending on the systematically varied upper bound of the standard deviation (rows 1–9)[4] and depending on the systematically varied expected gross margins (or loadings) of the derivative $E(GM^D)$.

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[3] Due to the discontinuity of the time series in the Brandenburg farm under consideration which was caused by the German reunification at the beginning of the 1990s, we use auxiliary gross margin time series instead of individual farm data for the period 1980–1992. These time series are synthesized by using site-specific yield data and West German prices. The individual gross margins from 1993 to 2005 are farm-specific.

[4] In order to generate four equal intervals between the empirical standard deviation and the standard deviation needed to achieve the maximum total gross margin, the standard deviation was varied in steps of € 1,883.

Table 1. Optimization Tableau Displaying the Information from the Farm Considered

	Activities										Additional Activities: Seasonal Labor				
	Winter Wheat	Summer Wheat	Winter Rye	Winter Barley	Summer Barley	Winter Canola	Corn	Non-food Canola	Weather Derivative	Land Set-Aside	March and April	May and June	July to Sept.	Sept. to Nov.	Factor Endowment
Objective Function Coefficient $E(GM^j)$ Activity Level x^j	410	290	367	365	317	610	13	559	0	75	-15	-15	-15	-15	
Acreage	1	1	1	1	1	1	1	1	0	1	0	0	0	0	703
Labor Requirement: March and April	0.31	2.60	0.28	0.31	2.55	0.36	2.60	0.36	0.00	0.00	-1	0	0	0	900
May and June	0.79	0.46	0.24	0.51	0.51	0.89	0.80	0.89	0.00	0.00	0	-1	0	0	1,050
Mid-July to mid-Sept.	2.41	2.35	2.18	2.05	2.04	3.50	0.00	3.50	0.00	2.00	0	0	-1	0	1,350
Mid-Sept. to mid-Nov.	2.89	0.39	2.60	2.82	0.00	0.65	2.20	0.65	0.00	0.00	0	0	0	-1	1,200
Crop Rotation Restrictions: Wheat I	0.47	0.47	-0.54	-0.54	-0.54	-0.54	-0.54	-0.54	0.00	-0.54	0	0	0	0	0
Wheat II	-0.85	-0.85	0.15	0.15	0.15	0.15	0.15	0.15	0.00	0.15	0	0	0	0	0
Rye	-0.41	-0.41	0.59	-0.41	-0.41	-0.41	-0.41	-0.41	0.00	-0.41	0	0	0	0	0
Barley	-0.40	-0.40	-0.40	0.60	0.60	-0.40	-0.40	-0.40	0.00	-0.40	0	0	0	0	0
Canola	-0.22	-0.22	-0.22	-0.22	-0.22	0.78	-0.22	0.78	0.00	-0.22	0	0	0	0	0
Land Set-Aside	0.10	0.10	0.10	0.10	0.10	0.10	0.10	-0.90	0.00	-0.90	0	0	0	0	0
Standard Deviation	165	146	133	166	135	260	170	228	25	0					100,493
Correlation Matrix: Winter Wheat	1.00	0.85	0.74	0.66	0.71	0.53	0.17	0.57	-0.32						
Summer Wheat		1.00	0.69	0.56	0.81	0.53	0.32	0.57	-0.38						
Winter Rye			1.00	0.68	0.64	0.66	0.08	0.67	-0.31						
Winter Barley				1.00	0.63	0.52	-0.02	0.48	-0.25						
Summer Barley					1.00	0.51	0.14	0.53	-0.41						
Winter Canola						1.00	0.24	0.98	-0.27						
Corn							1.00	0.19	-0.18						
Non-food Canola								1.00	-0.27						
Weather Derivative									1.00						

Note: A loading of the weather derivative of zero is a placeholder. In fact, the derivative price will be parameterized.

Table 2. Risk Efficiency Lines and Hedging Effectiveness for Varying Loadings of the Weather Derivative

		Expectation Value of the Total Gross Margin (in €) for Varying Loadings of the Weather Derivative [a]					Hedging Effectiveness (in %) for Varying Loadings of the Weather Derivative			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	Std. Dev. (in €)	w/o ($E(GM^D) = -\infty$)	Loading = 0 ($E(GM^D) = 0$)	Loading = 2 ($E(GM^D) = -2$)	Loading = 4 ($E(GM^D) = -4$)	Loading = 10 ($E(GM^D) = -10$)	Loading = 0	Loading = 2	Loading = 4	Loading = 10
1	92,962	271,280	286,880 (100,110)	284,050 (98,554)	281,580 (97,457)	275,710 (94,885)	7.1	5.7	4.6	2.0
2	94,844	275,620	289,370 (102,160)	286,570 (99,902)	284,310 (98,671)	279,610 (96,591)	7.2	5.1	3.9	1.8
3	96,727	279,920	291,250 (103,980)	288,480 (101,360)	286,360 (99,767)	282,650 (97,929)	7.0	4.6	3.0	1.2
4	98,610	284,170	292,940 (105,760)	290,190 (102,930)	288,170 (101,100)	285,230 (99,116)	6.8	4.2	2.5	0.5
5	***100,493***	***287,410***	***294,300 (107,320)***	***291,770 (104,510)***	***289,860 (102,620)***	***287,510 (100,570)***	***6.4***	***3.8***	***2.1***	***0.1***
6	102,376	289,610	294,700 (108,024)	292,850 (105,670)	291,430 (104,160)	289,610 (102,380)	5.2	3.1	1.7	0.0
7	104,258	291,520	294,700 (108,024)	293,640 (106,540)	292,690 (105,490)	291,520 (104,250)	3.5	2.1	1.2	0.0
8	106,141	293,280	294,700 (108,024)	294,220 (107,210)	293,760 (106,680)	293,280 (106,140)	1.7	1.0	0.5	0.0
9	108,024	294,700	294,700 (108,024)	294,700 (108,024)	294,700 (108,024)	294,700 (108,024)	0.0	0.0	0.0	0.0

Note: For the row relevant to the decision maker considered here (row 5), the values appear in boldface italics.

[a] The standard deviation which would have to be accepted for the respective total gross margin without a hedging opportunity is given in parentheses.

Row 5 of Table 2 represents the situation for a predefined standard deviation of €100,493, i.e., for the variability which has been implicitly accepted by the farmer with his own production program. Using this value as the relevant upper bound, an expected total gross margin of €287,410 can be obtained without the hedging opportunity or with a weather derivative with prohibitively high costs (column 2). At the other extreme, if the derivative could be purchased without a loading on the fair premium, the farmer could obtain an expected total gross margin of €294,300 (column 3) without exceeding his previously accepted variability. This is equivalent to a total gross margin increase of €6,890 in contrast to the situation without a derivative. In order to achieve this higher gross margin without a derivative, the farmer would have to accept a standard deviation of €107,320. This corresponds to a hedging effectiveness of (107,320 – 100,493)/107,320 = 6.4% (column 7).

A systematic comparison of the columns in Table 2 illustrates that the higher the derivative loading, the lower the increase in the total gross margin that can be obtained at a constant variability. With a loading of €2 per contract, for example, the expected total gross margin amounts to €291,770 (column 4). Without a derivative, the farmer would then have to accept a standard deviation of €104,510. The hedging effectiveness now is reduced to 3.8% (column 8).

A systematic comparison of the rows in Table 2 reveals that the additional benefit for the farm business and the hedging effectiveness provided by the weather derivative decreases with an increasing use of the "production factor" risk (decreasing marginal returns), i.e., with increasing risk tolerance on the part of the farmer. Row 9 makes this clear by referring to the extreme case: the production program which yields the maximum expected total gross margin of €294,700 is associated with a standard deviation of €108,024. For a risk-neutral decision maker who accepts this variability, no additional benefits are generated through the possibility of hedging weather risks.

Having limited the farmer's search in our extended risk-programming model to SSD solutions, the derived increase in the total gross margin can be interpreted as the minimum utility of the weather derivative for the farmer. In addition, using the risk-programming model we can also answer the question as to what price a monopolistic underwriter should demand per contract in order to maximize his net turnover (number of contracts sold multiplied by the loading per contract). Assuming fixed transaction costs independent of the number of contracts bought by the farmer, the maximum net turnover corresponds to the maximum profit.

Varying the derivative loading, Table 3 shows the number of weather derivatives an optimizing farmer would buy who tolerates a standard deviation of S_{emp} = €100,493 and who resorts to SSD solutions. At a contract price equivalent to the fair premium (i.e., a zero loading), no net turnover would remain for the underwriter. The farmer, however, would obtain a €6,890 higher total gross margin than without the derivative.

Comparing the columns of Table 3 indicates there is a corresponding fall in demand as the loading per derivative increases. Purchasing weather derivatives becomes unattractive for this farmer with a loading (cost) above €12.21. In other words, the contract costs are prohibitively high. Therefore, no demand is created above these derivative costs.

As the loading of the derivative increases, the net turnover of the underwriter increases in the beginning. However, due to the farmer's increasing price elasticity of demand, the net turnover of the underwriter decreases beyond a certain loading. The optimum price from the viewpoint of a monopolistic underwriter corresponds to the fair premium of €16.85 plus a loading of €4.45 per contract.

Table 3. Effects of the Weather Derivative for the Underwriter and the Farmer at Different Loadings per Contract

	Loading per Contract ($-E(GM^D)$)							
	0	**2**	**4**	**4.45**	**6**	**8**	**10**	**≥ 12.21**
Demand from the farmer (no. of contracts)	1,528	1,092	791	717	490	259	96	0
Net turnover of the underwriter from the weather derivative (€)	0	2,185	3,162	3,190	2,941	2,075	965	0
Increase of the farmer's expected total gross margin from the weather derivative (€)	6,890	4,361	2,451	2,111	1,181	441	101	0
Total benefit from introducing the weather derivative (€)	6,890	6,546	5,613	5,301	4,122	2,516	1,066	0

Note: Values are calculated for the farmer considered with an upper variability bound of S_{emp} = € 100,493 (row 5 of Table 2).

In other words, if the underwriter was only targeting bilateral business with the farmer considered here, the optimum price for the weather derivative, from his perspective, would be €21.30. At that price, the above-described optimizing farmer would demand 717 contracts and have—in comparison to the situation without a derivative—a €2,111 higher total gross margin. The underwriter would obtain a net turnover of €3,190. It is interesting to note that, even in the case of the simple weather derivative considered here and even at a loading of €4.45 (which is equivalent to 26.4% of the fair premium), the considered real-life farmer would create a significant demand.

Since weather derivatives avoid the moral hazard problem, we can plausibly assume that the transaction costs for (standardized) weather derivatives are relatively low—in any case much lower, e.g., than those for hail insurances which, in Germany, have a loading level of approximately 20% to 25% (BMELV, 2001, p. 26; Weber et al., 2008). In conjunction with our preliminary findings which indicate a significant demand even at relatively high loading levels, this suggests it could be advantageous both for insurers and farmers if the novel instruments were put on the market. From the perspective of the underwriter/insurer, there appears to be considerable room for maneuvering when offering the derivative at (low) costs, which would also make it appealing for farmers with a higher risk tolerance and/or on farms with a lower hedging effectiveness than the one we have showcased.

We have so far determined—from a monopolistic underwriter's point of view—the optimal loading for a weather derivative, assuming it is the sole hedging instrument within the farmer's portfolio. However, especially in the United States, both crop yield and crop revenue insurances are available. Yield insurance, often called multi-peril crop insurance (MPCI), allows farmers to hedge against various weather-induced volumetric risks. Revenue insurance additionally incorporates price risks.

While the introduction of crop insurances has generally required smoothing through subsidies, we now include a revenue insurance within the analysis. We assume that a full compensation payment is granted if the actual wheat revenue falls below the historical farm average. Furthermore, it is assumed that the farmer is able to partially insure[5] the wheat acreage but that the compensation payment, in order to limit moral hazard, depends on the entire revenues (from the total wheat acreage) being below average.

[5] The opportunity of a partial insurance on the revenues from winter wheat gives the farmer more flexibility and makes the instrument more flexible than farm revenue insurances offered in the United States, which only allow the farmer to insure the total acreage of the respective crop.

Table 4. Optimal Loading for the Weather Derivative and the Revenue Insurance from the Underwriter's Point of View

	Isolated View		Simultaneous View	
	[1]	[2]	[3]	[4]
Loading for Farm Revenue Insurance:	—	**Optimized**	**Given**	**Given**
Loading for Weather Derivative:	**Optimized**	—	**Optimized**	**Optimized**
Farm Revenue Insurance for Winter Wheat (actuarially fair premium = €78.80)				
Loading (€ and % of fair premium)		23.68 (30.1%)	15.76 (20.0%)	23.68 (30.1%)
Demand of the farmer (no. of contracts)		148	54	32
Net turnover of the underwriter from the farm revenue insurance (€)		3,481	854	760
Weather Derivative (actuarially fair premium = €16.85)				
Loading (€ and % of fair premium)	4.45 (26.4%)		2.01 (11.9%)	2.85 (16.9%)
Demand of the farmer (no. of contracts)	717		760	804
Net turnover of the underwriter from the farm weather derivative (€)	3,190		1,528	2,291
Increase of the farmer's expected total gross margin generated through the two hedging instruments (€)	2,111	2,161	4,569	3,578
Total benefit resulting from the introduction of the two hedging instruments (€)	5,301	5,642	6,950	6,629

Note: Values are calculated for the farmer considered with an upper variability bound of S_{comp} = € 100,493 (row 5 of Table 2).

In accordance with the analytical procedure chosen for weather derivatives (Table 3), we first analyze the farmer's willingness to pay if the revenue insurance was his sole hedging opportunity. In a second step, we simultaneously introduce the weather derivative *and* the revenue insurance as potential hedging opportunities within the farmer's portfolio. We are thus able to determine, from the underwriter's point of view, the derivative's optimal loading for varying loadings of the revenue insurance.

Columns 1 and 2 in Table 4 depict the farmer's demand if the respective hedging instrument (*either* insurance *or* derivative) was exclusively available to the farmer and if it was offered with the optimal loading from the underwriter's point of view. Neglecting transaction costs, the underwriter's net turnover from the revenue insurance exceeds the net turnover from the weather derivative by approximately €290. This difference is quite small if one takes into account the fact that transaction costs for revenue insurances can be expected to exceed those of weather derivatives considerably.

According to an empirical survey conducted by Weber et al. (2008), experts from European reinsurance companies estimated that 50% or more in transaction costs could be saved by using weather derivatives instead of classical insurances. Since the insurers' transaction cost levels and profit margins are well-kept secrets, we use this information to approximate the relative competitiveness of the two instruments. Even if the transaction costs for the revenue insurance amounted only to 20% of the actuarially fair premium (i.e., about €2,300 on our sample farm), it would be possible to save €1,150 in transaction costs when offering the weather derivative. Using these assumptions, the standardized weather derivative would easily outperform the farm revenue insurance.

Columns 3 and 4 in Table 4 depict a farmer's demand for the derivative and the insurance if he can use them both as hedging instruments. For this simultaneous analysis, we specify a priori a certain loading for the farm revenue insurance and then determine in the portfolio model the WTP for the weather derivative that a rational farmer would have.

Two variant calculations are carried out: one for an insurance loading of 20% which is considered to represent a lower cost limit due to the considerable moral-hazard and transaction cost problem, and one for an insurance loading of 30.1% which is considered to represent an upper limit since it is the optimal loading from the underwriter's point of view. The corresponding optimal loadings for the weather derivative are 11.9% (column 3) and 16.9% (column 4) of the actuarially fair premium. These results emphasize that a rational farmer has a considerable WTP for a standard weather derivative even if it must compete with alternative hedging instruments, at least as long as there are no subsidies (for crop insurances) which distort the price relations.

Summary and Conclusions

In this article, we propose an extended risk-programming approach to calculate a rational farmer's WTP for risk management instruments in general, and weather derivatives in particular. This approach enables us to avoid some of the drawbacks of previously suggested evaluation procedures:

- By resorting to SSD, we are able to consider the risk tolerance of the decision maker without having to elicit his risk attitude.

- By considering the production possibilities of the farm, we are able to explore the complexities and interdependencies of the farm as a system.

- We are able to examine the dynamic changes and portfolio adjustments made by an optimizing farmer following the introduction of a novel hedging instrument such as the weather derivative.

The farmer's WTP is the basis for determining the optimum derivative price from the viewpoint of a monopolistic underwriter who targets bilateral business with that farmer.

In the case of the cash-crop farm showcased here, we find a considerable WTP for weather derivatives. To avoid confusion, it should be emphasized that the price paid by the farmer for the derivative does not represent the costs of the risk management instrument "weather derivative." This information can be provided only after calculating the expectation value of the payoffs. Only the derivative loading represents its cost as a hedging instrument. The rather large optimum loading of more than 25% established in our exemplary study suggests that the question of the adequate discount rate may be rather irrelevant for assessing whether an innovative insurer should enter the market and how he should price derivatives for agricultural firms. However, the discount rate may become relevant if competition among insurers forces them to offer derivatives at increasingly attractive prices to farmers.

The optimum loading, from the underwriter's viewpoint, which was established for the exemplary farm considered here, cannot be generalized. The individual farmer's WTP depends both on his risk attitude and the farm-specific hedging effectiveness of the weather derivative. The latter is influenced by the distance between the reference weather station and the location of the farm (geographical basis risk) and the specification of the weather index (production basis risk). Future research regarding the evaluation of and the demand for weather derivatives should broaden the database and include more farms, thus shedding light, for example, on the farmers' (aggregated) WTP in a specific region.

Nonetheless, even broadening the database of the portfolio analysis will not reveal the true market potential. That is, modeling the "theoretical" WTP of a rational farmer does not facilitate conclusions regarding the actual market potentials in certain regions and countries. This requires classical market studies accompanied by adequate product information activities.

To avoid eroding the advantages of simplicity and of low transaction costs, simple weather derivatives which relate to existing weather stations should be "tested." We expect innovative underwriters/insurers will be able to determine the size of the target group in which demand is created by using their room for maneuvering. If the derivative is offered at a relatively low price, even farmers who are located far from the reference weather station will be interested in buying it. A higher price, by contrast, will reduce the demand and the size of the target group due to the increasing geographical basis risk. Thus, by comparing different pricing strategies, the underwriter should be able to determine his optimum price for the derivative in a certain region.

From a methodical stance, it would be interesting to analyze whether relevant changes in the calculated WTP would occur if one used a downside-risk measure instead of the variance in the target function of the portfolio approach (cf. Berg and Schmitz, 2007). From the farmers' point of view, it would be helpful to investigate how different hedging instruments (traditional insurances, traditional diversification practices, forward contracts, futures, different weather derivatives) should be optimally combined in a production and risk management activities portfolio.

Or, stated more pointedly: While the present article has basically probed the question of whether using an "ineffective" weather derivative can be economically efficient, it would be worthwhile to address the question of whether there are "ineffective" hedging instruments which are more efficient than effective ones. This would be the case if they (over-) compensated for the performance-related disadvantage (i.e., the lower risk-reduction potential) with cost-related advantages (i.e., a lower loading on the fair premium due to lower transaction costs).

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Basis Risk and Weather Hedging Effectiveness

Joshua D. Woodard and Philip Garcia

Abstract

Basis risk—the risk that payoffs of a hedging instrument do not correspond to the underlying exposure—is cited as a primary concern for implementing weather hedges. Using Illinois yields and weather data, we investigate several dimensions of weather basis risk in the U.S. corn market. Results suggest that while geographic basis risk can be significant, it should not preclude the use of geographic cross-hedging, particularly with temperature as opposed to precipitation derivatives. Risk reduction is appreciable and the degree to which geographic basis risk impedes effective hedging diminishes as spatial aggregation in the risk exposure and hedging instrument increases.

Key words: basis risk, hedging effectiveness, spatial aggregation, weather derivatives

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Weather derivatives are instruments which can be used to manage the effects of weather-related events on agricultural production. In recent years the interest in and the use of weather risk transfer products in the agricultural sector have increased significantly worldwide (Roth, Ulardic, and Trueb, 2007). Most research pertaining to the management of weather risk in agriculture has focused on pricing issues (e.g., Campbell and Diebold, 2005; Richards, Manfredo, and Sanders, 2004; Turvey, 2001, 2005; Turvey, Weersink, and Chiang, 2006), although several studies have examined hedging effectiveness directly (e.g., Vedenov and Barnett, 2004; Woodard and Garcia, 2008).

A common assumption in weather hedging studies has been that sufficiently liquid derivative markets exist for the remote agricultural regions considered and that hedgers can obtain reasonable prices on over-the-counter (OTC) derivative products. However, insufficient historical data often make it difficult to assess these assumptions, and/or speculators may require risk premiums significantly in excess of those charged in more liquid but distant large-city markets. Alternatively, hedging with non-local contracts may introduce basis risk as their payoffs may not offset losses in the underlying exposure being hedged.

Basis risk is defined as the risk that payoffs of a given hedging instrument do not correspond to shortfalls in the underlying exposure, and is often cited as a primary concern for the implementation of weather hedges (e.g., Brockett, Wang, and Yang, 2005; Deng et al., 2007; Roth, Ulardic, and Trueb, 2007; Shynkarenko, 2007; Turvey, 2001; Turvey, Weersink, and Chiang, 2006). Investigation of the characteristics of basis risk may be crucially important if weather hedging instruments are to be more widely adopted.

An understanding of basis risk may be particularly important in the agricultural arena where the acceptance of weather derivatives has likely been impeded by a lack of knowledge concerning their use and performance (Roth, Ulardic, and Trueb, 2007). Thus, a systematic investigation of basis risk may assist decision makers when hedging by identifying which types of contracts are useful, which risk factors can be successfully hedged, and who is most likely to benefit.

We investigate several aspects of the basis risk problem for Illinois corn yields at the Crop Reporting District (CRD) and state levels for the period 1971 through 2005. Both precipitation and temperature derivatives are considered. Following Vedenov and Barnett (2004) and Woodard and Garcia (2008), basis risk is examined for summer temperature and precipitation derivatives under the assumed objective of minimization of semivariance. An expected shortfall measure of risk (Dowd and Blake, 2006) is also used, and sensitivity analyses are conducted on assumptions about risk premiums and preferences.

We extend the literature in several dimensions.

- First, we investigate basis risk for and across multiple geographic locations, including those for which exchange-traded derivatives exist. To date, this topic has not been sufficiently addressed.

- Second, we assess the influence of spatial aggregation on basis risk—both the exposures being hedged as well as the hedging instruments. Analysis at greater levels of spatial aggregation may be of more interest to reinsurers and/or large agribusiness firms. Motivation for this dimension of the analysis emerges from research which questions the feasibility of producer risk management with weather derivatives in some agricultural markets (Vedenov and Barnett, 2004; Shynkarenko, 2007). Further, the analysis is stimulated by the notion that weather hedges likely may be more suitable for firms with large spatial exposures than for individual producers (Woodard and Garcia, 2008), and that these large market participants will inevitably play an important role if weather derivatives are to be widely adopted in agriculture.

- Third, we investigate basis risk across products by comparing the effectiveness of precipitation and temperature derivatives. While earlier studies have focused on both types of instruments, comparisons of the two have not been conducted.

- Finally, we examine the sensitivity of our findings to alternative assumptions about risk premiums. This may be particularly informative since much attention in the literature has been given to the risk premium issue, but little consideration has focused on the extent to which it may affect hedging decisions.

Basis Risk in Agricultural Weather Hedges

For any given hedging horizon, basis risk can be categorized into three types: local, geographic, and product—discussed more fully below.

Local Basis Risk

Local basis risk refers to the degree to which a weather derivative is an imperfect hedge against shortfalls for a given exposure, where the underlying index on the weather derivative and the exposure being hedged correspond to the same geographic location. For instance, a corn producer in central Illinois may wish to hedge against drought using a weather contract derived from weather at a local county station. Even if the payoffs of the derivative accurately reflect local weather conditions, it may not provide a perfect hedge because of an imperfect link between weather and the biological production process. Formally, *local basis risk* is defined as:

$$(1)\quad \sigma_k^{local} = E\left[f\left(y_{k,t} + h_k^{local} * \pi_{k,t} - E(y_{k,t})\right)\right],$$

where y is the value of the exposure being hedged; $f(\cdot)$ is a function relating deviations in the value of a hedged position from the expected value of the exposure (e.g., expected squared loss); h_k^{local} is the optimal hedge ratio in quantity of standardized weather derivative contracts per unit of exposure value which minimizes σ_k^{local} for a given $f(\cdot)$, time t, and location k; and $\pi_{k,t}$ is the profit per standardized unit of the corresponding weather derivative.

Geographic Basis Risk

Often, it may not be feasible to use a contract for the local area as measurement and monitoring may be too costly and more efficient markets may exist for larger cities. For example, the Chicago Mercantile Exchange (CME) offers temperature futures and options for several major international cities, and they are among the most liquid and fairly priced contracts available. These cities also have relatively liquid OTC markets for other weather products. Extra basis risk may arise, however, when the weather derivative employed is derived from a non-local city as opposed to a local area. As Jewson and Brix (2005) point out, there is usually a tradeoff between basis risk and price of a weather hedge.

Geographic basis risk is defined as the additional basis risk imposed by employing a non-local weather derivative:

$$(2)\quad \sigma_{k,l}^{geo} = E\Big[f\left(y_{k,t} + h_{k,l}^{geo} * \pi_{l,t} - E(y_{k,t})\right) - f\left(y_{k,t} + h_{k,k}^{geo} * \pi_{k,t} - E(y_{k,t})\right)\Big],$$

where all variables are as previously defined, l is a location index for the non-local derivative, and $h_{k,l}^{geo}$ denotes the optimal hedge ratio for the exposure in location k of a weather derivative derived from weather at location l. Thus, geographic basis risk is the additional risk that arises by using a non-local contract. While geographic basis risk is defined in terms of a particular non-local site, it is also possible for location indices to be specified as a weighted set of locations to identify the effect of offsetting an exposure risk using weather derivatives from multiple markets.

Product Basis Risk

Product basis risk refers to the difference in hedging effectiveness between alternative hedging instruments. Formally,

$$(3)\quad \sigma_{k,l,i,j}^{prod} = E\Big[f\left(y_{k,t} + h_{k,l,i}^{prod} * \pi_{l,i,t}^{prod} - E(y_{k,t})\right) - f\left(y_{k,t} + h_{k,k,j}^{prod} * \pi_{k,j,t}^{prod} - E(y_{k,t})\right)\Big],$$

where the indexes i and j refer to the type of weather derivative, and k and l are location indexes which may or may not refer to the same location(s), $h_{k,l,i}^{prod}$ denotes the optimal hedge ratio for the exposure in location k of a weather derivative of type i derived from location l, and $\pi_{l,i,t}^{prod}$ is the corresponding profit per standardized unit of the weather derivative during period t. Product basis risk can reflect the difference in hedging effectiveness between precipitation and temperature derivatives.

Yield and Weather Indexes

The study investigates the basis risk that arises when hedging corn yields with growing-season temperature and precipitation derivatives from various locations and levels of aggregation. This section describes the characteristics and treatment of the yield exposures and the selection and construction of the weather indexes, as well as the pricing of the weather derivatives.

Technology Change and Yield Trends

The exposures being hedged are corn yields, measured in bushels/acre. Failure to take into consideration technological advancements in yields may produce spurious results. To account for technology gains, yields are detrended using a simple linear trend model:

(4) $Y_t^{tr} = \alpha_0 + \alpha_1 t,$

$t = 1971, 1972, \ldots, 2005.$

Detrended yields to 2005 equivalents are calculated as:

(5) $Y_t^{det} = Y_t + \alpha_1 (2005 - t),$

$t = 1971, 1972, \ldots, 2005,$

where Y_t are observed yields and Y_t^{tr} are the corresponding yield trends.

Weather Indexes

It is well accepted that the critical development period for corn occurs during the summer months, and the derivatives are designed to reflect this pattern. Temperature derivatives and indexes based on accumulated cooling degree days (ACDDs) for the summer growing season—June, July, and August—are used. Agronomic experiments indicate that cooling degree days (CDDs) are more relevant to crop yields than outright temperature measurements (Schlenker, Hanemann, and Fisher, 2006). The number of CDDs for a single day is defined as the amount by which the average temperature is above the reference temperature, 65° Fahrenheit.

Explicitly, the number of CDDs on any day d is given by $CDD_d = \max(0, T_d - 65)$, where T_d is the simple arithmetic average of the daily maximum and minimum temperatures on day d. The index of ACDDs on any day d of the index period is defined as:

$$ACDD^{M,N} = \sum_{d \ M-N} CDD_d,$$

$$d = M - N, \ldots, M,$$

where $M - N$ is the first day of the contract period, and M is the expiration date.

A cumulative growing-season precipitation index is defined in a similar manner. Cumulative precipitation (CP) is denoted by:

$$CP^{M,N} = \sum_{d \ M-N} P_d,$$

$$d = M - N, \ldots, M,$$

where P is daily precipitation measured in inches. Since most days do not experience any precipitation, truncation of daily precipitation measurements is not generally carried out as is done with temperature.

The effectiveness of the temperature and precipitation indexes in part will be a function of their ability to reflect representative conditions. Temperature is highly spatially correlated, while precipitation tends to be more dispersed. Since measurements are taken at discrete points in space (i.e., individual weather stations), temperature measurements may be more representative of the surrounding region (e.g., a county in which the temperature measurement was taken) than are precipitation measurements.

From a hedging perspective, temperature derivatives may be naturally more suited for hedging crop production risk because their measurement reflects more systemic effects than precipitation. In practice, temperature derivatives also may be more attractive. Most estimates put the share of temperature derivatives as a percentage of the entire weather market in excess of 90%, and exchange-traded derivatives traded on the CME are based on ACDDs for major international cities. These features of temperature and precipitation suggest that temperature is likely the most feasible variable on which to structure weather hedges here. Nevertheless, since precipitation derivatives have attracted attention in the literature (see, e.g., Vedenov and Barnett, 2004; Martin, Barnett, and Coble, 2001) and extensive comparative assessments of temperature and precipitation derivatives have not been conducted, we choose to examine both alternatives.

While studies suggest benefits can accrue from using contracts that focus on shorter time intervals or specific events and allow more flexible strategies (e.g., Turvey, 2001; Turvey, Weersink, and Chiang, 2006), the use of growing-season indexes, particularly temperature derivatives, should permit identification of the relative magnitude of basis risk in an effective and useful manner. As confirmed by Namias (1986), the atmospheric flow patterns which control much of the North American climate tend to be persistent and can contribute to drought conditions. As a result, month-to-month temperatures are typically autocorrelated (Jewson and Brix, 2005), notably in extreme events likely to result in widespread crop losses (Namias, 1983, 1991). On a large scale, average temperature and precipitation conditions for a given region also tend to be highly negatively correlated in extreme weather events.

An investigation of seasonal contracts also may be useful as they tend to be more liquid compared to their time-disaggregated counterparts. Recent industry research has identified the limited success of highly specific weather-related instruments (Shynkarenko, 2007), and highlights a growth in the exchange-traded market relative to the OTC market because of higher perceived liquidity, lower credit and default risk, and lower transaction and information costs (Roth, Ulardic, and Trueb, 2007). Since transaction cost is a major impediment to the use of agricultural derivatives (Lence, 1996; Mattos, Garcia, and Nelson, 2008), an analysis of cumulative derivatives provides a focus that may be highly relevant for potential hedgers.

Derivative Pricing and Structure

In the initial analysis, all derivatives are priced using burn analysis (BA). BA is the simplest method for pricing weather derivatives, and is based on calculating what the contract would have paid out based on the observed historical distribution. The assumptions of BA are that the historical terminal index time series are stationary, statistically consistent with the prevailing climate (i.e., the historical distribution of weather accurately reflects the true underlying distribution), and that the values are independent across years (Jewson and Brix, 2005). Its use is supported by preliminary regressions of the weather indexes on a linear trend which suggested no significant trending patterns. Similarly, constant index variances indicate BA should produce unbiased estimates relative to alternative pricing procedures when used in the context here. Finally, BA is attractive because it does not require strong assumptions about the distribution of the underlying index, and it is straightforward to compute.[1]

Evidence suggests that the relationship between yields and weather variables is nonlinear (Vedenov and Barnett, 2004) and possibly quadratic (Woodard and Garcia, 2008). Accordingly, we examine hedging using call (put) option contracts for temperature (precipitation) which have been shown to be an effective risk management tool in similar situations (Manfredo and Richards, 2005).

The payoff, p, from a long call option is given by

$$p_t(I_t, K) = \max\left[0, D(I_t - K)\right],$$

and the profit, π, is given by

$$\pi_t(I_t, K) = \max\left[0, D(I_t - K)\right] - e^{r[(R-S)/360]} PREM_S(K),$$

[1] Sensitivity analysis using different pricing methods had only minor effects on prices and on hedging utility.

where t is the year index, I is the weather index value in year t, D is the tick value measured in \$/I, K is the strike price, r is the risk-free rate, *PREM* is the option price, or premium, and R and S are the dates of initiation and expiration of the option. The premium is compounded forward at the risk-free rate in order to account for opportunity costs of initiating the option position.

Pricing entails simply determining the fair premium or fair price, defined as the price where expected profit on the derivative is zero. The fair price is set equal to the discounted expected payoff of the contract for any given K. Formally, on any day S before expiration of the contract, the premium equals

$$PREM_S = e^{-r[(R-S)/360]}E_S(p),$$

where $E_S(\cdot)$ denotes the expectation on day S. Thus, pricing using BA simply consists of calculating the mean of the historical payoffs, p, given a strike, K. Put options are employed for precipitation hedges to protect against drought conditions and are expressed similarly.

Hedging Framework

Consistent with previous research, we concentrate on hedging quantity risk by assuming all price risk is hedged using price derivatives (e.g., Vedenov and Barnett, 2004; Woodard and Garcia, 2008). Since Hayes, Lence, and Mason (2003) conclude that most crop reinsurance risk stems from quantity risk (see also, Mason, Hayes, and Lence, 2003), this focus seems justified. Next, the hedging objective function is presented and the optimization procedure is described. The risk measures used to evaluate hedging effectiveness are also discussed.

Objective Function

The hedge ratio and option strike are estimated by minimizing the semivariance (SV) of a portfolio consisting of a detrended yield exposure and a weather derivative using a historical simulation (Vedenov and Barnett, 2004). SV only measures deviations below the mean, and thus is a measure of downside risk. The weight, or hedge ratio (contracts/\$ acre), h, and strike price, K, are chosen by minimizing SV:

$$(6)\quad \min_{h,K}\left[SV(R_t, \overline{Y})\right] = \min_{h,K}\left[\sum_t \left(\max\left\{\overline{Y} - R_t, 0\right\}\right)^2 * \frac{1}{T}\right],$$

where $R_t = Y_t^{det} + h\pi_t(K)$ is the value of the hedged portfolio, Y_t^{det} is detrended yields in bu./acre, $\overline{Y}$ is the long-run average detrended yield, T is the sample size, and $\pi_t(K)$ is the profit from a fairly priced option with strike price K which pays \$1 per unit of the weather index. The value of the hedge ratio h is set equal to zero for the unhedged portfolio. Optimal portfolios are estimated using a grid search over h and K for the hedges and basis risk considered—*local*, *geo*, or *prod*.

The tick on the weather option is normalized to \$1 per unit of the weather index for simplicity. This choice is arbitrary, and in practice could simply be rescaled to account for the tick of the particular contract. The hedge ratio h is expressed as the number of option contracts purchased per hedged acre.

Risk Measures

The criterion used to evaluate basis risk is the root mean squared loss (RMSL). RMSL is a simple function of SV,

$$RMSL_{k,l} = \sqrt{\sigma^2_{k,l^-}},$$

where σ^2_{k,l^-} is the SV from equation (6). In terms of equations (1), (2), and (3), this is equivalent to substituting RMSL for $f(\cdot)$.

In addition to expected net losses, agents also may be interested in the magnitude of losses given an extreme disaster event occurs. Hence, expected shortfall (ES) is also reported (Dowd and Blake, 2006).

ES is the probability weighted average of the worst α revenues. In the case of a discrete distribution, ES is given by:

$$ES_\alpha = \frac{1}{\alpha}\sum_{p\,0}^{\alpha} (p\text{th worst outcome})$$
$$\times\ (\text{probability of } p\text{th worst outcome}),$$

and is reported for $\alpha \approx 6\%$.[2] The ES measure used here is based on the return distribution, and is thus a modification of the measure reported in Dowd and Blake (2006) which is calculated in terms of the loss distribution. ES can be interpreted as an expectation of yields in the case that an extreme disaster event *does* occur, and therefore is a preference-free measure of tail-risk, approximating the expected value in the tail only. ES also can be interpreted as the utility of tail-risk for an agent with risk-neutral tail-risk preferences.

The ES measure is used rather than the value-at-risk (VaR)—which provides an estimate of the worst loss one might expect given an extreme disaster event does not occur—because the ES is subadditive, making it less likely to produce puzzling and inconsistent findings in hedging applications. As Dowd and Blake (2006) point out, subadditivity "reflects our expectation that aggregating individual risks should not increase overall risk, and this is a basic requirement of any 'respectable' risk measure, coherent or otherwise" (p. 198).

With regard to basis risk, a decrease (increase) in the RMSL corresponds to a reduction (increase) in risk as a result of using a weather derivative. In contrast, an increase (decrease) in the ES indicates a reduction (increase) in risk exposure from adding a weather derivative.

[2] Since the ES measurements are calculated using a historical simulation where each observation is assigned an equal probability of $1/T$ ($T = 35$), ES 6% approximately equals the average of the two lowest valued observations.

Table 1. Selected Weather Stations in Illinois Crop Reporting Districts, 1971–2005

District	City	County
D10 Northwest	Dixon	Lee
D20 Northeast	Ottawa	LaSalle
D30 West	LaHarpe	Hancock
D40 Central	Bloomington	McLean
D50 East	Hoopeston	Vermillion
D60 West Southwest	Whitehall	Greene
D70 East Southeast	Olney	Richland
D80 Southwest	Sparta	Randolph
D90 Southeast	Harrisburg	Saline

Data

The corn yield data are for the nine Illinois Crop Reporting Districts (CRDs) for 1971–2005. Temperature and precipitation data were collected for a location within each CRD as well as for nearby major cities, including Kansas City, Chicago, Minneapolis, Des Moines, Cincinnati, and St. Louis. An attempt was made to select the most centralized location in each district (Table 1). Yield data are obtained from the USDA's National Agricultural Statistics Service (2007) website, and weather data from the United States Historical Climatology Network website (Williams et al., 2006) and the National Climatic Data Center (National Oceanic and Atmospheric Administration, 2007). State-level (i.e., aggregated) yield and weather index measures are calculated as a simple average of the individual district yields and weather indexes.[3]

Results and Discussion

Figure 1 presents average temperature and precipitation for each of the nine CRDs during the 1971–2005 study period. In general, the climate in northwest Illinois is relatively cool and wet, while the southeast tends to be hotter and drier.

[3] Use of a production-weighted average did not materially change the findings.

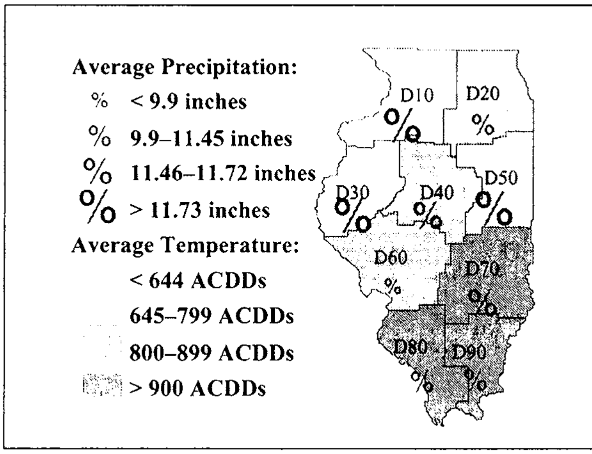

Figure 1. Average Summer Precipitation and Accumulated Cooling Degree Days at Selected Weather Stations in Illinois Crop Reporting Districts, 1971–2005

On average, the temperature and precipitation at each location are negatively correlated across years. For the entire sample, the average correlation between cumulative precipitation (CP) and accumulated cooling degree days (ACDDs) was -0.27. This negative correlation is even stronger during drought events. For example, during the 15 hottest years in the sample, as measured by the average of the ACDDs for the local stations, the correlation between average CP and ACDDs was strongly negative (-0.57, $p < 0.05$). In contrast, during the 15 coldest years, the correlation did not differ from zero significantly (-0.16, $p < 0.28$).

This finding suggests that payoffs from ACDD calls and CP puts may be highly congruent during events likely to result in large crop losses. For instance, the four driest years in the sample—1983, 1984, 1988, and 1991—were also among the hottest years. During these years the average CP was 6.75 and average annual ACDDs were 1,061.21 for the state. These values approximately corresponded to the 7th and 93rd percentiles of CP and ACDD measurements, respectively. Thus, while ACDD and CP derivatives are not perfect substitutes, because temperature and precipitation are highly negatively correlated in Illinois (particularly in drought events), they may act as substitutes when protection is needed most.

Unhedged Exposures

Table 2 presents results for the unhedged yield exposures for Illinois CRDs for the period 1971–2005. Average yield, RMSL, and ES 6% are reported for each district as well as for the state-level, or aggregated, exposure.

Table 2. Corn Yields and Unhedged Risk in Illinois Crop Reporting Districts (bu./acre), 1971–2005

District	Average Yield	RMSL	ES 6%
D10 Northwest	156.52	14.02	110.60
D20 Northeast	149.81	14.01	104.08
D30 West	158.22	16.00	107.20
D40 Central	162.82	16.28	108.61
D50 East	153.30	18.14	94.19
D60 West Southwest	160.83	13.52	114.89
D70 East Southeast	143.87	14.25	102.32
D80 Southwest	126.68	12.79	88.03
D90 Southeast	126.39	13.84	82.86
Average of Districts	148.72	14.76	101.42
State Level	148.72	12.84	106.64

Note: Risk is measured as RMSL, the root mean squared loss in a semivariance context, and ES, the expected shortfall, the expected yields in extreme crop disasters.

Table 3. Changes in Local and Product Basis Risk Using RMSL and ES Measures for Cumulative Precipitation (CP) and Accumulated Cooling Degree Days (ACDDs) Hedges at Selected Illinois Sites, 1971–2005

	[1] D10 Northwest		[2] D40 Central		[3] D80 Southwest		[4] Average of Districts		[5] State Level (aggregate)	
Description	CP	ACDD	CP	ACDD	CP	ACDD	CP	ACDD	CP	ACDD
Hedge Ratio	22.40	0.48	12.40	0.20	4.60	0.14	10.44	0.21	6.00	0.20
Optimal Strike	6.20	820.00	8.60	910.00	12.80	1230.00	10.33	874.44	13.00	940.00
Average	156.52	156.52	162.82	162.82	126.68	126.68	148.72	148.72	148.72	148.72
RMSL	9.95	9.32	12.63	8.72	9.94	10.74	11.20	10.38	9.85	7.50
% Reduction RMSL	29.05%	33.52%	22.43%	46.45%	22.27%	16.01%	23.90%	28.95%	23.34%	41.56%
ES 6%	127.76	130.07	126.67	139.06	98.33	92.17	117.99	118.05	123.52	127.81
% Change ES 6%	15.52%	17.61%	16.63%	28.04%	11.70%	4.70%	16.34%	16.40%	15.82%	19.85%

In Table 2 the "average of districts" row is an average of the district-level statistics, and provides a basis of comparison for the state-level exposure. Yields varied across the individual districts. D40 was the most productive with an average yield of 162.82 bu./acre, while D90 was the least productive with 126.39 bu./acre. The RMSL also varied, from 18.14 (D50) to 12.79 (D80). The state-level RMSL was 12.84 compared to 14.76 for the average of districts, revealing that the individual yields are not perfectly correlated, and suggesting that some of the risk in the individual districts is "self-diversified" with aggregation. The ES measures generally followed the RMSL pattern, but perhaps are easier to interpret. For example, at the state level, the expectations of yields given an extreme disaster event occurs are 106.64 bu./acre for ES 6%.

Local and Product Basis Risk

Local basis risk [equation (1)] is defined as the hedging effectiveness of a locally written derivative. Results for the average of the districts as well as the state level for a hedged portfolio with a local precipitation (CP) and degree day (ACDD) derivative are presented in Table 3. Three representative individual district-level results are also reported (D10, D40, and D80). The "state-level" (aggregate) results are based on hedging results obtained by constructing ACDD and CP indexes which are averages of the local weather indexes, while the "average of districts" results are averages of the district-level statistics.

Local basis risk is measured as the percentage change in the risk measure (RMSL, ES 6%) between the hedged and unhedged exposures (Table 2). For instance, in D10, the downside risk (RMSL) was 14.02 for the unhedged exposure which declined to 9.32 when hedged using ACDD. The percentage reduction in risk (% reduction in RMSL) was 33.52%. Similarly, in D10, the expected yields in the tail increased from 110.60 bu./acre (ES 6%) for the unhedged exposure to 130.07 bu./acre when hedged using ACDD—a 17.61% (% change in ES 6%) increase.

Hedging effectiveness varied greatly for local ACDD derivatives, which is consistent with variation in hedging effectiveness obtained by Woodard and Garcia (2008) using a different sample period. Percentage reductions in the downside risk measured by RMSL ranged from 16.01% (D80) to 46.45% (D40) for the individual districts. The state-level, or aggregate, hedged RMSL (% reduction in RMSL) was 7.50 bu./acre (41.56%), compared to 10.38 bu./acre (28.95%) for the average of the hedged individual districts. Thus, relative hedging effectiveness of local ACDD derivatives at the aggregated level was about 30%, which is better than

Table 4. Changes in Geographic and Product Basis Risk Using RMSL for Cumulative Precipitation (CP) and Accumulated Cooling Degree Days (ACDDs) Hedges in Selected Sites, 1971–2005

	[1]	[2] Local		[3] Kansas City		[4] Chicago		[5] Minneapolis	
Description	**Unhedged**	**CP**	**ACDD**	**CP**	**ACDD**	**CP**	**ACDD**	**CP**	**ACDD**
Panel A. State Level:									
‣ RMSL	12.84	9.85	7.50	9.28	9.10	11.83	8.59	11.23	8.17
‣ % Reduction RMSL	—	23.34	41.56	27.71	29.14	7.85	33.09	12.53	36.40
‣ Geographic Basis Risk (RMSL)	—	—	—	-0.56	1.59	1.99	1.09	1.39	0.66
‣ % Geographic Basis Risk (RMSL)	—	—	—	-4.37	12.42	15.48	8.47	10.80	5.17
Panel B. D20 Northeast:									
‣ RMSL	14.01	10.82	11.09	10.04	11.38	10.80	10.63	12.34	11.45
‣ % Reduction RMSL	—	22.77	20.86	28.36	18.82	22.92	24.12	11.92	18.32
‣ Geographic Basis Risk (RMSL)	—	—	—	-0.78	0.29	-0.02	-0.46	1.52	0.36
‣ % Geographic Basis Risk (RMSL)	—	—	—	-5.58	2.04	-0.15	-3.26	10.86	2.54
Panel C. D50 East:									
‣ RMSL	18.14	12.72	10.60	13.19	13.04	15.13	13.20	16.00	13.41
‣ % Reduction RMSL	—	29.86	41.16	27.28	28.10	16.56	27.20	11.78	26.07
‣ Geographic Basis Risk (RMSL)	—	—	—	0.47	2.44	2.41	2.61	3.28	2.81
‣ % Geographic Basis Risk (RMSL)	—	—	—	2.58	13.46	13.31	14.37	18.09	15.49
Panel D. Avg. of Districts:									
‣ RMSL	14.76	11.20	10.38	11.03	11.03	13.52	10.92	13.21	10.44
‣ % Reduction RMSL	—	23.90	28.95	25.36	25.14	8.22	25.80	10.27	29.24
‣ Geographic Basis Risk (RMSL)	—	—	—	-0.17	0.65	2.31	0.54	2.00	0.06
‣ % Geographic Basis Risk (RMSL)	—	—	—	-1.46	3.81	15.68	3.15	13.63	-0.29

(table extended ‣)

would have been identified by considering a simple average of the individual districts, suggesting a benefit to aggregation.

Analysis of the ES statistics identified similar results. The ES 6% for the aggregated portfolio hedged with ACDD derivatives was 127.81 compared to 118.05 for the average of the district portfolios, and the increase in ES 6% over the unhedged portfolio was 19.85% at the state level compared to 16.40% for the average of the districts.

At the disaggregate level, the hedging effectiveness of CP compared to ACDD derivatives varied, but local basis risk for CP derivatives was higher on average. For instance, the average reduction in RMSL for the individual districts when hedging with ACDD derivatives was 28.95% compared to 23.90% for CP contracts. For local contracts, additional product basis risk is imposed on average by using CP rather than ACDDs.

The added risk from using CP derivatives rather than ACDDs was even more pronounced at higher levels of spatial aggregation. At the state level, the reduction in RMSL for CP derivatives (23.34%) was much lower than for ACDD

Table 4. Extended

	[6] Des Moines		[7] Cincinnati		[8] St. Louis		[9] Avg. of Cities		[10] All Cities	
Description	**CP**	**ACDD**	**CP**	**ACDD**	**CP**	**ACDD**	**CP**	**ACDD**	**CP**	**ACDD**
PANEL A. State Level:										
▸ RMSL	11.70	8.17	11.96	8.39	11.15	7.22	11.19	8.27	9.10	7.07
▸ % Reduction RMSL	8.92	36.40	6.90	34.71	13.18	43.79	12.85	35.59	29.10	44.94
▸ Geographic Basis Risk (RMSL)	1.85	0.66	2.11	0.88	1.30	-0.29	1.35	0.77	-0.74	0.43
▸ % Geographic Basis Risk (RMSL)	14.42	5.17	16.43	6.86	10.16	2.23	10.49	5.97	5.77	-3.38
PANEL B. D20 Northeast:										
▸ RMSL	11.53	11.45	12.98	9.15	12.38	9.57	11.68	10.60	9.16	10.00
▸ % Reduction RMSL	17.75	18.32	7.40	34.71	11.68	31.71	16.67	24.33	34.64	28.62
▸ Geographic Basis Risk (RMSL)	0.70	0.36	2.15	1.94	1.56	-1.52	0.86	0.49	-1.66	1.09
▸ % Geographic Basis Risk (RMSL)	5.02	2.54	15.38	13.85	11.10	10.85	6.10	3.47	11.87	7.76
PANEL C. D50 East:										
▸ RMSL	16.78	13.41	17.46	12.66	15.78	10.47	15.73	12.70	11.32	11.20
▸ % Reduction RMSL	7.49	26.07	3.71	30.21	13.01	42.28	13.30	29.99	37.58	38.25
▸ Geographic Basis Risk (RMSL)	4.06	2.81	4.74	2.06	3.06	-0.13	3.00	2.10	-1.40	0.60
▸ % Geographic Basis Risk (RMSL)	22.38	15.49	26.15	11.35	16.86	-0.72	16.56	11.57	7.72	3.32
PANEL D. Avg. of Districts:										
▸ RMSL	13.64	10.44	13.67	10.51	13.42	9.77	13.08	10.52	11.12	9.47
▸ % Reduction RMSL	7.73	29.24	7.78	28.80	9.06	33.60	11.40	28.64	24.16	35.59
▸ Geographic Basis Risk (RMSL)	2.44	0.06	2.46	0.13	2.21	0.61	1.88	0.14	-0.08	0.91
▸ % Geographic Basis Risk (RMSL)	16.17	-0.29	16.12	0.15	14.84	-4.65	12.50	0.31	-0.26	6.64

derivatives (41.56%). Importantly, the spatial aggregation effect was not present for CP contracts as the reduction in RMSL for the average of districts (23.90%) was very similar to that obtained for the state-level portfolio (23.34%).

Similar results were obtained for the ES measure regarding product basis risk for CP and ACDD derivatives. Changes in the ES measure were always greater for ACDD derivatives compared to CP derivatives. In fact, the change in ES 6% for CP derivatives was actually greater on average at the district level (16.34%) than at the state level (15.82%). Overall, the difference in findings between CP and ACDD derivatives is consistent with the notion that the share of idiosyncratic risk relative to systemic risk for CP is much higher than for ACDD in an aggregated portfolio. Higher degrees of idiosyncratic risk for precipitation measurements result in CP contracts having higher basis risk than ACDD contracts.

Geographic and Product Basis Risk

The results for geographic basis risk for RMSL and ES are reported in Tables 4 and 5. Geographic basis risk is measured between local and non-local (i.e., city)

Table 5. Changes in Geographic and Product Basis Risk Using ES for Cumulative Precipitation (CP) and Accumulated Cooling Degree Days (ACDDs) Hedges in Selected Sites, 1971–2005

	[1]	[2] Local		[3] Average of Cities		[4] All Cities	
Description	**Unhedged**	**CP**	**ACDD**	**CP**	**ACDD**	**CP**	**ACDD**
PANEL A. State Level:							
▸ ES 6%	106.64	123.52	127.81	115.03	126.23	123.97	127.98
▸ % Change ES 6%	—	15.82	19.85	7.86	18.36	16.25	20.01
▸ % Geographic Basis Risk (ES 6%)	—	—	—	7.96	1.49	-0.42	-0.16
PANEL B. Average of Districts:							
▸ ES 6%	101.42	117.99	118.05	109.36	118.47	116.98	120.01
▸ % Change ES 6%	—	16.34	16.40	7.83	16.81	15.34	18.33
▸ % Geographic Basis Risk (ES 6%)	—	—	—	8.51	-0.42	1.00	-1.94

based derivatives [equation (2)]. Positive values of geographic basis risk in Tables 4 and 5 indicate that hedging with city as opposed to local contracts introduces extra basis risk. Negative values of geographic basis risk show that the city derivatives are more effective hedging instruments.

In Table 4, panel A refers to the state-level analysis, and panel D presents results for the average of the districts. Panels B and C provide results for two representative districts, D20 and D50. The columns indicate the location for the derivative. Column 1 reports the unhedged exposure, column 2 presents hedged exposure based on a derivative written on local weather, and the remaining columns give the hedging results when city derivatives are used for hedging. Column 9 ("average of cities") is a simple average of the individual city hedging results, and can be viewed as indicative of a "typical city." Finally, column 10 ("all cities") displays hedging results where the derivatives are constructed using an average of weather indexes for the cities.

In effect, these results reflect the potential benefits of diversifying risk by using an equally weighted portfolio (or basket) of the individual city derivatives. All of the cities selected have exchange-traded ACDD contracts on the CME except St. Louis. Table 5 is structured similarly to Table 4, except the representative districts and the individual hedging instruments (i.e., contracts for each city) are excluded for brevity.

First, consider the state-level findings for ACDD derivatives in Table 4. Here "local" reflects a derivative written on an equally weighted index of all local CRD indexes (Table 3). ACDD derivative performance varied but provided reasonable hedges in all cases. Reductions in RMSL when hedging with city derivatives ranged from 29.14% for Kansas City to 43.79% for St. Louis. On average, the reduction in RMSL was 35.59% when hedging with a single city contract, compared to 41.56% when hedging with a derivative derived from an equally weighted index of the local CRD indexes. In terms of RMSL, geographic basis risk increased by 5.97% when hedging with a typical city. Interestingly, a derivative written on the average of all city indexes ("all cities") performed *better* than a derivative on an index of the average of the local CRD indexes; the percentage reduction in RMSL was 44.94% when hedging the state-level exposure with a derivative from the average of the city indexes, compared to 41.56% when hedging the state-level exposure with a derivative on an average of the local indexes.

Relative hedging effectiveness was about 8% better when hedging with a city derivative rather than a local derivative.

This result was somewhat unexpected, and is likely due to the aggregation of systemic weather risk factors. Aggregating hedging instruments across a large geographic area results in a hedging portfolio with a very large systemic relative to idiosyncratic component. Since the cities are spread over a larger geographic area than are the local weather stations, the degree to which the idiosyncratic components self-diversify is likely greater for the "all cities" index.

The findings for the CP derivatives at the state level are somewhat similar, but on average ACDD contracts perform better. The aggregation effect—i.e., *aggregating the hedging instruments* into one portfolio—was very strong when hedging with an index of all cities. The reduction in RMSL at the state level when hedging with an average (or typical) individual city contract was 12.85%, whereas it was 29.10% when hedging with a portfolio of all cities. Again, this is likely due to the idiosyncratic components of the derivative returns at the local level which are difficult to associate with production. City contracts, spread over larger areas, must be able to more effectively reflect the systemic component of production shortfalls.

Analysis of the district results (Table 4, panels B, C, and D) leads to similar findings regarding geographic basis risk and the effect of aggregating across city contracts. Despite the presence of smaller exposures, geographic basis risk from hedging with city contracts was generally small, and the hedging effectiveness of an equally weighted portfolio (or basket) of city contracts was more effective than with local contracts. These findings on the effects of spatial aggregation are consistent with the state-level and average-of-districts results found earlier in Table 3, and suggest the degree of geographic basis risk is not prohibitive.

As observed in Table 5, the ES results were consistent with the RMSL findings. The ACDD contracts performed better than CP contracts, and the use of aggregated portfolios of hedging instruments is more effective at eliminating geographic basis risk than are individual contracts. Again surprisingly, the ES results indicate that the geographic basis risk from hedging a state-level exposure or an average of the districts with an equally weighted portfolio of city contracts actually resulted in *negative* basis risk.

Implications

As revealed by the results reported above, temperature-based derivatives generally perform better than precipitation contracts. These results also corroborate our own earlier research (Woodard and Garcia, 2008) which found that hedging effectiveness appears to be greater at higher levels of spatial aggregation, indicating the most likely users will be reinsurers and possibly large agribusiness firms. Further, the degree to which these hedges are effective is substantial. Specifically, the use of simple seasonal temperature derivatives can reduce downside risk of an aggregated exposure by about half, and can also decrease the severity of major shortfalls significantly.

For example, the reduction in RMSL when hedging a state-level exposure with an equally weighted portfolio of city ACDD options was 44.94% (Table 4). The expectation of yields in the worst 6% of cases for the state-level exposure (as evidenced by ES 6%) was 106.64 bu./acre for an unhedged exposure. Yield expectation increased more than 20%, to 127.98 bu./acre, when hedging with an all-cities ACDD option (Table 5). Strikingly, the findings also suggest that geographic basis risk may not be a large impediment to the implementation of weather hedges, and in fact that it may be *better* to hedge with a portfolio of city contracts than with local contracts in certain contexts.

Sensitivity Analysis

Much of the weather derivative literature has emphasized issues regarding how best to determine the fair price of a derivative and how to estimate its market price of risk. Little consideration has focused on the extent to which alternative pricing assumptions influence the attractiveness of weather hedges. Specifically, since weather is inherently nontradable, some have suggested it is not appropriate to discount the expected payoff of the option at the risk-free rate when determining the price. This means the market price of risk should be incorporated into the price of the derivative.

Studies by Richards, Manfredo, and Sanders (2004) and Cao and Wei (2004) both employ procedures which directly estimate the market price of risk using equilibrium models. The implication of a nonzero market price of risk is that the derivative will now have a risk premium, and the expected payoff from holding the option is no longer equal to zero.

In contrast, Turvey (2005) argues that the market price of risk should be zero when spatial aggregation provides an opportunity to develop a risk-free portfolio in a capital asset pricing model (CAPM) framework. While Turvey's argument is conceptually attractive, particularly in well-developed liquid markets, questions emerge about its applicability to more isolated agricultural locations where markets and information may be incomplete, and limited liquidity can create an opportunity for speculative gains.

In this context, we examine the impact of risk premium on the utility of weather derivative hedges. In the presence of liquidity risk and incomplete information, risk premiums are likely to be smaller in more liquid large-city markets. In addition, the market price of risk is likely to have an even smaller impact on exchange-traded products due to their lower credit and default risk as well as lower transaction and information costs. This view is consistent with Jewson and Brix's (2005) observation of the tradeoff between basis risk and price of the hedge.

This notion also appears to be supported by recent industry research indicating movement toward exchange-traded derivatives and away from OTC contracts (Roth, Ulardic, and Trueb, 2007). In the context of our study, this issue is of particular importance since the use of OTC contracts—which can be related to the local (CRD) contracts in our previous analysis—may entail higher costs in the form of risk premiums than exchange-traded products. Here, we perform sensitivity analysis to assess the possible effects of risk premiums on hedging effectiveness.

Utility and Hedging

Burn analysis (BA) was used to price the derivatives as in the previous analysis. BA assumes that the market price of risk is zero (i.e., the expected payoff is discounted at the risk-free rate to obtain the price) and the "true" ending distribution of the weather index is equivalent to the observed empirical distribution. Because BA assumes the derivative is fairly priced, there was no need to consider utility models earlier as the choice of hedging instrument did not affect the expected return, which was zero for all derivatives. However, if the derivatives being compared have different expected returns, then analyzing risk alone is insufficient and utility models are needed.

Recently, Deng et al. (2007) examined dairy hedging with weather derivatives using a mean-variance (MV) criterion. The MV uses the first two moments of the return distribution and allows for analysis of both risk and return. Following Deng et al., we examine weather derivatives by employing a similar framework but substitute semivariance for variance. The mean-semivariance (MSV) criterion may be a better approximation of utility when the investor values losses differently than gains and the return distribution is not symmetric (Markowitz, 1991). For crop losses, the MSV may be a more appropriate utility approximation because of the negative skew typical in crop yield distributions.

Here, we employ the MSV to assess the sensitivity of the main results to alternative pricing assumptions regarding the risk premium, using the following redefined objective function:

$$(7) \quad \max_{h,k}[MSV] = \max_{h,k}[E(R) - A * \sigma^{2-}],$$

where R and σ^{2-} are the portfolio return and semivariance from equation (6), and A is a risk-aversion coefficient. Identical to the earlier analysis, R represents either a hedged or unhedged portfolio and is assumed to follow the historical distribution.

The effect of the risk premium on utility is influenced by the change in option premium as risk changes and the degree of risk aversion, A. The option premium is estimated as the discounted value of the expected payoff of the option, where the risk premium is levied as a function of the expected payoff.

Here, a call option premium which includes the risk premium is represented by:

$$PREMLOADED_{S,\gamma} = \left(\gamma + e^{-r(R-S/360)}\right)\int_{-\infty}^{\infty} \max\left[D(I_t - K), 0\right] g_d(I)\, dI,$$

where $g_d(I)$ is the estimated probability distribution (the empirical distribution of the weather index I) at expiration, and γ is the risk premium. When $\gamma = 0$, *PREMLOADED* represents a fairly priced option. Specifying the risk premium in this manner makes it invariant to the number of days to expiration.

We investigate the implications of our pricing assumptions using the MSV criterion for differing levels of risk aversion. For brevity, we use only the case of hedging the state-level exposure with a call option derived from an equally weighted index of city ACDDs. The framework will likely produce overall conservative estimates of the detrimental effects of risk premiums on the utility of weather hedges since the hedging effectiveness was better for the portfolio of city contracts than for local contracts, and city weather markets which are likely to be more liquidly traded are likely to have smaller risk premiums than rural local markets.

Sensitivity Results

Choosing the appropriate level of A and γ can be somewhat problematic. Nelson and Escalante (2004) present empirical evidence that suggests parameter values for A within the range of [0.000004, 0.346574] may be reasonable for an MV specification, while Dillon and Scandizzo (1978), using survey data for risk-averse producers, estimate values in the range of [0, 0.06]. It is also difficult to assess what levels of γ may be appropriate, but Richards, Manfredo, and Sanders (2004) find that a fair option price can be distorted as much as 30% by a risk premium.

Table 6 presents results of the MSV analysis for the unhedged and hedged exposure for four different risk premiums, γ = 0%, 10%, 30%, and 50%, and three different levels of risk aversion, A = 0.01, 0.02, and 0.03.

Within the context of our framework, the implied tradeoff between RMSL and return for the MSV specification varies depending on the level of RMSL. For example, when RMSL = 15 bu./acre, then for A = 0.03 the agent is willing to give up 0.45 bu./acre in expected return to decrease RMSL by 1 bu./acre; at a level of A = 0.01 the agent is willing to give up 0.15 bu./acre in expected return to obtain a 1 bu./acre reduction in RMSL.

The results indicate that the presence of risk premiums can significantly alter the magnitude of the maximizing hedge ratio and can severely diminish its risk-reduction potential. As expected, the effects are most noticeable at lower levels of risk aversion, because at high levels of risk aversion the maximization problem in (6) simply reduces to minimization of semivariance.

For A = 0.01, the effects of a risk premium are substantial. For example, at γ = 50%, the hedge is no longer desirable, as the maximizing hedge is zero.

Table 6. Hedge Ratios and Their Effectiveness with Different Levels of Risk Premiums (γ) and Risk Aversion (A)

Description	Unhedged	γ = 0%	γ = 10%	γ = 30%	γ = 50%
PANEL A. A = 0.01:					
▸ Hedge Ratio	—	0.154	0.108	0.024	0.000
▸ Optimal Strike	—	940.000	940.000	940.000	940.000
▸ Average	148.715	148.715	148.252	148.406	148.715
▸ RMSL	12.842	7.068	7.704	11.447	12.842
▸ % Reduction RMSL	—	44.96%	40.01%	10.86%	0.00%
▸ ES 6%	106.643	127.817	125.727	112.053	106.643
▸ Mean Semivariance	147.066	148.216	147.659	147.095	147.066
PANEL B. A = 0.02:					
▸ Hedge Ratio	—	0.154	0.130	0.087	0.045
▸ Optimal Strike	—	940.000	940.000	940.000	940.000
▸ Average	148.715	148.715	148.160	147.600	147.755
▸ RMSL	12.842	7.068	7.237	8.413	10.324
▸ % Reduction RMSL	—	44.96%	43.65%	34.49%	19.61%
▸ ES 6%	106.643	127.817	127.505	123.225	116.328
▸ Mean Semivariance	145.417	147.716	147.112	146.185	145.623
PANEL C. A = 0.03:					
▸ Hedge Ratio	—	0.154	0.137	0.107	0.080
▸ Optimal Strike	—	940.000	940.000	940.000	940.000
▸ Average	148.715	148.715	148.128	147.334	147.011
▸ RMSL	12.842	7.068	7.144	7.721	8.697
▸ % Reduction RMSL	—	44.96%	44.37%	39.87%	32.27%
▸ ES 6%	106.643	127.817	127.948	124.755	122.011
▸ Mean Semivariance	143.768	147.217	146.597	145.545	144.742

At γ = 30%, the effects are still substantial; the optimal hedge ratio is only 0.024 compared to 0.154 when γ = 0%. Importantly, the effectiveness of the maximizing hedge is severely diminished at a 30% risk premium, where the reduction in RMSL is only 10.86% compared to 44.96% when there is no risk premium. Further, the increase in ES 6% relative to the unhedged exposure was only 5.41 bu./acre when γ = 30% compared to 21.17 bu./acre for the fairly priced option. The increase in ES 6% for the option premium including the risk premium was only 25.55% of that for the case without any risk premium.

The effects are diminished at low levels of γ and higher levels of A, but even at moderate levels of risk aversion and risk premiums, the effects are not trivial. For instance, at a moderate level of risk aversion, A = 0.02 and γ = 30%, the reduction in RMSL is only 76.71% of that implied by the case with no risk premium. Further, the increase in ES 6%, i.e., the expected yield in the worst 6% cases, in the presence of a risk premium is only 16.582 bu./acre compared to 21.174 bu./acre when there is no risk premium.

Overall, the results indicate that the presence of risk premiums can significantly erode the effectiveness of weather hedges. This implies the hedging effectiveness of the local contracts in less well-developed and illiquid markets can be highly overstated, further motivating the use of geographic cross-hedges which showed little geographic basis risk.

Summary and Concluding Comments

Basis risk is often cited as a primary concern for implementing weather hedges. Using Illinois yields and related weather data, we investigate several dimensions of weather basis risk in the U.S. corn market. Conventional wisdom is that geographic basis risk may be severe and will decrease hedging effectiveness. Yet, results here indicate this may not always be the case. For instance, when hedging is implemented using an equally weighted portfolio of derivatives which are highly spatially correlated, hedging effectiveness may be as good as, if not slightly better than, what can be obtained using locally derived contracts.

Overall, risk reduction, particularly for temperature derivatives, appears to be substantial and lends support to the notion that relatively simple contracts can be developed to obtain reasonable hedging effectiveness. The less attractive performance of precipitation derivatives is likely attributable to a difference in the degree of spatial correlation among the indexes; precipitation correlations decline quickly as distance increases and appear to be less representative of conditions that influence crop development.

Supporting results reported by Woodard and Garcia (2008), hedging appears to be more effective at greater levels of aggregation. However, here we also demonstrate that hedging effectiveness can be increased by using a basket of derivatives from diverse locations. Both findings support the notion that weather hedges are most likely to be used by reinsurers and large agribusinesses who can more easily gain from the benefits of this diversification.

Clearly, highly well-tailored weather hedges for small-level exposures are possible, but our sensitivity findings highlight the importance of developing relevant linkages to liquid markets to reduce possible adverse effects of risk premiums and high transaction costs in localized areas. Specifically, the presence of risk premiums can significantly erode the effectiveness of weather hedging. Since derivatives on illiquid rural weather stations are likely to have a higher risk premium than large-city markets, our findings further motivate the use of geographic cross-hedges.

The nature of weather derivatives and how they relate to crop risk is complex. Future work should place greater emphasis on the specification of the risks faced by likely end-users, on identification of instruments which may be of the greatest benefit to them, and on the role that liquidity may play in weather hedging. This can include investigation of the interaction between price and quantity hedging instruments, investigation of the interaction between different types of weather hedges (e.g., temperature and precipitation jointly), comparisons of different time-aggregated derivatives (e.g., seasonal and monthly), and the effects of differing transaction costs on the hedging attractiveness of various instruments. Future research may also consider incorporating more complex pricing models to investigate dynamic weather hedging situations.

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Weather-Based Instruments in the Context of Whole-Farm Risk Management

Ernst Berg and Bernhard Schmitz

Abstract

Recent and presumable future developments tend to increase the risks associated with farming activities. These include climate risks, which have always played an important role in farming. Weather-based instruments can be valuable tools to reduce the risk associated with unfavorable climatic events. However, a number of factors could limit the hedging effectiveness of these tools. These factors include basis risk, the impacts of remaining price uncertainty, and diversification effects. This paper addresses the influence of each of these factors. In the final section, an integrated approach for a comprehensive assessment of weather derivatives and other hedging instruments is proposed that is based on the concept of portfolio optimization.

Key words: downside risk, portfolio optimization, risk management, risk-value models, weather derivatives

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When the first weather derivatives appeared, i.e., the temperature-based heating and cooling degree-days contracts in the United States, agriculture was soon identified as a promising field of application, since production quantities as well as input requirements are heavily dependent on weather patterns. Since then, in a number of theoretical studies, the fundamentals have been laid out and several empirical analyses have indicated the potential of those new hedging instruments (cf. Turvey, 2001; Vedenov and Barnett, 2004; Berg et al., 2006; Turvey, Weersink, and Chiang, 2006; Musshoff, Hirschauer, and Odening, 2007; Woodard and Garcia, 2007a, b).

Yet, despite these promising results, applications are still rare (Roth, Ulardic, and Trueb, 2007). One reason for this is certainly that it always takes some time for new instruments to enter the market. However, there may be more impediments for a wider adoption—e.g., these tools provide financial compensation only for shortfalls of produced output or excessive input needs, respectively, while other risks, such as unpredictable price changes, remain unchanged. Furthermore, besides weather derivatives, farmers have other opportunities to influence the risk exposure of their firms. Among them are the choice of the production program as well as marketing activities, including contractual agreements and hedging with futures and options. Last but not least, farm programs like the direct payments under the European Common Agricultural Policy, which clearly influence the risk exposure of farms, may crowd out other risk management instruments.

In total, all available opportunities comprise a portfolio of activities which ultimately determines the extent of risk to which a farm operation is exposed.

Because of a multitude of interdependencies, assessing the relative value of each instrument requires the consideration of the entire set of possible actions. Treating an instrument separately is likely to lead to an overestimation of its potential use. Similar phenomena have been observed with respect to farmers' use of price hedging instruments, as discussed by Turvey and Baker (1990) and Collins (1997).

In our paper we address the above issues. At the outset, we provide a broad classification of the risk management instruments available to the farmer. Next, the major factors that influence the effectiveness of weather derivatives as hedging instruments are addressed. These include basis risk, the impacts of remaining price uncertainty, and diversification effects. With regard to these aspects, we document the actual state of the art and indicate possible future improvements. A leading argument throughout the paper is that each instrument must be assessed in the context of all other available options. In the final section, we therefore outline an approach that aims at assessing the value of weather derivatives and other hedging instruments comprehensively in the context of portfolio optimization.

Risk Management Instruments

Farmers have a wide variety of possibilities for influencing the risk associated with their operations. Following Hardaker et al. (2004, p. 268ff.) and Berg (2005, pp. 55–56), these can be broadly classified into on-farm risk management instruments and market-based or risk-sharing instruments (Figure 1). The former include all measures that seek to avoid or reduce the exposure to risks, such as precautionary actions to prevent accidents, fire outbreaks, or burglaries. Furthermore, strategies to control pests and diseases in plant and animal production belong to this category. Spreading the risk through the diversification of farming activities is based on the fact that the dispersion of the overall return can be reduced by selecting a portfolio of activities which have outcomes with low or negative correlations. Finally, building financial reserves aims at creating a risk-bearing potential that allows for compensating the effects of unfavorable events if necessary.

Risk-sharing instruments presuppose the existence of market partners. If risk pooling is possible, insurance contracts that certainly belong to the most popular risk management instruments may be the appropriate risk-sharing devices. In addition, risks can be shared with market partners by entering a contractual agreement. Popular examples include forward contracting of inputs and outputs as well as hedging with futures and options. Weather derivatives also belong to this group.

All of these instruments are interdependent in the sense that the effect of a certain measure on the overall risk exposure depends on the constellation of all other instruments. For instance, a broadly diversified production program limits the benefit of additional risk management instruments. In principle, this requires an integrated approach to risk management which considers the full set of risk management instruments simultaneously to ultimately arrive at an optimal mix of instruments.

Weather Derivatives versus Insurance Contracts

While standard insurance contracts confirm indemnity payments in the event of damage occurrence, weather derivatives base their payoffs on the value that an underlying index takes on. Thus, they are equivalent to regular insurance

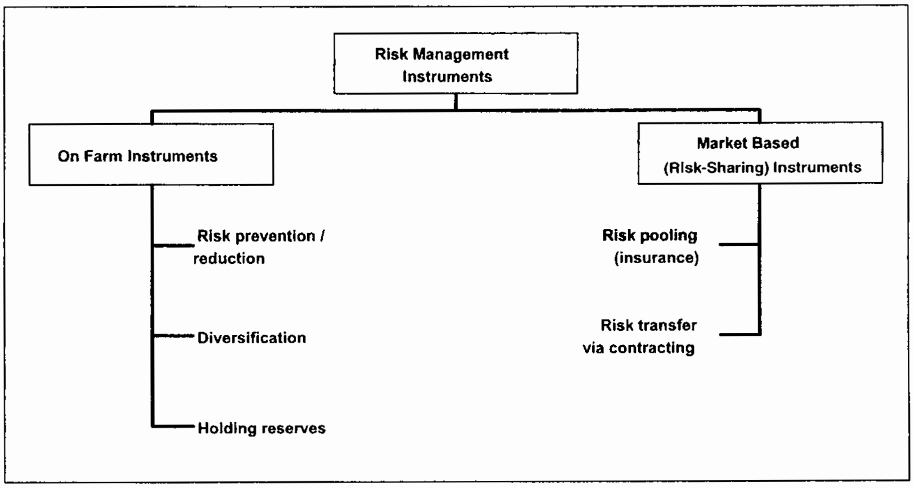

Figure 1. Risk Management Instruments

contracts only in the absence of any basis risk. A simplistic example demonstrates the impacts of this circumstance.

As increasing values of weather indices often improve yields only up to a certain limit, we restrict our discussion to option contracts. In the case of a long put option, the payoff is given by:

(1) $A = V \cdot \text{Max}[0, (K - x)]$,

where V denotes the tick size and K is the strike level. The fair premium P_f of the option equals the discounted expected value of the payoff, $E(A)$, i.e.:

(2) $$P_f = e^{-rh} E(A) = e^{-rh} VE\left(\text{Max}\left[0, (K - x)\right]\right),$$

where the factor e^{-rh} discounts the payment over the duration h using the interest rate r. The expected value of the Max function, $E(\text{Max}[\cdot])$, represents the weighted average of the payments that occur if the index falls above or below the strike level K, respectively.

Since no payment occurs at index values above K, we can write:

(3) $$E\left(\text{Max}\left[0, (K - x)\right]\right) = H(K) \cdot \left(K - E(x \mid x \le K)\right).$$

In equation (3), H marks the probability that x falls below K. If $h(x)$ represents the density function of the weather index, then $H(K)$ is given by:

(4) $$H(K) = \int_{-\infty}^{K} h(x)\, dx.$$

Since the main purpose of this section is to illustrate the impact of basis risk, which represents the fundamental difference between weather derivatives and individual yield insurance, we can simplify the analysis without loss of generality by assuming that the index x is normally distributed. In this case $H(K)$ becomes:

(5) $$H(K) = \Phi(z), \quad \text{with } z = \frac{K - E(x)}{\sigma},$$

where $\Phi(z)$ represents the standard normal distribution. We still must determine the expected value of x, given that x falls below K as represented by the term $E(x \mid x \le K)$. This is essentially the expected value of the distribution of x truncated above K. The expected value of the truncated normal distribution is written as:

(6) $$E(x \mid x < K) = E(x) + \sigma \frac{-\phi(z)}{\Phi(z)},$$

where $\Phi(\cdot)$ is the standard normal distribution and $\phi(\cdot)$ the respective density function (Hartung, 1998, p. 149).

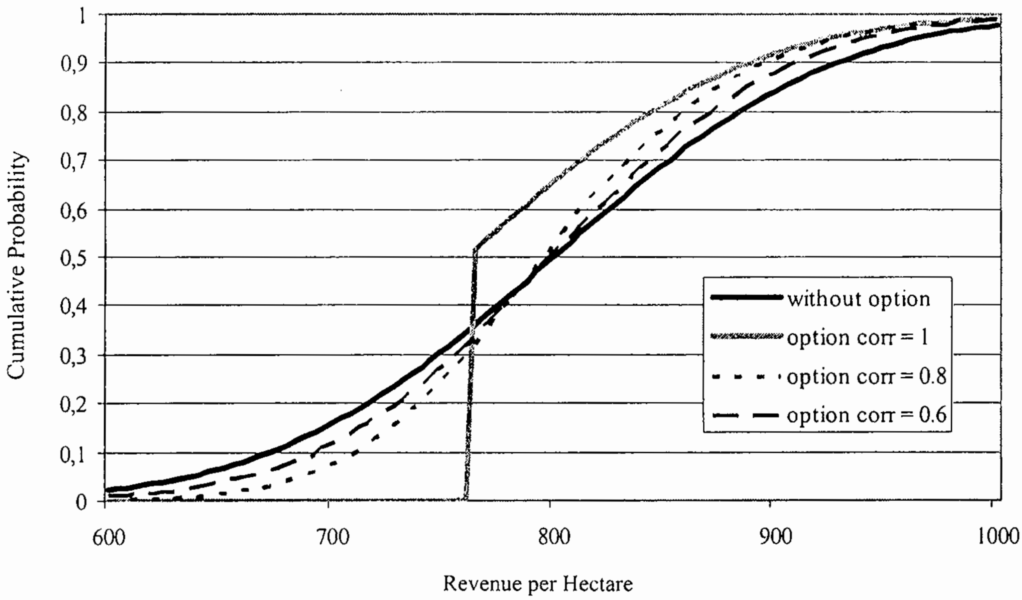

Figure 2. Impact of Basis Risk on the Effectiveness of Weather Derivatives

In what follows, we examine the effect the option has on the total net return per ha W_p, which comprises the market revenue plus the option payoff minus the fair premium P_f. It is therefore given by:

$$(7)\ W_p = yp_y + V \cdot \text{Max}\left[0, \left(E(x) - x\right)\right] - P_f.$$

In the above formula, y is the yield and p_y represents the product price. Now let y be the yield of wheat, which we assume to be normally distributed with a mean of 80 dt/ha and a standard deviation of 10 dt/ha. If the product price p_y is contractually fixed at 10 €/dt, with these assumptions, the distribution of the revenue corresponds to the solid black line in Figure 2 with an expected value of 800 €/ha and a standard deviation of 100 €/dt.

Let the weather index x represent the amount of rainfall during a certain period, and likewise be normally distributed with a mean of $E(x)$ = 100 mm and standard deviation of s = 125 mm. Setting the strike level at the expected value (i.e., K = 100), we derive the probability $H(100) = 0.5$ and the conditional expectation $E(x \mid x \leq K)$ = 90 mm. Thus, the average negative deviation of the index from K, according to equation (3), is 5 mm. Multiplying by a tick size V = 8 €/mm yields a fair premium of 40 €/ha.[1]

Assuming y and x are positively correlated random variables with the above characteristics, we can simulate the model of equation (7) stochastically. The simulation results are depicted in Figure 2. As can be seen from the graph, buying an option completely eliminates the downside risk if and only if we assume a perfect correlation between the yield and the weather index.

In this case, the weather derivative is equivalent to an insurance contract based on the individual yield. In turn, at correlations less than +1 (even though they may be close to one), very low revenues can no longer be excluded. Although the weather derivative always reduces the probability of low returns, it cannot secure a certain revenue because of the basis risk that is always present. This means that financial disasters caused by a local event,

[1] Since all payments are evaluated at harvest time, discounting is not necessary.

e.g., a hailstorm, flood, or even pest damage, are still possible although fairly unlikely. Weather derivatives can therefore reduce the variability of profits, but they cannot prevent the occurrence of the worst-case scenario as one would expect from an insurance contract. Likewise, they cannot replace other types of disaster assistance. Consequently, labeling them as index *insurances* may be somewhat misleading.

Limits to the Effectiveness of Weather Derivatives

The major factors that influence the effectiveness of weather derivatives as hedging instruments include basis risk, the impacts of remaining price uncertainty, and diversification effects. These are discussed in the following subsections.

Basis Risk

Basis risk, in general, refers to the phenomenon that the payoffs of a derivative do not perfectly correspond to the shortfalls of the underlying exposure. In the case of weather derivatives this may be caused either by an imperfect relationship between the weather index and the biological production process or by the fact that the index is monitored some distance away from the site where the crop is grown. The latter is normally referred to as geographical basis risk, while the former describes the local basis risk that remains even if monitoring takes place in close proximity to the production site.

The following case study is presented to illustrate the risk-reducing effect that weather derivatives can have if geographical basis risk is negligible. The empirical data stem from experiments with starch potatoes carried out by the Chamber of Agriculture of Hannover on its experimental fields at Bremervoerde, Germany. The weather data were recorded next to the production site.

Table 1. Correlation Coefficients Between Yield and Weather Variables (starch potato experiments, Bremervoerde, Germany)

Month	Cumulative Precipitation (mm)	Average Temperature (°C)
April	-0.30	-0.01
May	-0.17	0.11
June	0.57	-0.20
July	0.47	-0.57
August	0.35	-0.24
September	0.27	0.07
May–September	0.67	0.02

Source: Authors' calculations based on data from the Chamber of Agriculture, Hannover.

As observed from the correlation coefficients reported in Table 1, the yields of potatoes at this location exhibit a remarkable dependency on weather variables, particularly rainfall. While the accumulated rainfall between May and September is yield increasing, high temperatures during the summer obviously have a negative impact. Trying different accumulation periods, we found the highest correlation between the yield and the accumulated rainfall from May to September.

Figure 3 depicts the relation between yield and precipitation using detrended yield data of the years 1980 to 2002. According to the diagram, yield depression can be expected in years where the cumulative rainfall falls below around 340 mm; above this amount, yields remain largely constant. This relationship corresponds to a Leontief-type production function (cf. Berg, 1997) that grows linearly with increasing x, until x reaches the amount where the yield achieves its maximum. It can be represented by a linear limited function of the form:

$$(8)\quad y = \text{Min}\left[(a + bx), \hat{y}_{\max}\right] + e_B .$$

In the above equation, y marks the estimated yield and x the cumulated rainfall from May to September. The parameters a and b are the constant and the slope of the linearly increasing

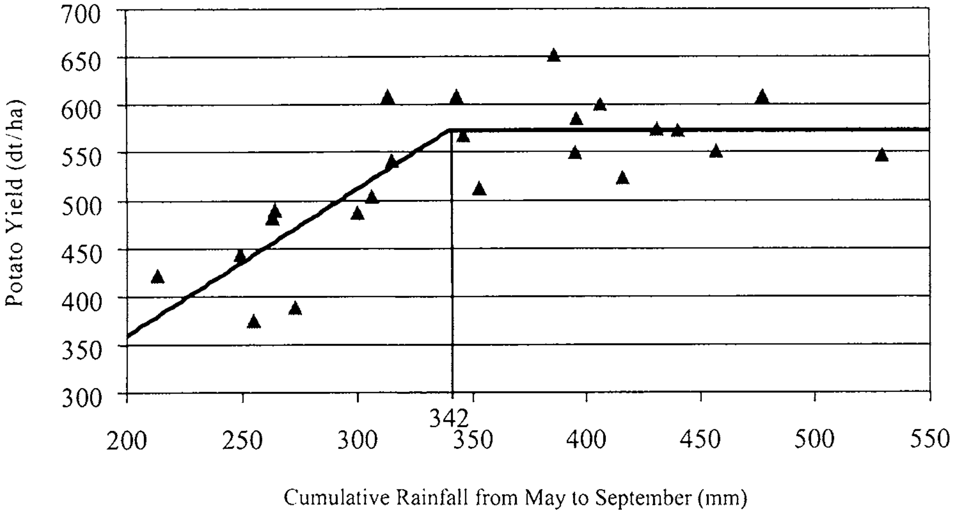

Figure 3. Yield Response to Rainfall (starch potato experiments, 1980–2002)

Table 2. Parameters of Yield Response Function and Rainfall Distribution

Yield Response Function				Rainfall May–September (mm)	
Parameter		Estimation Error (dt/ha)			
$\hat{y}_{max}$ (dt/ha)	573	Mean	0	Mean	353
a (dt/ha)	55.3	Standard Deviation	43	Standard Deviation	82
b (dt/ha/mm)	1.52	χ^2 [a]	1.28	χ^2 [a]	7.9
K (mm)	342	Degrees of Freedom	4	Degrees of Freedom	8

[a] Normality hypothesis is not rejected at a 5% error level.

function, respectively; $\hat{y}_{max}$ is the maximum yield caused by increasing amounts of rainfall; and e_B represents an error term that accounts for the estimation error. Using least squares estimation leads to the parameters given in Table 2.

The graph in Figure 3 clearly indicates that a put option with the payoff structure given in equation (1) is an appropriate tool to hedge against the risk of low rainfall. The strike level K corresponds to the amount of rainfall that just leads to the maximum expected yield ($\hat{y}_{max}$):

$$(9)\quad K = \frac{\hat{y}_{max} - a}{b}.$$

The optimal tick size V can be expressed by the slope b and the product price p_y:

$$(10)\quad V = bp_y.$$

Since starch potatoes are subject to market regulations and because of the fairly low quality requirements, the product price can be considered as almost deterministic. With these assumptions, the revenue without derivative (W_0) is given by:

$$(11)\quad W_0 = p_y y = p_y\left(\text{Min}\left[a + bx, \hat{y}_{max}\right] + e_B\right),$$

where the rainfall index x is a random variable. Thus, the variability of yield is determined by the variability of rainfall and the unexplained remaining variability e_B which then represents the basis risk. A chi-squared test of the residuals led to the conclusion that the normality hypothesis cannot be rejected at a 5% error level. Hence, we assume e_B to be normally distributed with zero mean and a standard deviation of 43 dt/ha, as derived from the data.

The total revenue with the put option (W_p) is composed of the market return as given in (11), plus the option payoff according to (1):

$$W_p = p_y\left(\text{Min}\left[a + bx, \hat{y}_{\max}\right] + e_B\right) + V \cdot \text{Max}\left[0, (K - x)\right] - P_f.$$

Using the relations given by (9) and (10) and rearranging the terms finally yields equation (12):

$$\begin{aligned}(12)\quad W_p &= p_y\left(\text{Min}\left[a + bx, \hat{y}_{\max}\right] + e_B\right) + p_y b \cdot \text{Max}\left[0, (K - x)\right] - P_f \\ &= p_y\left(\hat{y}_{\max} + \text{Min}\left[a + bx - (a + bK), 0\right] + e_B + \text{Max}\left[0, b(K - x)\right]\right) - P_f \\ &= p_y\left(\hat{y}_{\max} + \text{Min}\left[b(x - K), 0\right] + e_B - \text{Min}\left[0, b(x - K)\right]\right) - P_f \\ &= p_y\left(\hat{y}_{\max} + e_B\right) - P_f.\end{aligned}$$

As can be seen from equation (12), the total revenue with the put option is no longer dependent on the rainfall index itself but only on the basis risk.

To compute the fair premium, we need to analyze the historical rainfall data. The comparison of the empirical frequencies of the rainfall index from 1980 to 2002 with a normal distribution led to the conclusion that the normality hypothesis cannot be rejected at a 5% error level. Thus, the approach of equations (3)–(6) can be used to derive the fair premium. With the distributional parameters given in Table 2, an interest rate of 5% p.a., and a duration of five months, the resulting fair premium amounts to 273 €/ha.

Figure 4 depicts the simulation results with and without the weather derivative.[2]

The graph indicates that buying the option significantly reduces the risk of experiencing low returns. The standard deviation is almost cut by half, and the 5% and 10% percentiles are notably shifted upward. The derivative turns the originally negatively skewed distribution into a symmetrical one, indicating that the downside risk is effectively reduced.

These results show that in the absence of geographical basis risk, even a simple option contract would lead to a significant mitigation of production risk. The remaining local basis risk could still be further reduced by using a portfolio of hedging instruments composed of a set of options based on different indexes. In our case, the correlations given in Table 1 would call for the construction of additional put options based on the monthly precipitation, and call options based on the monthly temperature averages from June to August. Since the tick size V corresponds to the number of contracts with normalized payoffs, finding the best mixture then becomes a problem of portfolio selection.

The effect of the option would be less evident if the correlation was lower. The relatively high correlation in the present case is certainly due to the fact that the weather station is located adjacent to the experimental field. While for temperature the geographical basis risk is less important (cf. Berg, Schmitz, and Starp, 2006), in the case of rainfall it is undoubtedly significant. Musshoff, Odening, and Xu (2005) have investigated the impact of geographical basis risk of rainfall for the state of Brandenburg using an empirically estimated decorrelation function. Their simulation results indicate that the risk reduction of a rainfall option—defined by the upward shift of the 5% percentile—drops by roughly 45% if the index is measured using a distance of 25 km, and by almost 70% if the distance increases to 100 km.

Even geographical basis risk could probably be reduced substantially by utilizing the information of several surrounding weather

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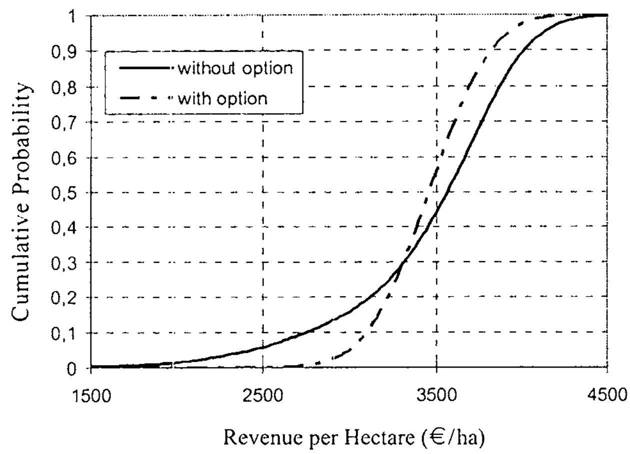
[2] The results are based on 10,000 random simulation runs.



	Without Option	With Option
Mean	3,483 €	3,480 €
Standard Deviation	519 €	278 €
5% Percentile	2,457 €	3,023 €
10% Percentile	2,766 €	3,124 €
90% Percentile	4,026 €	3,838 €
95% Percentile	4,139 €	3,935 €
Skewness	-1.14	0.00

Figure 4. Simulation Results for the Potato Example, with and without the Weather Derivative

stations instead of only the nearest one. This would involve employing (statistical) climate models to provide site-specific estimates based on the measurements from different stations. These could then be used to design structured contracts (or a set of standardized ones) based on several, spatially distributed weather indexes. As the results of the above case study indicate, further research on this topic appears to be very promising.

In summary, one can state that basis risk—although certainly important—could be kept within acceptable boundaries. This, however, requires the consideration of a portfolio of derivatives based on different underlyings rather than dealing with single instruments. Determining the structure of this portfolio involves solving an optimization problem which considerably increases the complexity of the task.

Remaining Price Risk

While weather derivatives aim at reducing the risk associated with the uncertainty of yields, the price risk still remains with the farmer. Even if certain quantities are forward contracted at a fixed price, a remaining risk can be caused by the fact that in case of low yields the producer is urged to purchase the shortfall quantity at uncertain market prices.

To analyze the impacts of price uncertainty, we start looking at the difference in the variance of returns. In the case of a deterministic price, the variance of revenues with the weather derivative can be derived from equation (12) as:

$$(13)\quad \mathrm{Var}(W_p) = p_y^2 \mathrm{Var}(e_B),$$

where Var(·) denotes the variance operator. Now let us assume that the product price p_y is a normally distributed random variable. Note, in this case for a product of random variables, i.e., $z = x \cdot y$, the variance of z can be computed according to the following formula (Bohrnstedt and Goldberger, 1969, p. 1439):

$$\begin{aligned}\mathrm{Var}(z) = {} & E(x)^2\mathrm{Var}(y) + E(y)^2\mathrm{Var}(x) \\ & + 2E(x)E(y)\mathrm{Cov}(x, y) \\ & + \mathrm{Var}(x)\mathrm{Var}(y) + \mathrm{Cov}(x, y)^2.\end{aligned}$$

The above formula, in which $\mathrm{Cov}(x, y)$ represents the covariance between x and y, yields an exact measure of the variance if the density functions of the two random variables are symmetric. Otherwise the result is an approximation. Applying the above formula along with (12), and observing that $E(e_B) = 0$, yields the variance of returns as follows:

$$(14)\ \mathrm{Var}(W_p) = E(p_y)^2\mathrm{Var}(e_B), + \mathrm{Var}(p_y)\left[\hat{y}_{\max}^2 + \mathrm{Var}(e_B)\right] + \left[2E(p_y)\hat{y}_{\max} + \mathrm{Cov}(p_y, e_B)\right]\mathrm{Cov}(p_y, e_B).$$

If the expected price $E(p_y)$ in (14) equals the deterministic price p_y in (13), the comparison of the two formulas shows that price uncertainty adds to the variance through the second and the third terms of (14), where a negative correlation between price and yield reduces the variance as it constitutes a natural hedge.[3] Furthermore, the product of the second term indicates the interdependence between price uncertainty and the effectiveness of the weather derivative since $\hat{y}_{\max}$ is related to the contract parameters through (9).

To investigate the orders of magnitude of this interdependence, Monte Carlo simulation experiments were conducted using the model presented in the basis risk subsection above, with one modification: instead of the deterministic price p_y, a stochastic price was assumed that is normally distributed with a mean of 6.55 €/dt and a standard deviation of 1 €/dt, representing a coefficient of variation of roughly 15%.

The simulation results are reported in Table 3. Hedging effectiveness is measured by the reduction of the standard deviation through the derivative and by the upward shift of the 5% percentile, the latter especially referring to the reduction of downside risk. As observed from the values in Table 3, even the assumed moderate volatility of prices cuts the risk-reduction potential of the weather derivative by more than half.

Table 3. Influence of Price Uncertainty on the Effectiveness of Weather Derivatives

	Reduction of Std. Dev.		Shift of 5% Percentile	
Price Classification	**€/ha**	**%**	**€/ha**	**%**
Deterministic Price (6.55 €/dt)	241	46.4	566	23.0
Stochastic Price[a]	102	13.7	222	9.9

[a] Normally distributed with mean 6.55 €/dt and standard deviation 1 €/dt.

Diversification Effects

Farmers have a variety of opportunities to influence the risk exposure of their operations. Among them, the diversification of the production program plays an important role. This is particularly true for Europe where farms are typically set up as multi-commodity operations. If a diversified production program already exists, additional hedging instruments are less valuable than in the case of a high degree of specialization.

This effect is illustrated in the following section using an expected value-variance (EV) framework. Specifically, we define the certainty equivalent (CE) as expected income minus a risk premium, where the latter is expressed using the Pratt approximation (cf. Robison and Barry, 1987, p. 34). Assuming constant absolute risk aversion, the CE is given by:

$$CE = E(y) - \frac{\lambda}{2}\mathrm{Var}(y),$$

where $E(y)$ denotes expected income, $\mathrm{Var}(y)$ is the variance of income, and λ represents the coefficient of absolute risk aversion. For simplicity, let us assume that the expected returns of all activities are the same, so we can limit the analysis to inspecting the variance. Considering n production activities realized in quantities q_i, the variance of income becomes:

$$(15)\ \mathrm{Var}(y) = \sum_{i=1}^{n}\sigma_i^2 q_i^2 + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} q_i q_j \mathrm{Cov}_{ij},$$

where σ_i^2 represents the variance of the return of the ith activity, and Cov_{ij} denotes the covariance of returns between the activities i and j. If we assume a portfolio of activities in which all quantities are equal, i.e., $q_i = 1/n$, the above equation becomes:

[3] Note that the expected value of a product of random variables also is increased by a positive and decreased by a negative covariance.

$$(16)\ \mathrm{Var}(y) = \frac{1}{n^2}\sum_{i=1}^{n}\sigma_i^2 + \frac{2}{n^2}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\mathrm{Cov}_{ij}.$$

We now observe that a portfolio of n elements is comprised of $n(n-1)/2$ covariances. Thus, we can define an average covariance as:

$$(17)\ \overline{\mathrm{COV}} = \frac{2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\mathrm{Cov}_{ij}}{n(n-1)}.$$

Substituting the second term in equation (16) by this relation, the variance of the portfolio becomes:

$$(18)\ \mathrm{Var}(y) = \frac{1}{n^2}\sum_{i=1}^{n}\sigma_i^2 + \frac{n-1}{n}\overline{\mathrm{COV}}.$$

On introducing the average variance $\bar{\sigma}^2$, this equation further reduces to:

$$(19)\ \mathrm{Var}(y) = \frac{1}{n}\bar{\sigma}^2 + \frac{n-1}{n}\overline{\mathrm{COV}}.$$

Let us assume identically distributed returns for all activities. From $\mathrm{Cov}_{ij} = \sigma_i \cdot \sigma_j \cdot \rho_{ij}$, where ρ_{ij} marks the correlation coefficient, we can rewrite the average covariance as:

$$\overline{\mathrm{COV}} = \bar{\sigma}^2\bar{\rho},$$

where $\bar{\rho}$ denotes the average correlation coefficient. Equation (19) then becomes:

$$(20)\ \mathrm{Var}(y) = \frac{1}{n}\bar{\sigma}^2 + \frac{n-1}{n}\bar{\sigma}^2\bar{\rho} = \frac{\bar{\sigma}^2}{n}\left(1+(n-1)\bar{\rho}\right).$$

The above equations indicate that the portfolio risk decreases as n increases, however at diminishing rates. As the term $(n-1)/n$ approaches one for large n, the portfolio variance reduces to the average covariance which is not diversifiable.
If the returns of all activities are stochastically independent, i.e., the correlation coefficients and covariances are zero, then the portfolio variance approaches zero for large n, indicating the risk is completely diversifiable. If the correlation coefficients amount to +1, no diversification effect occurs, as can be seen from equation (20). In turn, at correlation coefficients of −1, the portfolio variance completely vanishes at $n = 2$.

Now assume that in a production program composed of n commodities a derivative is introduced to hedge against weather risk for one commodity. This can be represented by replacing the ith element in (18) by one that exhibits a reduced variance, i.e., σ_i^2 is replaced by $\bar{\sigma}_i^2$. For simplicity, assume the average covariance remains unchanged. Then the difference of the portfolio variance caused by introducing the derivative is given by the term $\mathrm{Var}(y) - \mathrm{Var}'(y)$, where $\mathrm{Var}'(y)$ considers the reduced variance.
Expanding the summation in (18), we can write:

$$\mathrm{Var}(y) = \frac{1}{n^2}\left(\sigma_1^2+\sigma_2^2+\ldots+\sigma_i^2+\ldots+\sigma_n^2\right) + \frac{n-1}{n}\overline{\mathrm{COV}}$$

and

$$\mathrm{Var}'(y) = \frac{1}{n^2}\left(\sigma_1^2+\sigma_2^2+\ldots+\bar{\sigma}_i^2+\ldots+\sigma_n^2\right) + \frac{n-1}{n}\overline{\mathrm{COV}}.$$

From this the difference $\mathrm{Var}(y) - \mathrm{Var}'(y)$ can be derived as:

$$(21)\ \mathrm{Var}(y) - \mathrm{Var}'(y) = \frac{\sigma_i^2 - \bar{\sigma}_i^2}{n^2}.$$

From equation (21) we can see that within a portfolio of n activities the variance-reducing power of a single derivative is downscaled by n^2. For a farm with a broadly diversified production program, weather derivatives are therefore of much less value than for a highly specialized operation. Model calculations conducted by Schmitz for a farm in Germany that grows five different crops clearly demonstrate this effect: a rainfall-based weather derivative that is introduced for onions reduces the variance of the total profit by only 7.5% (Schmitz, 2007, p. 123 ff.).

While this effect as such is fairly general, the extent to which it becomes palpable depends on the nature of the derivative.

The relation of formula (21) applies only if the derivative is highly specific in the sense that it only affects the variance of returns of a single commodity. In most cases though, the weather index will be correlated with the yields of several commodities which, in turn, will enhance the reduction of the portfolio variance. However, if such cross-effects exist, they must be considered in the construction and in the valuation of the derivatives, further adding to the complexity of the problem.

Assessing the Value of Weather Derivatives in the Context of Portfolio Optimization

The discussion so far has shown the necessity for an integrated approach to risk management, which can best be characterized as portfolio optimization. Portfolio selection is often associated with Markowitz's approach of determining an expected value-variance-efficient frontier. In this setting, the expected value serves as a measure of worth while the variance is used to assess the risk that must be assumed in order to achieve a certain level of expected income. Thus, the Markowitz model can be viewed as a particular member of a more general class of models which are often referred to as "risk-value models." In general, the preference function of a risk-value model is defined as:

$$(22)\quad \Phi\big(F_i(x)\big) = H\big(W\big[F_i(x)\big], R\big[F_i(x)\big]\big),$$

where $W[F_i(x)]$ is the measure of worth and $R[F_i(x)]$ represents the risk measure. $F_i(x)$ marks the cumulative distribution function of the risky prospect i, and $H(\cdot)$ determines the tradeoff between risk and worth according to the decision maker's preferences. The usual assumption is that $H(\cdot)$ grows with increasing worth and falls with increasing risk. Neither the value measure nor the risk measure depends on wealth. Only the tradeoff function is wealth dependent, unless we assume constant absolute risk aversion.

If the decision maker is able to specify the tradeoff function, comparing pairs of distributions leads to an optimal choice. If $H(\cdot)$ remains unspecified, it is still possible to determine the efficient set consisting of the distributions which are not dominated. A distribution $F_i(x)$ dominates the distribution $F_j(x)$ if the conditions

$$W\big[F_i(x)\big] \geq W\big[F_j(x)\big]$$

and

$$R\big[F_i(x)\big] \leq R\big[F_j(x)\big]$$

hold with at least one strict inequality (Fishburn, 1977, p. 118). All non-dominated alternatives lie on the efficient frontier, which can be determined by solving the optimization problem:

$$(23)\quad W\big[F(x)\big] \rightarrow \text{Max!} \qquad \text{s.t.: } R\big[F(x)\big] \leq c,$$

where c must be varied across all possible numerals of $R[F(x)]$.

While the appropriateness of risk measures is still controversially discussed in the relevant literature, it is widely agreed that the expected value is the best measure of worth in risk-value models, i.e., $W[F(x)] = E[x]$. In the Markowitz approach, the risk measure is given by the variance, i.e., $R[F(x)] = E[(x-\mu)^2]$, where μ denotes the mean and $E[\cdot]$ represents the expectation operator. While the expected value-variance (EV) approach is widely used because of its deductive strength and its relative ease of application, it nevertheless has some shortcomings:

- The EV approach yields similar results as the more general expected utility (EU) approach only if the outcomes are approximately normally distributed. Since weather derivatives specifically reduce downside risk, the normality assumption may not be valid, and the number of activities in the portfolio of a farm is likely to be too small for the central limit theorem to apply.

- If moments of the distribution are used as risk measures, the mean is (implicitly) considered as the relevant target, and risk is quantified using the magnitude of deviations from this target. Because the target is determined endogenously, these measures do not change if a certain amount d is added to an uncertain outcome X, i.e., $R[X] = R[X + d]$. This implies the assumption of constant absolute risk aversion, which is widely regarded as unrealistic. In contrast, if the target is determined exogenously, adding a certain quantity to an uncertain prospect reduces the risk associated with it, i.e., $R[X] > R[X + d]$, whereby the assumption of constant risk aversion is released.

- The variance is a two-sided measure in that it considers the magnitude of the distances between the realizations of x and $E[x]$ in both directions. Most decision makers, however, associate risk with an outcome that is worse than some specific target rather than with the variability of outcomes as such. For instance, Collins (1997) concluded from his analyses that "hedging is motivated by a desire to avoid financial failure rather than by a desire to reduce income variability" (p. 498).

This leads to a further class of risk measures which explicitly refer to downside risk wherein only those outcomes falling below a specific target are considered. This class of measures dates back to the work of Fishburn (1977) and was later revisited by Sarin and Weber (1993). Considering only the lower part of the distribution, these measures account for the downside risk and are called "lower partial moments" (LPMs). They are defined as:

$$(24)\quad LPM_n(z) = \int_{-\infty}^{z} (z-x)^k f(x)\,dx, \quad k \geq 0.$$

Setting the target z and the order k of the LPM yields a specific measure. Basic cases that play an important role in applications are obtained for $k = 0$, 1, and 2. Setting $k = 0$ yields the "shortfall probability" $LPM_0(z)$ that is closely related to the value-at-risk:[4]

$$(25)\quad LPM_0(z) = \int_{-\infty}^{z} (z-x)^0 f(x)\,dx = F(z).$$

For $k = 1$, the resulting measure is the "shortfall expectation":

$$(26)\quad LPM_1(z) = \int_{-\infty}^{z} (z-x)^1 f(x)\,dx = E[z-x \mid x<z]F(z),$$

where $LPM_1(z)$ denotes the (conditional) expected value of shortfalls multiplied by the probability of the occurrence of below-target returns. Thus, it accounts for the probability as well as for the magnitude of shortfalls. Finally, $k = 2$ leads to the "shortfall variance":

$$(27)\quad LPM_2(z) = \int_{-\infty}^{z} (z-x)^2 f(x)\,dx = E[(z-x)^2 \mid x<z]F(z),$$

the square root of which denotes the "shortfall standard deviation." Here, the squared downside deviations from the target are considered in the risk measure.

The preference function of the risk-value model using the expected value $E(x)$ as the value measure and a lower partial moment $LPM_k(z)$ as the risk measure can be stated as:

$$(28)\quad \Phi\big(F(x)\big) = E[x] - cLPM_k(z),$$

where $c > 0$ denotes a weighting factor and k is the order of the LPM. Increasing c therefore means increasing risk aversion. As shown by Schneeweiss (1967, p. 89ff.), the corresponding utility function has the following form:

$$(29)\quad u(x) = \begin{cases} x & \text{if } x > z, \\ x - c(z-x)^k & \text{if } x \leq z. \end{cases}$$

As can be seen from (29), above the target z all three cases result in the same utility function which is given by $u(x) = x$. The differences between them occur in the range where x falls below the target.

[4] For details on the value-at-risk concept see, e.g., Jorion (1997) and Manfredo and Leuthold (1999).

For $k = 0$, the utility function is linearly increasing at a constant slope but has a discontinuity at the target z. This neither allows a general statement about the decision maker's attitude toward risk nor is it consistent with decision theory. Consequently, this measure receives no further attention here.

The shortfall expectation, i.e., $k = 1$, considers not only the shortfall probability but also its extent. The corresponding utility function is piecewise linear with the steeper slope in the lower part. Only if all possible outcomes fall either below or above the level, respectively, does the utility function imply risk-neutral behavior. Otherwise the shape of the utility function is approximately concave and therefore implies risk aversion.

The use of higher-order LPMs, i.e., higher values of k, implies stronger local risk aversion in the lower part of the domain while above the target local risk neutrality remains. Using $LPM_2(z)$, i.e., the shortfall variance, the shortfalls are squared, thus giving particular weight to the higher losses. The corresponding utility function is quadratic in the range below the target level, and therefore also implies risk aversion. Different from the former case, the utility function is strictly concave in the lower part.

From the above framework, the shortfall expectation and the shortfall variance appear as suitable risk measures for risk-averse decision makers. Since a desirable feature of any measure is that it has an obvious meaning for the decision maker, the shortfall expectation (LPM_1) is particularly appealing.

Implementing the general approach given in (23) using LPM_1 as the risk measure implies that the expected profit enters the objective function while the risk measure is considered as a constraint. Thus, the objective function is to select the portfolio of activities $\mathbf{x}$ that maximizes the expected profit π:

$$(30)\quad \max_{\mathbf{x}} \int_0^{\infty}\int_0^{\infty} \pi(\mathbf{p},\mathbf{y},\mathbf{x})g(\mathbf{p},\mathbf{y}\,|\,\mathbf{\Omega})\,d\mathbf{p}\,d\mathbf{y},$$

subject to the resource constraints $\mathbf{Ax} \le \mathbf{b}$, and the constraint on the risk measure $LPM_1(z) \le c$, where c is parameterized in order to compute the efficient frontier. In (30), the term $\pi(\cdot)$ denotes the profit function and $g(\cdot\,|\,\mathbf{\Omega})$ is the joint density function of prices and yields conditional on $\mathbf{\Omega}$, the set of information available when the portfolio is selected. The random price vector $\mathbf{p}$ consists of cash prices for all products and, in addition, futures and forward contract prices as far as they are available. The random yield vector $\mathbf{y}$ contains the individual crop yields. The resource constraints reflect the physical capacities of the farm as well as institutional constraints, e.g., rotational restrictions and agricultural policy regulations. Finally, the vector of activities $\mathbf{x}$, besides the production processes also contains risk management measures including hedging price risks with futures and options and production risks with weather derivatives.

Starp has applied the above modeling framework to German farms, yet without consideration of weather derivatives (Starp, 2006; Berg and Starp, 2006). Risk management instruments considered in the model include hedging with futures and cash forward pricing. The target was set to $z = 0$, so the $LPM_1(0)$ essentially measures the loss expectation. The model results indicate that the effective use of risk management instruments can reduce the loss expectation up to 70%. However, this is achieved only at the expense of a declining expected profit, where the tradeoffs become less favorable as risk decreases. Compared with the EV approach, the LPM_1 model yields superior results: the probability distributions resulting from the expected value-LPM_1 approach are mostly first-degree stochastically dominant over those resulting from the EV approach.

Conclusions

Our discussion has shown that a comprehensive assessment of hedging instruments, including weather derivatives, requires an integrated approach as suggested in this paper. While this approach is certainly a complex one, it is the only way to assess the value of risk management tools comprehensively. Since most research to date focuses on single instruments, more efforts are needed toward this end.

Important aspects to be considered with regard to weather derivatives include structured (i.e., combined) contracts and cross-effects resulting from the fact that most weather indexes are correlated with the yields of several crops. Furthermore, climate models could be employed to reduce geographical basis risk. Considering all of these aspects leads to the challenge of selecting an optimal portfolio of risk management instruments.

Selecting a portfolio of hedging instruments is a complex task. It is therefore doubtful that farmers—in addition to all other tasks they must accomplish in their predominantly small- to medium-sized operations—will ever be able to successfully cope with this problem. Left to themselves they would certainly be overcharged. Instead, one could imagine that other institutions, possibly formed under participation of agricultural commerce, the banking sector, insurance companies, and the advisory service, take over the task of creating and managing such portfolios designed to fit the needs of particular farm types.

This idea corresponds to similar thoughts expressed by Vedenov and Barnett (2004) and Woodard and Garcia (2007b). The farmers themselves would then only have to deal with one aggregate instrument aimed at reducing their downside risk of income.

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The Pricing, Structure, and Function of Weather-Linked Bonds, Mortgages, and Operating Credit

Calum G. Turvey

Abstract

This paper outlines approaches to valuating weather-linked bonds, mortgages, and operating lines of credit. Using historical data from weather stations in Ardmore, Oklahoma, and Ithaca, New York, indemnities and insurance premiums are computed for specific-event rainfall insurance. The main contribution of the paper is the development of new and accurate formulae for determining the coupon rates on weather-linked bonds and the interest rates on weather-linked mortgages and lines of credit. The empirical aspects of the paper indicate that linking weather risk to debt may be very costly if the risks are common, but the risk premiums on rare or low-frequency weather risks can be very manageable.

Key words: precipitation insurance, rainfall insurance, weather derivatives, weather insurance, weather-linked bonds, weather-linked mortgages

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With increasing interest in weather insurance and derivatives across a number of industries such as energy and agriculture, there is a need to explore and expand opportunities for other structured financial products such as weather-linked bonds and other forms of credit for weather-sensitive industries. These instruments link the payoff from a weather insurance or derivative products to the repayment covenants of a loan or bond.

In recent years there has been a significant interest in weather derivatives based on precipitation or heat, particularly in agriculture where crop yields can be severely impacted by weather events (Bardsley, Abey, and Davenport, 1984; Patrick, 1988; Quiggen, 1986; Sakurai and Reardon, 1997; Turvey, 2001, 2005; Martin, Barnett, and Coble, 2001; Richards, Manfredo, and Sanders, 2004; Cao and Wei, 2003). Weather insurance in these contexts is viewed as supplementary to existing problems in many countries through crop insurance, revenue insurance, or ad hoc governmental disaster payments.

The purpose of weather insurance and the emerging market for weather derivatives is in direct response to weather-induced volumetric risk. In energy markets weather derivatives are used to hedge excessive electricity demand through the use of cooling and heating degree-day contracts, and in agriculture weather is used to hedge production yield risk, usually through precipitation contracts. From a business perspective, the advantage of tying weather risk to debt is that any weather-induced increase in business risk will significantly increase the financial risk faced by the firm. In addition, the agency relationship between borrower and lender is unambiguous.

O'Hara (1990) demonstrates that conventional loans can be pareto dominated by financial contracts explicitly incorporating characteristics of the borrower's product market, identifies conditions under which (commodity-) linked debt is desirable and when more complicated revenue-linked loans are optimal, and shows how the type of lending contract can have real effects on production decisions.

Morellec and Smith (2003) have examined how firms jointly determine financing, hedging, and investment decisions. They argue that optimum leverage reflects the tradeoff between under- and overinvestment and show that hybrid debt financing [e.g., a (commodity-) linked bond with a linked forward contract] can reduce agency costs and incentives to over- and underinvestment, increasing firm value. A linked bond precommits the firm to a risk management strategy for the life of the bond in a business and legal environment where covenants to using futures, options, or swaps are often prohibited.

The relationship between employing risk management strategies and financial leverage is well developed. In commodity markets, Turvey and Baker (1989, 1990) and Mello and Parsons (2000) show that a firm with no debt gains little from hedging its price risks because the agency costs of debt are reduced or zero. However, a firm that is highly leveraged will find significant economic benefits if the source of business risk such as weather can be managed, and as with commodity-linked loans (Turvey, 2006), the degree by which benefits accrue is directly related to the degree of leverage. This transcends clearly into the notion of risk balancing (Collins, 1985; Featherstone et al., 1988), the leverage effect of beta in the Sharpe-Lintner Capital Asset Pricing Model, and the free cash flow problem (Jensen, 1986).

More generally, managing weather risk involves a transaction that shifts risks from states in which the opportunity costs of liquidity are low to those in which the opportunity costs of liquidity are high (Mello and Parsons, 2000). In this sense, the purpose of hedging weather risk is to improve liquidity, reduce financial distress and the costs of external financing, and make value-maximizing investments affordable.

In addition, maintained liquidity provides the flexibility to undertake and plan future investment opportunities (Mello and Parsons, 2000) and higher firm value. It has been argued by Morrelec and Smith (2003) that risk management policies also allow the firm to control the underinvestment incentives associated with debt financing by increasing the number of states of nature in which shareholders are residual claimants.

Not only can weather-linked debt be useful in developed economies, but there is an increasing interest in weather risk management in developing countries where "index" insurance has been used or proposed (Hess, Richter, and Stoppa, 2002; Stoppa and Hess, 2003; Skees et al., 2005; Skees, Hartell, and Hao, 2006; Hazell and Skees, 2006). Gautman, Hazell, and Alderman (1994) appear to be among the first to consider weather-linked bonds in terms of World Bank or International Monetary Fund loans to developing countries.

From a conceptual base, the repayment of sovereign debt of developing agrarian economies is largely conditioned on specific weather events such as drought or flood. The risk attached to third-world debt is high, default is not infrequent, and for countries that do not default on sovereign debt, the impact on national treasuries can be severe.

As previously discussed, O'Hara (1990) has shown how the type of lending contract can have real effects on production decisions. Atta-Mensah (2004) further argues that in the event of sovereign debt default, substantial bankruptcy, legal and renegotiating costs incurred, and introduction of new uncertainties constitute dead-weight losses (as opposed to simple wealth transfer) to the parties involved in the contract. Thus, derivative securities may serve to minimize these dead-weight losses, in that state-contingent payments may be tailored to the risk preferences of either borrow or lender, which would avoid these transaction costs and so would minimize the probability of default. Chantarat et al. (2007) provide a mechanism for using weather insurance and weather-linked bonds to fund humane famine relief efforts.

Theoretical Framework for Pricing Weather-Linked Bonds

As a starting point we treat the structure of a weather-linked bond (WLB) as a modification of the commodity-linked bond (CLB) discussed and presented in detail by Atta-Mensah (1992); Schwartz (1982, 1997); Carr (1987); Gibson and Schwartz (1990); Miura and Yamauchi (1998); Milterson and Schwartz (1998); Jin and Turvey (2002); and Turvey (2006). A general structure of CLBs that we believe can be adapted to numerous forms of WLB has been provided following the structure outlined in Milterson and Schwartz (1998), Harrison and Kreps (1979), and Harrison and Pliska (1981).

The most general form of a weather insurance product is given by:

$$\text{(1a)}\quad v_W^p = e^{-(r+\lambda\sigma)T} \times \psi \int_0^{K_W} \text{Max}\big(0,\, K_W - W(t)\big) g(W_t)\, dW_t$$

for a put option, and

$$\text{(1b)}\quad v_W^c = e^{-(r+\lambda\sigma)T} \times \psi \int_{K_W}^{\infty} \text{Max}\big(0,\, W(t) - K_W\big) g(W_t)\, dW_t$$

for a call option. Note that we are using the notation $W(t)$ on the weather variable. We do this to indicate that the measured weather variable need not be a linear function of the natural weather process W_t. Asian and other options on average, as well as dependencies such as heating, cooling, or growing degree-days, can all be considered for a WLB.

Note also that we are discounting the terminal value by $e^{-(r+\lambda\sigma)}$, which accounts for the market price of risk often associated with nontradable or nonhedgable risk [see Cao and Wei (2003); Richards, Manfredo, and Sanders (2004); and Turvey (2005) for discussions on the market price of risk for weather derivatives]. Finally, since the weather variable and the strike value K_W are measured in physical rather than in currency units, we need to include the parameter ψ to obtain a currency (e.g., convert degree-days to dollars) denominated option; ψ may also take into consideration the number of weather options required to cover F.

If there is a risk of bankruptcy (Schwartz, 1982; Carr, 1987; Miura and Yamauchi, 1998), then bondholders receive the maximum of firm value V_T or bond value F. Also complicating pricing issues is the fact that the value of the bond is equal to the present value of coupons plus the present value of the payoff. Following the structure outlined in Milterson and Schwartz (1998), Harrison and Kreps (1979), and Harrison and Pliska (1981), the idea is to calculate the discounted expected value of payment directly:

$$\text{(2)}\quad B(0) = E\left[\int_0^T e^{-\int_0^v f(s,s)\,ds} c\,dv\right] + E\left[e^{-\int_0^T f(s,s)\,ds} \text{Min}\Big[V(T),\; F + \psi \text{Max}\big(0,\, W(t) - K_W\big)\Big]\right],$$

where

$$\int_0^v f(s,s)\,ds, \quad v = t, T$$

is the adjusted discount rate which can consist of convenience yield and interest rate risk under a variety of assumptions including the market price of risk of the nontraded weather variable. In the simplest of cases with zero default risk [exclude $V(T)$ or set $V(T) = 0$], no convenience yield, and no interest rate risk, the value of a weather-linked bond with constant coupon rate and a linked call option is given by:

$$(3)\ B(0) = \frac{c}{r}(1 - e^{-rT}) + Fe^{-rT} \pm \psi E\left[\text{Max}(0, W(t) - K_W)\right]e^{-rT}.$$

This expression is similar to Schwartz (1982) and Atta-Mensah (1992) except in this case the payout is based on the evolution of a weather event over time rather than a commodity. In other words, the simplest of structured products is simply the sum of the present value of the cash flow from the bond investment plus the option value of the weather linkage. It is also similar to some components of the bond design in Barrieu and Karoui (2002) who construct a bond pricing model based on expected utility.

As equation (3) is written, it suggests that when the bond matures there is an option effective at the maturity date which will, if exercised, reduce the face value or coupon obligation of the issuer. This is a simple variant. Consider the following model:

$$(4)\ B(0) = \frac{c}{r}(1 - e^{-rT}) + Fe^{-rT} \pm \psi \int_0^T \int_{-\infty}^{\infty} e^{-(r+\lambda\sigma)t}\text{Max}(0, K_W - W(t)) \times g(W_t)\, dW dt,$$

which provides a payout on the put option for each year of the bond's life.

An Economics Justification for Weather-Linked Credit

The value of the option relative to the bond is an important economic criterion, as is the timing and sequencing of the option payoff relative to the cash flow associated with the bond. In the most general instance, the option payoff will be tied to the face value of the bond, but it can also be tied to the coupon payments and/or the required sinking fund for disposing of the bond at expiry.[1] Regardless, the nature of the option is to mitigate downside weather-related risks that could jeopardize bond or coupon repayment.

A bond issue will customarily require a sinking fund be established so that in each year some proportion of the bond's face value can be retired. Typically the cash required in each year will be $S_t = F/T$. In addition, if the bond pays a periodic coupon, then an additional amount of cash flow c will also have to be paid each year. Thus the cash required to pay for a bond on an annual basis is given by:

$$(5)\ C_t = c_t + \frac{F}{T}.$$

However, the sinking fund requirement is a legal provision that must be made, and while in most cases coupon payments must also be made, in times of adversity they would be sacrificed to ensure the sinking fund requirement is met. Thus we proceed with a model which attaches the option to the coupon in such a way that if the specific weather event does not occur bondholders receive an enhanced coupon, but if it does occur, bondholders forego coupons in order to ensure liquidity for the sinking fund.

The economic justification for weather-linked bonds (and other forms of credit to be discussed presently) proceeds as follows. Consider first the use of F, which is assumed to have purchased some form

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[1] There are, of course, any number of variations to consider and it is therefore worthwhile to examine some variants in order to establish some general rules or guidelines. The broadest categorization establishes whether the bond will be sold at a premium or a discount. A premium bond will provide a weather option as an incentive to the bondholder. In this case, the issuer will pay in excess of the bond value if specific weather events are favorable to the firm's business. The premium can be in the form of a call or a put. A discount bond is one in which the bondholder is willing to accept less than par in the event of an adverse weather outcome. Because there is the risk that the bond will not be paid in full, the bond will be issued at a discount. The symbol ψ in equations (3) and (4) reflects these structures, with "+" indicating the value of a bond sold at a premium and "-" a bond sold at a discount.

of capital K. The economic value-added (EVA) return from K must, on expectation, generate sufficient cash flow to satisfy (6):

$$(6)\quad r_K \geq \frac{c + \frac{F}{T}}{K}.$$

Note that the right-hand side of (6) is an agency restriction, but the left-hand side is a random variable. We can write the expected EVA as a weather-dependent random variable:

$$(7)\quad E[r_K] = \int_a^b r_K(W_t)g(W_t)\,dW_t,$$

and by setting (6) as a strict equality and defining

$$r_K^* = \frac{c + \frac{F}{T}}{K},$$

we can consider $W^* = g^{-1}(r_K^*)$ and rewrite (7) as:

$$(8)\quad E[r_K] = \int_a^{W^*} r_K(W_t)g(W_t)\,dW_t + \int_{W^*}^b r_K(W_t)g(W_t)\,dW_t,$$

where the first term on the right represents the downside risk. The second term reflects those weather states in which EVA is sufficiently high to meet all agency cash requirements. W^* therefore becomes the "strike," K_W, for the insurance or derivative product measured directly as a precipitation number or degree-days, or as the outcome to any other single or multiple specific event.

We are, in principle, concerned with adversity. Consequently, the major focus here is on the value of a bond, on which the bondholder accepts the risk of an adverse weather outcome. To avoid the agency costs associated with adversity, assume a contingent claim with the following indemnity structure: Max[0, $W^* - W(t)$]. In the event of an adverse weather event where $W^* > W(t)$, a "quantity of weather" equivalent to $W^* - W(t)$ is returned to the investment.

Hence, by substituting $W^* = W(t)$ into (8), we have:

$$(9)\quad E\left[r_{K,W^*}\right] = \theta r_K(W^*) + \int_{W^*}^b r_K(W_t)g(W_t)\,dW_t,$$

where $\theta = G(W^*)$ is the probability that the specific event will occur and the option part will be "in-the-money." Subtracting (8) from (9), and multiplying by K provides the value to the firm of the weather bond:

$$(10)\quad \left(E\left[r_{K,W^*}\right] - E\left[r_K\right]\right)K = \left(\theta r_K(W^*) - \int_a^{W^*} r_K(W_t)g(W_t)\,dW_t\right)K \geq 0.$$

Defining $K_W = W^*$ as the appropriate strike price or specific event criterion that triggers a payment, we can now establish the proxy:

$$(11)\quad v_W^p = \left(E\left[r_{K,W^*}\right] - E\left[r_K\right]\right)K = \psi \int_0^{K_W} \text{Max}\left(0, K_W - W(t)\right)g(W_t)\,dW_t.$$

And from this,

$$(12)\quad \psi = \frac{\left(E\left[r_{K,W^*}\right] - E\left[r_K\right]\right)K}{\int_0^{K_W} \text{Max}\left(0, K_W - W(t)\right)g(W_t)\,dW_t}.$$

The numerator in (12) is currency denominated (e.g., \$), while the denominator is measured in weather units (e.g., inches of rain, growing degree-days, etc.). Thus, if the bond is a precipitation bond to protect against low rainfall measured in inches, the "tick" price or payout per inch below K_W is ψ\$/inch.

Agricultural Business and Corporate Finance

We examine the instance of an agribusiness (or any other) whose cash flow is affected by adverse weather events. The investment in capital requires an amount F at $t = 0$ financed through a bond issue with coupon rate c. The ability to finance coupons and establish a sinking fund for the retirement of the bond is also affected by weather. In the absence of a weather option, the present value of the (default-free) bond is given by:

$$(13)\quad B(0) = \frac{c}{r}\left(1 - e^{-rT}\right) + Fe^{-rT}.$$

In each period the cash flow removed from retained earnings is equal to the coupon payment plus the sinking fund allotment:

$$(14)\quad C = c + \omega\frac{F}{T}.$$

In (14), F/T is the annual contribution to the sinking fund, and ω is the proportion of sinking fund to be retired (normally, $\omega = 1$). If net cash flow from the investment falls below C, then the firm will have to use funds from non-invested projects to make up the shortfall. Thus one might consider C as an apt level for the strike price on the weather option.

There are several possibilities. First, the firm can hedge the entire cash flow requirement using a weather option with the proceeds going toward any cash flow shortfall in coupons and sinking fund obligations. In other words, $C = K_W\psi$, or $\psi = C/K_W$. Second, the firm can ask bondholders to forego coupon payments in order to make up at least part of the shortfall, and $\psi = c/K_W$. A third possibility is that the option applies only to the weather risk in the year during which the bond matures. But this alternative may present a dilemma because all of the risk is placed in a single basket and probably does not, at least on an accrual basis, establish a hedge versus a speculative position.

Our approach is to assume the weather event has an equal probability in all years of the bond issue, whereby the value of the bond is equal to the present value of the coupon payments plus the present value of redemption, less the present value of the weather insurance payoff:

$$(15)\quad B(0) = \frac{c}{r^*}\left(1 - e^{-r^*T}\right) + Fe^{-r^*T} - \left(\frac{c + \omega\frac{F}{T}}{K_W}\right) \times E\left[\text{Max}\left(0, K_W - W(t)\right)\right]\frac{\left(1 - e^{-r^*T}\right)}{r^*}.$$

If the bond yields $r^* = r$, then one can see immediately that the bond will be sold at a discount equal to the present value of the annualized expected payout from the option (assuming payouts from one year to the next are independent, and intertemporal volatility in the underlying weather condition does not change on expectation).

In the alternative, the issuer may alter the coupon rate to reflect the risk to the bondholders. In this scenario the intent is to offer a coupon rate that will make the value of the weather-linked bond equivalent to the value of the bond without weather risk, i.e.:

$$(16)\quad \frac{c}{r}\left(1 - e^{-rT}\right) + Fe^{-rT} = \frac{c^*}{r}\left(1 - e^{-rT}\right) + Fe^{-rT} - \left(c^* + \omega\frac{F}{T}\right) \times \frac{E\left[\text{Max}\left(0, K_W - W(t)\right)\right]}{K_W}\frac{\left(1 - e^{-rT}\right)}{r}.$$

Solving yields

$$(17)\quad c^* = \frac{\left(c + \omega\frac{F}{T}\frac{E\left[\text{Max}\left(0, K_W - W(t)\right)\right]}{K_W}\right)}{\left(1 - \frac{E\left[\text{Max}\left(0, K_W - W(t)\right)\right]}{K_W}\right)}.$$

To compensate for the weather risk, the coupon would increase from c to c^*. The coupon rate on a WLB will always be larger than the rate of a straight bond if the bond yields are to be equivalent. If the option is designed to compensate the sinking fund, then the coupon will increase even further, i.e., $\partial c^*/\partial\omega > 0$. However, in the examples provided in this paper, the coupon rate is set to offset the coupon liability only.

Using actuarial results from the WeatherWizard computer program (Turvey and Norton, 2008), the coupon rate is calculated as follows. This example uses a 42-day drought event between June 1 and August 31 at Ardmore, Oklahoma, with a \$1,000/inch payout if cumulative rain falls below 1". Up to two events can be considered in the 91-day span. The weather insurance premium was \$186 per \$1,000/inch/event and the maximum payout recorded was $1,160, occurring in the "dust bowl" year of 1934 when only 2.5" of rain fell. The issue is a 10-year $1,000,000 bond with an annual sinking fund requirement of $100,000. The base coupon rate is 8% or $80,000/year.

The firm issuing the bond requires drought protection to offset cash reduction in extreme drought years so that the coupon and sinking fund can be hedged. The calculated coupon rate is 11.437%, obtained as follows:

$$c^{*}\% = \frac{\left(\frac{0.08 + 1\left[\frac{1{,}000{,}000}{10}\right]\left[\frac{186}{1{,}160}\right]}{\left[1 - \frac{186}{1{,}160}\right]} \right)}{1{,}000{,}000}$$

$$= 0.11437.$$

Specifically, in return for a coupon of 11.437%, the holder of the bond will forego payments should the specific event or events occur. If no event occurred, then the total coupon payment would be $114,373 plus the sinking fund requirement, for an annual liability of $214,373. However, if this bond were held under conditions equivalent to 1934, no coupon payment would be made, thus leaving reserves to cover the sinking fund only.

Note in this example (as well as those to follow) how the terms $E[\text{Max}(0, K_W - W(t))]$ and K_W are used. In equations (16) and (17), the assumption is that the weather insurance or derivative part is a put option with a single-event payout if the weather event falls below the strike/trigger K_W.

In practice, the expectation so represented can be the premium associated with any weather insurance or derivative product whether it consist of multiple or single events, and K_W is the maximum possible payout. Thus, in the above example, we substitute $186 for $E[\text{Max}(0, K_W - W(t))]$, and the maximum payout recorded, $1,160, for K_W.

Agricultural Finance

There are two obvious applications to agricultural finance. The first is a very simple structure in which the repayment of a nonrevolving operating loan is contingent on the performance of a weather variable. The second is with loan repayment on a farm mortgage. The most likely weather risk would be precipitation to protect crop yield losses from drought.

Weather-Linked Operating Credit

In this section we derive the formula for pricing an operating loan which is linked to a specific weather event. As done above for the corporate bond, the imbedded insurance is not paid as a premium per se, but as an increment to the interest rate on the loan. For simplicity, it is assumed the counterparty is a commercial agricultural lender.

The value of the operating loan to the lender's portfolio is denoted by:

(18a) $B(0) = e^{-rT}\left[F - \psi E\left[\text{Max}(0, K_W - W(t))\right]\right]$

for the put, and

(18b) $B(0) = e^{-rT}\left[F - \psi E\left[\text{Max}(0, W(t) - K_W)\right]\right]$

for the call. Here $F = fe^{r^{*}T}$, where f is the initial amount borrowed for operating costs and r^{*} is the interest rate charged on the operating loan as opposed to r which reflects the lender's cost of capital. This rate will reflect the risk that the option will be exercised and will differ from a rate r^{**} that would be charged on operating loans without the option (i.e., $F = fe^{r^{**}T}$).

Finally, ψ captures the size of the insurance position required to repay the loan amount. For the put $\psi = f/K_W$, and for the call it is $\psi = f/\text{Max}[W(t) - K_W, 0]$, where the denominator reflects the maximum payoff to the insurance whereby in the worst-case scenario the loan is fully repaid. (Note, these can be defined in weather units or currency units.)

The interest rate that would make the lender indifferent toward an operating loan with the linked weather (put) insurance and one without is equal to:

$$(19)\ r^{*} = \frac{\ln\left[\dfrac{\dfrac{f}{K_W} E\left[\operatorname{Max}(0, K_W - W(t))\right]}{f} + e^{(r^{**})T}\right]}{T},$$

with $r^{*} > r^{**} > r$.

We now provide the calculation for weather-linked operating credit. The operating loan is for $100,000 with a one-year repayment. The specific weather event is a cumulative rainfall measure that pays $1,000/inch for every inch or portion thereof below a cumulative 6" between June 1 and August 31 (91 days) at Ardmore, Oklahoma. The base rate is 8%. The insurance cost for this weather event is $451.63, and the maximum indemnity recorded was $3,670 in 1925, when only 2.33" of precipitation fell over this period. The calculated rate is therefore 18.8%, computed as follows:

$$r^{*}_{ardmore6''} = \frac{\ln\left[\dfrac{\dfrac{100{,}000}{3{,}670} 451.63}{100{,}000} + e^{(0.08)1}\right]}{1}$$

$$= 0.188.$$

To indemnify the $100,000 loan, 27.24 units are purchased. Suppose actual rainfall is only 2". Then the insurance pays $2,000 on each of 27.24 units for a benefit of $54,480. At the end of the year, the farmer would only have to repay $45,520 plus interest of $18,800. If no precipitation event occurred, then the farmer would have to repay $118,800, but if the precipitation event described by conditions in 1925 occurred with a maximum payout of $3,670 after only 2.33" of rain fell, then the farmer would have to pay only the interest.

Weather-Linked Mortgage

For a weather-linked mortgage, we note that the annuity on a mortgage of value F is given by:

$$(20)\ A(i) = F\left(\frac{1-(1+i)^{-T}}{i}\right)^{-1},$$

where i is the interest rate on the mortgage. The value of this mortgage to the lender with an attached weather option is:

$$(21)\ B(0) = \frac{A}{r}\left(1-e^{-rT}\right) - \left(\frac{A}{K_W}\right) \times E\left[\operatorname{Max}(0, K_W - W(t))\right]\frac{\left(1-e^{-rT}\right)}{r}.$$

As before, we assume the lender will offer this mortgage at a higher interest rate so that the present value of the mortgage with the weather insurance is equivalent to the mortgage without weather insurance, i.e.:

$$(22)\ \frac{A(i)}{r}\left(1-e^{-rT}\right) = \frac{A(i^{*})}{r}\left(1-e^{-rT}\right) - \left(\frac{A}{K_W}\right) \times E\left[\operatorname{Max}(0, K_W - W(t))\right]\frac{\left(1-e^{-rT}\right)}{r}.$$

The solution cannot be solved in closed form, but will be the numerical solution to i^{*} in:

$$(23)\ \left[\frac{1-(1+i^{*})^{-T}}{i^{*}}\right] = \left[\frac{1-(1+i)^{-T}}{i}\right] \times \left(1 + \frac{E\left[\operatorname{Max}(0, K_W - W(t))\right]}{K_W}\right)^{-1}.$$

The premium for a multiple-event 35-day drought at Ardmore (up to two 35-day drought events) was priced using the WeatherWizard program at $362 with a maximum payout of $1,400. The drought was defined as 35 consecutive days in which the total cumulative rainfall was less than or equal to 1". The payout was $1,000/inch of rain deficit. Assuming a base mortgage rate of 8% and 10 years amortization, the annual interest rate on the weather-linked mortgage, calculated numerically, is 13.44%, i.e.:

$$\left[\frac{1-(1+0.1344^{*})^{-10}}{0.1344^{*}}\right]=\left[\frac{1-(1+0.08)^{-10}}{0.08}\right]\times\left(1+\frac{362}{1{,}400}\right)^{-1}.$$

At 8%, the amortization is $14,902, and for the weather-linked mortgage at 13.44% it is $18,756. The scaling factor, indicating the number of weather-linked units required, is 10.644 (ψ = 18,756/1,400 = 10.644) to cover a mortgage of $100,000 on a worst-case scenario basis. Under a single event (it does not rain for 35 days), the amortization would be reduced by 10.644 × $1,000 = $10,644 so that the farmer would only pay $8,111. Under the worst-case scenario recorded in 1914, when only 6.47" of rain fell, the total payout was $1,400, resulting in a mortgage liability of only $3,853.

Comparing Ithaca and Ardmore

The expectation of loss from specific-event risk is uniquely defined at any location by the functional relationship between duration, frequency, and intensity. Duration is a definition in time ranging from a day, week, month, year, or more or less. The model additionally uses the concept of multiple events which infers a second dimension of time. The first dimension therefore measures the period over which the weather event is to be investigated while the second dimension is a time frame within that period. For example, *duration* is measured by any non-overlapping 21-day period between June 1 and August 31. There is a possibility of four non-overlapping events. If it were measured on a 7-day basis, there could be as many as 13 non-overlapping events.

Frequency measures the probability scale defined in terms of the frequency that the event occurs over the specified duration. Frequency here can be based on historical fact (often referred to as the burn rate) or by a defined distribution (e.g., an assumption of lognormality).

Intensity is a measure of scale and refers to the quality or condition under investigation, and thus requires a point of reference from which quality can be measured and a directional indicator by which condition can be measured. The former will usually be measured by a quantitative criterion such as rainfall or temperature, and the condition is normally defined by whether the actual quantity is above or below the point of reference.

To investigate the pricing of weather-linked credit, we compare two distinctly different locations in the United States, using the exact same criteria for frequency, intensity, and duration. All that differs is the location of the two weather stations—but this is enough to illustrate the functionality of the three linked financial products. We use for our example the city of Ardmore, Oklahoma, which has continuous daily heat and precipitation data from 1902 to 2001, and as a point of comparison Cornell University in Ithaca, New York. The data in this paper were obtained from an online weather risk management program (www.weatherwizard.us; see Turvey and Norton, 2007) which uses National Oceanic and Atmospheric Administration (NOAA) weather station data up through 2002.

Figure 1 and Table 1 provide a summary of the precipitation history in Ardmore and Ithaca. Ithaca, New York, averages approximately 10.74" of rain in the 91 days between June 1 and August 31, while Ardmore, Oklahoma, accumulates on average only 9.08". The variability in rainfall is substantially different between the two stations, but what is strikingly different is the distribution of rainfall. The second and third columns in Table 1 show that Ardmore is much more prone to drought than Ithaca. For example, there is a 30% chance that Ardmore could receive less than 6" of rain, while the chance of this occurring in Ithaca is only about 1%; there is a 57.6% chance that rainfall in

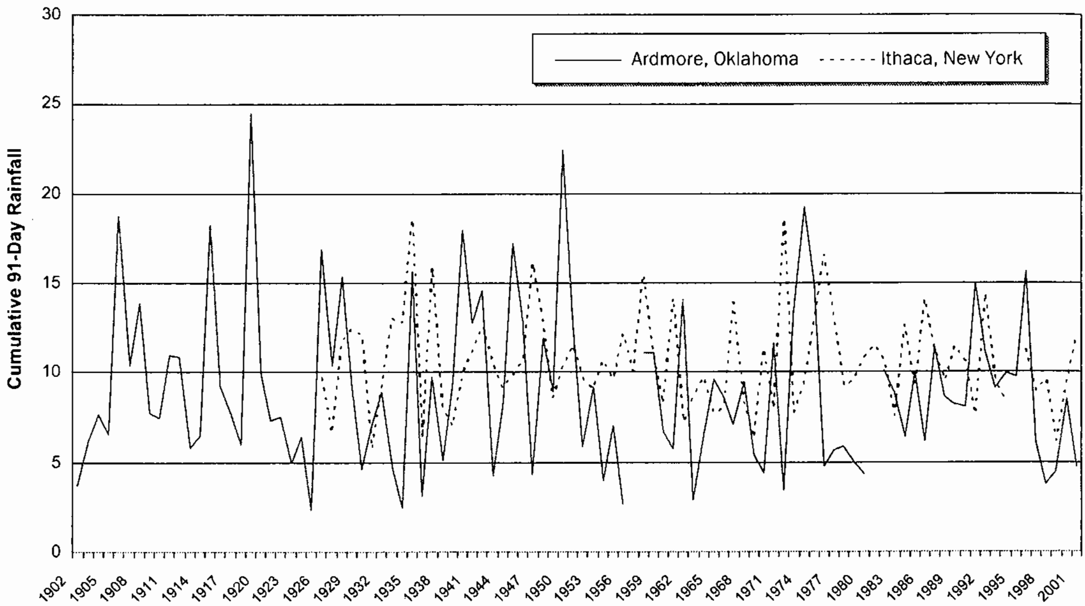

Figure 1. Cumulative Rainfall, June 1 through August 31: Ardmore, OK (1902–2002) and Ithaca, NY (1926–2002)

Table 1. Seasonal Cumulative Precipitation Insurance, 91 Days, June 1–August 31

ARDMORE, OKLAHOMA		ITHACA, NEW YORK	
Average: 9.08"		Average: 10.74"	
Std. Dev.: 4.57"		Std. Dev.: 2.77"	
Precipitation Less Than:	**Frequency**	**Precipitation Less Than:**	**Frequency**
2"	0.0101	2"	0
3"	0.0505	3"	0
4"	0.1010	4"	0
5"	0.2121	5"	0
6"	0.3030	6"	0.0135
7"	0.3838	7"	0.0811
8"	0.4747	8"	0.1622
9"	0.5758	9"	0.3108

Ardmore will fall below 9", whereas there is only a 31% chance that rainfall in Ithaca will fall below 9". Oklahoma is prone to drought while in Ithaca, drought of serious consequence is rare. It becomes clearly evident that the metrics of frequency, intensity, and duration cannot be generalized and that weather events must be measured to each particular weather station. We use the longest time frame allowed by the data—from 1902–2002 for Ardmore, Oklahoma, and 1926–2002 for Ithaca, New York.[2]

We examine only precipitation insurance, although identical procedures hold for any heat insurance product. Frequency is determined by the historical record. Duration is established by a time scale, while intensity is established by event length and the indemnity trigger. Two contracts serve our purpose here. The first is a multi-event precipitation contract in which a single event is defined by the number of days in which the cumulative rainfall does not exceed 1". For example, a 7-day event is one in which a payout is made if, in any non-overlapping 7-day period, at most 1" of accumulated rainfall is recorded. There are a possible 13 such events in a 91-day span (June 1 to August 31), and while it is quite unlikely that such a product would be offered from a practitioner's point of view, for illustrative purposes the present computations allow for all possible events. Likewise, a specific event of not more than 1" of rain for any non-overlapping 35 days provides for a maximum of two such events in a 91-day period. The tick is $1,000/inch and is paid on any fraction of deficit below 1", i.e., $\$1{,}000 \times \text{Max}[1 - W(t), 0]$ for each event. The premiums are based on the historical mean of the annual indemnities.

The second example is based not on days without rain, but on the seasonal accumulation of rain over the 91-day period. For example, a strike or trigger of 6" will pay an indemnity of $1,000/inch on any deficit rainfall below an accumulated 6", i.e., $\$1{,}000 \times \text{Max}[6'' - W(t), 0]$. Because this is seasonal there is only one event.

The procedures follow those provided in the examples above for the weather-linked bond, mortgage, and operating credit. The premiums and maximum values obtained from the WeatherWizard program are provided in Table 2, and the interest/coupon rates for the two types of specific events are reported in Table 3.

For the first case, the premiums fall as the number of days defining the specific events increase. In other words, it is far more likely to receive less than 1" of rainfall in a 7-day period as in a 42-day period, and it is far more likely to occur in Oklahoma than in New York. The 7-day event has a maximum payout of $11,160 in Ardmore and $8,720 in Ithaca, for an expected difference of $2,440. Consequently, the premiums are higher in Oklahoma than in New York. The premiums for the 7-day event are $7,380 and $5,712 for Ardmore and Ithaca, respectively, yielding a difference of $1,668, whereas the 42-day event with an historical maximum payoff of $1,160 would cost only $186 in Ardmore and virtually zero in Ithaca.

The seasonal insurance premiums under the headings of 3" through 9" in Table 2 provide the seasonal measures. In Ithaca there were no years in which less than 5" of rain fell between June 1 and August 31, so to insure for such a drought would appear to be impractical. This is not so in Oklahoma, where low rainfall seasons are not entirely infrequent. A rainfall deficit below 3" would have historically provided about $670 in payoff at a cost of only $16 per $1,000 unit. Compare that to a 9" trigger which historically would have paid off $7,670 in Ardmore but only $3,220 in Ithaca. The premiums in Ardmore at $1,745 are more than three times the $409 at Ithaca, even though the definitions for the specific events are identical.

[2] There is no advantage to aligning data to the most recent start date, because any bias in probability rests with shorter series and not the longer series. Indeed, had the assessment been carried out from 1926 in both locations, serious droughts in Oklahoma occurring in 1902, 1913, 1918, 1923, and 1925 would have been missed.

Table 2. Insurance Premiums and Payouts for Specific-Event Rainfall Insurance

	Multiple-Event Cumulative Rainfall (days with less than 1" cumulative rainfall)					
	7 days	**14 days**	**21 days**	**28 days**	**35 days**	**42 days**
Ardmore, OK:						
Premium	7,380	2,626	1,200	609	362	186
Maximum	11,160	5,160	3,160	2,160	1,400	1,160
Ithaca, NY:						
Premium	5,712	1,051	245	67	15	0
Maximum	8,720	3,090	2,000	1,000	540	30
Difference:						
Premium	1,668	1,575	955	542	347	186
Maximum	2,440	2,070	1,160	1,160	860	1,130

	Single-Event Seasonal Rainfall (less than stated volume of rain between June 1 and August 31)							
	2"	**3"**	**4"**	**5"**	**6"**	**7"**	**8"**	**9"**
Ardmore, OK:								
Premium	0	16	78	218	452	796	1,228	1,745
Maximum	0	670	1,670	2,670	3,670	4,670	5,670	7,670
Ithaca, NY:								
Premium	0	0	0	0	3	51	167	409
Maximum	0	0	0	0	220	1,220	2,220	3,220
Difference:								
Premium	0	16	78	218	449	745	1,060	1,336
Maximum	0	670	1,670	2,670	3,450	3,450	3,450	4,450

The various coupon and interest rates from linking these weather risks to the credit instruments are given in Table 3. For the multiple-event instruments, the interest and coupon rates differ significantly. In Ardmore, the high probability of a payout on the 7-day event results in rates of 43.1%, 21.1%, and 55.7% for the bond, mortgage, and operating instruments, respectively, and these are close to the corresponding rates of 42.2%, 21.0%, and 55.3% computed for Ithaca. The differences occur as the events become more extreme and rare. For the 28-day event the rates are 15.1%, 13.9%, and 31.1% for bond, mortgage, and operating instruments at Ardmore, but are substantially lower at 9.3%, 9.5%, and 14% at Ithaca. The heavy cost of credit protection for high-frequency events may make such contracts prohibitively expensive, suggesting that the more significant marketing of such products would be for the lower-frequency events.

Similar findings hold for the seasonal events reported in Table 3. At a 3" measure of risk, debt protection could be purchased at 8.4%, 8.5%, and 10.2%, respectively, for bond, mortgage, and operating credit in Ardmore, but because such events have never been recorded in Ithaca, managing such risk would be redundant. There are significant differences between the rates on the bonds and mortgages and those on the operating line of credit. The operating line of credit has a 1-year duration, so any indemnity applied to the credit line will have a high present value cost to the counterparty. In contrast, both the bond and the mortgage have 10-year durations, so the time value of money plays a critical role; the present value of an indemnity 10 years hence is

Table 3. Coupon and Interest Rates on Weather-Linked Bonds, Mortgages, and Operating Loans

	Multiple-Event Cumulative Rainfall (days with less than 1" cumulative rainfall)					
	7 days	**14 days**	**21 days**	**28 days**	**35 days**	**42 days**
Ardmore, OK:						
Bond	0.431	0.267	0.190	0.151	0.143	0.114
Mortgage	0.211	0.183	0.158	0.139	0.134	0.114
Operating	0.557	0.465	0.381	0.311	0.294	0.218
Ithaca, NY:						
Bond	0.422	0.173	0.105	0.093	0.085	0.082
Mortgage	0.210	0.151	0.106	0.095	0.086	0.083
Operating	0.553	0.353	0.187	0.140	0.105	0.093
Difference:						
Bond	0.010	0.094	0.085	0.058	0.058	0.032
Mortgage	0.001	0.032	0.052	0.044	0.048	0.031
Operating	0.004	0.112	0.193	0.171	0.189	0.125

	Single-Event Seasonal Rainfall (less than stated volume of rain between June 1 and August 31)							
	2"	**3"**	**4"**	**5"**	**6"**	**7"**	**8"**	**9"**
Ardmore, OK:								
Bond	0.080	0.084	0.089	0.096	0.105	0.117	0.130	0.133
Mortgage	0.080	0.085	0.090	0.098	0.107	0.116	0.126	0.128
Operating	0.080	0.102	0.122	0.153	0.188	0.226	0.262	0.271
Ithaca, NY:								
Bond	0.080	0.080	0.080	0.080	0.082	0.088	0.095	0.106
Mortgage	0.080	0.080	0.080	0.080	0.083	0.089	0.096	0.107
Operating	0.080	0.080	0.080	0.080	0.092	0.118	0.147	0.191
Difference:								
Bond	0.000	0.004	0.009	0.016	0.023	0.029	0.035	0.027
Mortgage	0.000	0.005	0.010	0.018	0.024	0.027	0.030	0.021
Operating	0.000	0.022	0.042	0.073	0.095	0.108	0.115	0.080

significantly discounted to an indemnity one year hence, even if (as assumed here) the distribution of risk is equivalent in all years. Consequently, the rates on these instruments are relatively low. Indemnifying a 9" risk results in a bond coupon rate of only 13.3% in Ardmore and 10.6% in Ithaca, while the mortgage rate is only 12.8% in Ardmore and 10.7% in Ithaca. In comparison, the interest rates on the 1-year operating loan are 27.1% and 19.1%, respectively, embedding risk premiums that may be too high for some farmers.

Conclusions

This paper has discussed the role that weather-linked credit can play in managing firm liquidity and agency costs, justified the use of weather as a means to manage strategic risks, and developed formulae for the interest and coupon rate pricing on weather-linked bonds, mortgages, and operating lines of credit. The interest in weather derivatives has not formally been presented in relation to bonds, loans, mortgages, and other credit instruments as outlined in this paper.

The presentation in this paper follows closely the logic, economics, and model formulation of the more popular commodity-linked loans, and from a mathematical point of view the logic, benefits, and costs are interchangeable. Using historical precipitation data for two distinct agricultural economies and climate zones at Ardmore, Oklahoma, and Ithaca, New York, the formulae and their uses were illustrated.

The key objective was to present and illustrate the formulae, but further contributions have been made in the comparison itself. Oklahoma is far more drought prone than Ithaca, and consequently the rates charged for weather-linked credit are uniformly higher in Oklahoma, sometimes by a substantial margin. The difference between the base rate and the weather-indexed rate can be viewed as the risk premium above the base rate for which the lender would be indifferent toward providing linked credit versus a conventional loan.

It is clearly represented that the nature of the risks is important and that the premium will increase as risks increase and will also differ depending upon how the specific precipitation event to be insured is defined. Only two types of risk were presented in the paper, although the same procedures can be used for virtually any well-defined and measurable single or multiple heat or precipitation event, as well as for any type of payout (e.g., unit payout or lump-sum payout).

The usual problems that hamper weather derivatives or weather insurance, however, are no more resolved when attached to a bond as when used to manage volumetric risk in isolation of credit. These include the nature of the stochastic process and probability distribution determining the risk and payoffs to the option, the location of measurement and basis, the comprehension by end users, and so on. Nonetheless, there are many specific weather events that are highly correlated with production variability which can be indexed to a credit product. The models provided in this paper can be used in many applications, and examples have been introduced.

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Creating Insurance Markets for Natural Disaster Risk in Lower Income Countries: The Potential Role for Securitization

Jerry R. Skees, Barry J. Barnett, and Anne G. Murphy

Abstract

This article considers the potential for securitizing index-based insurance products that transfer weather and natural disaster risks from lower income countries. It begins with a brief overview explaining why markets for natural disaster risks are important, yet often missing, in lower income countries and a review of some recent activities using index-based weather insurance. Next, we describe how natural disaster risks are handled in higher income countries. These examples, along with the example of an innovative index-based livestock insurance pilot project in Mongolia, illustrate how layers, or tranches, of natural disaster risk can be financed during the product development phase by creating structures similar to the Special Purpose Vehicles used in catastrophe bond, mortgage bond, and the emerging microfinance bond markets. We refer to these investment alternatives as micro-CAT bonds since the principal amounts would be small relative to the existing CAT bond market.

Key words: catastrophe risk, index insurance, reinsurance, socially responsible investing, weather risks

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Many lower income countries (LICs) are highly exposed to losses caused by extreme weather events and other natural disasters, yet insurance markets for transferring these risks are often missing in LICs. The working premise presented here is that a lack of domestic capital and limited access to global financial markets restrict opportunities for the ex ante transfer of natural disaster risks in many LICs.[1] This article explores some new approaches to creating insurance markets for natural disaster risk in LICs.[2] The increased use of index-based risk transfer products (IBRTPs) opens the way for these new approaches.

Several authors have addressed the challenges associated with managing catastrophic risk in small LICs (Pollner, 1999; Andersen, 2002; Hofman and

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[1] To the extent that global reinsurers are willing to participate in experimental programs and provide reinsurance for small volumes of business, this premise may not be correct. Regardless, the purpose of this article is not to debate that topic. Rather, the major objective is to consider alternative mechanisms for financing experimental natural disaster risk transfer products in LICs.

[2] It is important to note that the Mongolian World Bank team and some key individuals in Mongolia advanced the financing structure used in Mongolia that motivates much of the discussion contained in this article. In particular, the authors acknowledge Rodney Lester, Tungalag Lailan, Nathan Belete, Olivier Mahul, and Andrew Goodland. Richard Carpenter, who was also involved in the IBLI design, provided useful perspectives on the legal and regulatory challenges associated with pursuing the ideas presented in this article. His review made us aware that many of these legal and regulatory issues are not fully addressed here.

Brukoff, 2006; Mahul and Gurenko, 2006). Pollner (1999) introduces the idea of using capital markets to finance natural disaster risk as an alternative to insurance in lower income countries and presents a variety of ways in which this could be structured and facilitated with the assistance of donors. Andersen (2002) describes the vulnerability of LICs to natural disasters and the role of donors in facilitating access to global markets for transferring risk while also building risk management capacity at the local level.

Hofman and Brukoff (2006) review a number of public- and private-sector mechanisms that could be used to transfer natural disaster risk, as well as the challenges to the widespread adoption of these mechanisms in LICs. Mahul and Gurenko (2006) review the problems with ex post disaster assistance and discuss how catastrophe insurance pools, catastrophe bonds (CAT bonds), and contingent loans can be used to provide LICs with more efficient and effective ex ante financing for disaster relief.

This study extends the literature on financing natural disaster risks in LICs by presenting conceptual arrangements that use the basic workings of CAT bonds with a unique structure for prefinancing natural disaster risk. Building on the financing structure of the Mongolian Index-Based Livestock Insurance (IBLI) pilot, we consider the potential for marketing layers, or tranches, of risk to investors—especially during the early stages when the market for transferring risk outside the country is under development.

As natural disaster risk transfer markets mature, a wider range of options for financing disaster risk should become more feasible; in particular, traditional reinsurers are likely to become more involved. Options for financing natural disaster risks in LICs could eventually include a blend of global reinsurance and securitized risks, as is occurring in higher income countries.

Natural Disaster Risk Transfer and Economic Development in LICs

By providing opportunities to transfer natural disaster risks out of the local economy, insurance markets can directly spur increased investment by agricultural producers in LICs in riskier but highly productive activities. Emerging evidence suggests that LICs with both banking and insurance markets experience the greatest economic growth [U.S. Agency for International Development (USAID), 2006].

Insurance markets can also indirectly stimulate increased investment through linkages to credit markets. Lenders often ration credit in areas that are exposed to spatially correlated natural disaster risks since a widespread natural disaster can simultaneously cause a large number of loan defaults. However, lenders should be more willing to provide loans if borrowers can insure against natural disaster losses. For these reasons, markets for transferring natural disaster risk are important for reducing vulnerability to risk and stimulating economic growth in many LICs.

LICs are disproportionately affected by extreme weather events and other natural disasters. Losses caused by natural disasters, when measured as a percentage of gross national income, are highly negatively correlated with per capita income (Linnerooth-Bayer, Mechler, and Pflug, 2005). A single natural disaster can stunt economic growth for many years due to lost production, damaged infrastructure, and the diversion of scarce development resources for recovery efforts (Carter et al., 2007). An example is Hurricane Mitch, which struck Honduras in 1998. Four years after the hurricane, the annual gross domestic product (GDP) in Honduras was still 6% less than pre-disaster projections (Linnerooth-Bayer, Mechler, and Pflug, 2005).

LICs are relatively more susceptible to natural disaster losses in part because their economies are more dependent on agriculture. In LICs, agricultural production accounts, on average, for almost 23% of GDP (World Resources Institute, 2007). This figure does not include the additional GDP generated by industries that provide agricultural inputs or that transport or process agricultural commodities. Employment in the agricultural sector in LICs is almost two times the GDP contributions. This dependence on agricultural production makes LICs more susceptible to economic losses caused by extreme weather events and other natural disasters.

Extreme weather events and other natural disasters can have devastating effects on private-sector businesses and local governments. Natural disasters destroy both private and public infrastructure. Private entities can experience long periods of business interruption, while local governments are forced to divert scarce resources from long-term investment priorities, such as education or health, to short-run disaster recovery needs.

At the household level, natural disaster risk also contributes to chronic poverty. Approximately 1 billion people live on less than US$1 per day. Three-quarters of these "poorest of the poor" live in rural areas of LICs (Chen and Ravallion, 2007) and over one-half depend on agriculture or agricultural labor as their primary livelihood strategy (International Fund for Agricultural Development, 2001). Extreme weather events and other natural disasters can destroy productive household assets that have been accumulated at high opportunity cost (Carter et al., 2007; Carter and Barrett, 2006; McPeak and Barrett, 2001; Dercon, 1998). Recognizing the potential for such losses, households are prone to choose livelihood strategies that reduce risk exposure but likely also generate lower expected returns (Carter and Barrett, 2006; Dercon, 2005; Rosenzweig and Binswanger, 1993).

By reducing exposure and vulnerability to natural disaster risks at all levels, the availability of risk transfer markets can create a more stable and attractive environment for investment. Using financial markets to prefinance natural disaster risk can create more stability in an economy following a natural disaster by reducing the government's fiscal burden and providing a guaranteed source of relief funds. Likewise, the ability of rural businesses and agricultural intermediaries to protect themselves against economic shocks from natural disaster risks supports the sustainability and growth of the rural economy and should encourage greater investment in the rural sector. Finally, access to insurance or other means of transferring disaster risk can encourage households to invest in higher-return activities by reducing their exposure to natural disaster risk, thereby improving their access to credit.

Missing Insurance Markets for Natural Disaster Risks in LICs

While markets for transferring weather and natural disaster risks are important for economic development in LICs, these markets are often underdeveloped or absent due to asymmetric information, high transaction costs, and exposure to spatially correlated losses (Skees and Barnett, 2006). Also, governments in most LICs are unable to provide subsidies for these markets as is done in many higher income countries (Hess et al., 2005). Difficulties with weather insurance markets (e.g., crop insurance) exist to some degree in any setting, yet they can be insurmountable when attempting to provide insurance to poor households in LICs (Barnett, Barrett, and Skees, forthcoming).

Asymmetric information problems are inherent to various types of insurance products. Careful underwriting of risk exposure and monitoring of policyholder behavior are necessary to address asymmetric information problems. However, there is a large fixed-cost component to underwriting and monitoring activities, so, for small insurance policies, underwriting and monitoring costs are extremely large relative to the insured value. Similarly, there is a large fixed-cost component to the transaction costs of selling insurance policies and adjusting any claims. For small insurance policies, these costs are also large relative to the insured value.

Because natural disaster losses tend to be spatially correlated, insurers cannot effectively pool these losses within the region, or often times even within the country. Thus, insurers are reluctant to offer coverage against natural disaster losses unless they can obtain reinsurance to transfer these spatially correlated losses into international markets. However, due to extreme uncertainty about the probability of occurrence, reinsurers will sometimes refuse to cover catastrophic loss exposure resulting from natural disasters. Even if reinsurance is offered, premium rates will be loaded to account for the extreme uncertainty. Reinsurers will also conduct due diligence on the insurer's book of business. All of these costs must eventually be passed on to policyholders. The result is that insurance against correlated natural disaster losses is often either unavailable or unaffordable in LICs.

Markets for Natural Disaster Risk in Higher and Middle Income Countries

Even in higher income countries, financing correlated losses is a major challenge for any form of insurance that covers losses caused by extreme weather events and other natural disasters (Skees and Barnett, 1999). Correlated risks result in large numbers of claims at the same time in the same geographic area. This means that if a major loss event occurs in the early years of establishing any form of indemnity fund or reserves, premiums may not be adequate to cover losses. Indemnities for a single event can exceed premiums collected in a single year by several times. It requires careful planning to ensure that adequate capital is available when major loss events create claims that exceed premiums.

These issues are critical to the financial viability of any insurance company offering insurance against adverse weather events.

Reinsurance is the most common mechanism for transferring large risks from primary insurers to international markets. While reinsurance is a very effective means of transferring risk, it does have some limitations. The reinsurance market is thin and there is limited price transparency. Also, there are significant transaction costs to reinsurance. Each reinsurance contract is customized, requiring costly legal fees. Conducting due diligence on the primary insurer's book of business is costly. Finally, after the reinsurance contract is in place, the reinsurer must engage in costly monitoring to reduce moral hazard.

In the case of catastrophic weather risks, an "ambiguity" load is often added to reinsurance premiums. In this context, ambiguity refers to the tremendous uncertainty that exists about the likelihood and magnitude of extreme weather events. To be cautious, reinsurers load premium rates to account for this ambiguity. Reinsurance pricing is also very volatile. Following a major loss event, premiums tend to rise dramatically in the affected markets. Over time, premiums gradually fall until the next big loss event. For example, following very active hurricane seasons in 2004 and 2005, reinsurance prices increased dramatically for 2006 in U.S. and Mexican markets. Compared to 2005, reinsurance prices increased 76% in the United States and 129% in Mexico, while reinsurance prices in other parts of the world rose only 2% (Guy Carpenter and Co., 2007).

A number of scholars have also expressed concern that the lack of understanding of the risks and events being insured may result in relatively high prices (Camerer and Kunreuther, 1989; Hogarth and Kunreuther, 1989). Froot (1999) provides more in-depth analysis of this issue for catastrophe reinsurance with a list of explanations for this phenomenon: (*a*) the market power of reinsurers, (*b*) high moral hazard and adverse selection problems at the insurance level, and (c) inefficient corporate structure within the reinsurance industry.

As a response to volatile reinsurance markets, CAT bonds and other risk-linked securities emerged in the mid- to late 1990s as an alternative means to transfer catastrophic risk. These risk-linked securities transfer specific types of catastrophic risk from the holder to the investor.

Scholars have described the evolution of this new form of risk financing as the convergence of reinsurance and capital markets (Cole and Chiarenza, 1999; Cummins, Lalonde, and Phillips, 2002; Doherty, 1997; Lamm, 1997). CAT bonds involve the creation of a marketable security that is tied to a specific catastrophic event and is financed by premiums flowing from contingent claims transactions—generally traditional insurance or reinsurance transactions. If the catastrophic event does not occur, the investor receives a rate of return that is generally a few hundred basis points higher than the LIBOR.[3] If the catastrophic event does occur, the investor loses the interest and some predefined portion (up to 100%) of the principal invested. The funds are then used by the seller of the CAT bond to pay claims to policyholders.

Since the volume of capital markets is many times that of the entire reinsurance industry, access to capital markets could compensate for some of the limitations of traditional reinsurance. For example, in 2005, the U.S. General Accountability Office (GAO) reported insurers were beginning to believe that "the presence of catastrophe bonds as an alternative means of transferring risk may have moderated reinsurance premium increases over the years" (GAO, 2005, p. 27).

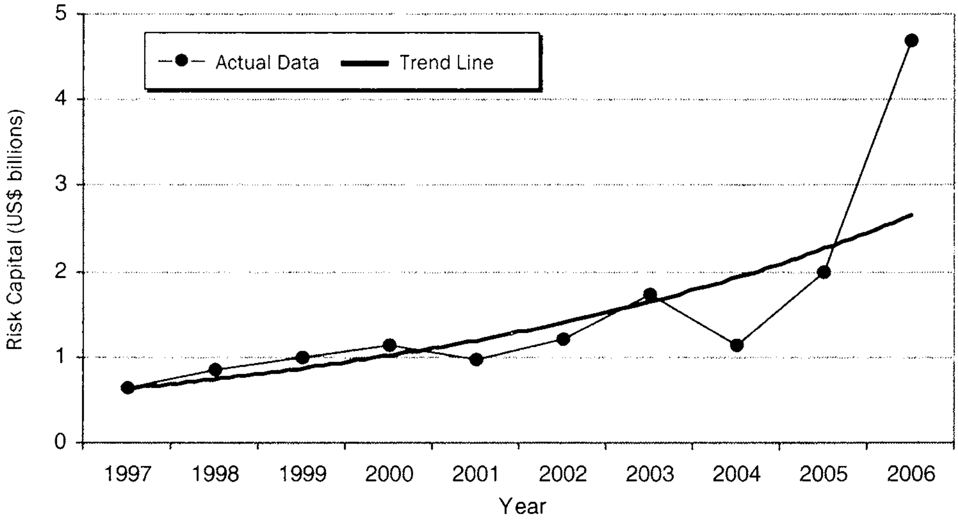
[3] London Interbank Offered Rate (LIBOR) is a daily reference rate based on the interest rates at which banks offer to lend unsecured funds to other banks in the London wholesale or "interbank" money market.

A defining characteristic of CAT bonds is that the occurrence of a prespecified catastrophic event will cause the investor to lose some, or all, of the principal. However, CAT bonds differ based on how the catastrophic event is measured. Indemnity-triggered CAT bonds measure the occurrence of the catastrophic event based on losses actually incurred by the seller. A limitation of indemnity-triggered CAT bonds is that, as with reinsurance, the purchaser will insist on conducting due diligence on the seller's book of business. This adds transaction costs and also requires the seller to disclose potentially proprietary underwriting information. Moreover, due to the potential for moral hazard, the purchaser will also have to monitor the activities of the seller—adding further transaction costs.

In recent years, the use of indemnity-based triggers has declined relative to contracts that utilize various index-based triggers. Index-based CAT bonds do not define the triggering catastrophic event based on losses incurred by the seller, but rather, based on some objective measure that is highly correlated with losses incurred.

An example is parametric-triggered CAT bonds that trigger principal forfeitures based on physical parameters such as weather variables (Turvey and Chantarat, 2006). Modeled loss-triggered CAT bonds trigger principal forfeitures based on loss predictions from a statistical model that incorporates one or more physical parameters (e.g., weather variables). Industry loss-triggered CAT bonds trigger principal forfeitures based on the average loss experience for an industry in a region rather than losses experienced only by the seller of the bond. Another example is hybrid-triggered CAT bonds, which require more than one underlying index to trigger before the principal is forfeited.

Index-based CAT bonds are simply a specific form of a more general class of financial instruments we refer to as index-based risk transfer products (IBRTPs).



Source: Authors' representation based on Guy Carpenter and Co. (2007, p. 5).

Figure 1. Growth in CAT Bond Market (1997–2006)

Other examples of IBRTPs include products such as weather derivatives, weather index insurance, and area-yield insurance. As with other IBRTPs, index-based CAT bonds have the advantage of much lower transaction costs relative to traditional reinsurance or indemnity-triggered CAT bonds. The use of index-based CAT bonds also reduces moral hazard, which may be of particular importance in areas where regulatory oversight and monitoring of the insurance sector is less developed. CAT bonds that use direct parametric measures (referred to as indexes in this article) comprised about 30% of CAT bond risk capital in 2006. Hybrid products that use some form of indexing comprised another 37% in 2006 (Guy Carpenter and Co., 2007).

Indemnity-triggered or index-based CAT bonds can be sold for different layers (or tranches) of risk, much like reinsurance. For example, to protect against flood losses in a given region, an insurer may sell parametric-triggered CAT bonds based on aggregate rainfall over a period of time measured at a specified weather station. By selling CAT bonds with different trigger levels of aggregate rainfall, the seller can match the proceeds from the CAT bonds with expected losses due to different levels of rainfall.

The market for CAT bonds in the United States, Western Europe, and Japan has been growing since the first transactions in the mid-1990s. In 2006, the market nearly doubled from the previous year, with 20 issues worth nearly US$5 billion (Figure 1). Following the record losses from Hurricane Katrina, reinsurance premiums increased dramatically in some markets, leading to greater interest in the use of CAT bonds to transfer hurricane risk. This increased demand led to higher yields on CAT bonds which, in turn, generated more interest from investors. Standardization and experience with these instruments have also contributed to the growth of this market as investors become more familiar and comfortable with CAT bonds. Importantly, reinsurance companies are also using CAT bond markets to reduce some of their extreme exposure.

In 2006, Mexico became the first middle income country to issue CAT bonds to provide disaster financing in the event of a high magnitude earthquake. The bonds were underwritten by SwissRe and issued by CAT-Mex, Ltd. The CAT bonds provide US$160 million in contingent disaster financing for the most catastrophic layer of risk: earthquakes of 8.0 or greater on the Richter scale that occur in a defined zone in Mexico. An index insurance contract provides up to an additional US$290 million for earthquakes of the same magnitude occurring in either of two other zones. Under the structure of this bond, if an earthquake of this magnitude occurs, investors lose their entire principal, which is transferred to the government for disaster relief.

At issue, the bonds were offered at 235 basis points above LIBOR. The Mexican government paid US$26 million to secure this financing arrangement (Cardenas, 2006; Malkin, 2006). These CAT bonds were structured to complement a World Bank loan of up to US$180 million that is triggered by earthquakes of magnitude 7.0 or greater on the Richter scale. By layering these catastrophic risks and transferring them into international markets, Mexico can maintain a smaller disaster reserve fund, allowing more of the country's limited financial resources to be invested in health, education, infrastructure, and other public needs.

While there will always be an important role for reinsurance in transferring the risk of extreme weather events and other natural disasters, CAT bond markets are evolving into a cost-effective and efficient means of transferring catastrophic risks. Since the average CAT bond term is three years, the price and terms of the contract are stable for multiple years. Additionally, there is little credit risk. Just as is done when securitizing credit risks, funds are secured in a Special Purpose Vehicle (SPV) so payment upon a triggering event is assured. CAT bonds do have important limitations. There are significant transaction costs to establishing CAT bonds. These costs include risk analysis, product design, legal fees, and the establishment of SPVs. They also include the special regulatory considerations that are needed to protect investors. Regulatory burdens can increase when attempting to protect individual investors as opposed to institutional investors.

Emergence of Risk Transfer Markets for Natural Disaster Risk in LICs

In recent years, a number of promising approaches have emerged to assist LICs in transferring natural disaster risk (Skees and Hartell, 2006; Skees et al., 2005). Most of these have required significant support from donors to pay for the large upfront costs of developing these markets in countries that have previously had little access to risk-transfer for natural disasters. Largely due to World Bank efforts, index-based rainfall insurance in India has been expanding since its introduction in 2003. These policies are sold to small farm households by both private-sector insurance companies and the parastatal insurance company—the Agricultural Insurance Company of India. In Malawi, the World Bank has also been involved in introducing index-based drought insurance tied to both lending and the sale of seed. A number of other World Bank pilot projects are in development to expand the use and applications of index-based insurance for weather risks in LICs (Hess et al., 2005).

One of the most recent examples of a much larger index-based insurance project is the World Bank-facilitated Caribbean Catastrophic Risk Insurance Facility (CCRIF). The CCRIF is designed to provide Caribbean countries with ready liquidity in the event of a hurricane or earthquake (World Bank, 2007). Parametric triggers are used to make timely payments in each individual country using information from a third party such as the U.S. Geological Survey or the U.S. National Oceanic and Atmospheric Administration (NOAA). Donor funds are paying for much of the development costs of this risk-pooling facility. Each country pays a premium rate consistent with the underlying parametric risk for the country.

Furthermore, each country can select the sum insured. Payments will be made based on the country's choice of parametric measures, trigger levels, and sum insured.

The countries involved in the CCRIF are pooling their risk exposure to reduce the variability in losses. The CCRIF is to be reinsured by a major reinsurer. By pooling their loss exposure, the member countries can reduce the premium cost of reinsurance. Structures such as the CCRIF allow smaller countries to pool their risks and obtain sufficient scale so that other approaches to risk financing become feasible, including the potential to securitize some of the risks using instruments such as CAT bonds.

Extending the Mongolian IBLI Project to Securitize Weather Risk in LICs

While the details for the CCRIF structure are being settled as this article is written, it is useful to turn to the case of Mongolia to highlight key ideas. The CCRIF could offer similar opportunities to the financing structures being presented here using the Mongolia project. Livestock in Mongolia are highly vulnerable to extreme weather events, locally known as dzud. Dzud is a series of compounded weather events that create poor conditions for grazing livestock. For example, in 2001, a major dzud (summer drought followed by a harsh winter) led to widespread livestock losses. Mongolia lost nearly one-third of all cattle and yak. Specific areas of the country experienced even higher livestock losses in 2001 and 2002.

The government of Mongolia entered into a loan agreement with the World Bank as a means of financing a tranche of extreme risk in a pilot project for index-based livestock insurance (IBLI). The IBLI policy is sold to individual herders but payments are based on an aggregate index of livestock mortality at the soum (county) level. IBLI is being pilot-tested in three different aimags (provinces/states).

The Base Insurance Product (BIP) pays an indemnity any time mortality in the soum exceeds either 6% or 10% (depending on the policyholder's choice). Payments from the BIP reach a maximum when the soum livestock mortality rate exceeds a prespecified level (25% in one aimag and 30% in the other two aimags). For herders purchasing the BIP, the government provides an additional benefit to pay for all losses beyond those covered by the BIP. This is done to clearly separate the government social role from the market-based BIP product.

Since the same underlying parametric index (aggregate livestock mortality) is used for the BIP in each soum, it was possible to create a unique pooling arrangement for the participating insurance companies. Given that each insurance company is selling the same index insurance policy (though perhaps in different soums), they are willing to participate in a collective pool of these policies without needing to perform due diligence on one another's book of business. It is also useful to recognize that every insurance company is selling a uniform product at the same premium rate for the risk portion of the premium and that the actuarial development was performed by an independent third party.

The pool, known as the Livestock Insurance Indemnity Pool (LIIP), is funded from two sources. Each year, before any BIP policies are sold, every participating insurance company seeds the LIIP with a capital infusion representing approximately 40% of their expected BIP premiums for that year. This capital infusion is known as the Guaranteed Indemnity Contribution (GIC). The second source of funds comes from participating insurance companies which deposit the premiums received (minus their administrative load) from the sale of BIP policies into the LIIP. Insurance companies are allowed to place their own administrative load on the premiums charged to herders. The administrative load portion of the collected premiums is directly transferred to the insurance companies.

Given the experimental nature of the project, it was not practical to secure reinsurance. Thus, the Mongolian government is providing reinsurance on the LIIP at favorable terms. Herder premium rates were developed using 33 years of historical mortality data and standard actuarial procedures to risk-load for the catastrophic risk represented in these data. In 2006 and 2007, the government stop loss was set at 105% of the total contributions to the LIIP. On average, approximately 35% of the premiums deposited in the LIIP is used to build a reinsurance reserve; however, the percentage varies by company depending on the riskiness of their book of BIP policies. The reserve can build value over time (i.e., any unused funds will remain in the reinsurance reserve from one year to the next). This is important, as it affords the opportunity to create a more sustainable insurance program. Finally, if the BIP reserve is exhausted in any given year, the World Bank contingent loan is called to pay all remaining losses.

After the reinsurance contribution is made, the remaining funds in the LIIP (105% of herder premiums) earn interest over the entire insurance cycle. Even in a catastrophic year when all of the funds in the LIIP are needed to pay herder indemnities, insurance companies will recover the interest earnings. Each insurance company owns a share of underwriting gains in the LIIP equal to its portion of premium sales. Insurance companies are provided software to evaluate their risk-return profile given their book of business (i.e., their premium volume by soum and species) and their capital-at-risk, which is equal to the prepaid indemnity contributions. While the pilot has organized the LIIP account to be closed out at the end of each insurance cycle, structures of greater complexity are more desirable to impose a proper discipline for reserving.

The structure of the IBLI financing is presented in Figure 2. There are three distinct tranches within this structure:

- Tranche 1—the LIIP which is a prepaid indemnity pool similar in structure to an SPV;

- Tranche 2—a reinsurance tranche or layer that pays for losses which exceed the funds available in the LIIP (105% of herder paid premiums) up to the point where the BIP reinsurance reserve funds are exhausted (alternatively, the upper bound could be explicitly established); and

- Tranche 3—a catastrophe reinsurance reserve (currently financed by the World Bank contingent loan) for losses beyond those which can be paid under Tranche 1 and 2.

At the current time for the Mongolian project, Tranche 1 is the commercial tranche. However, depending on how the herder premium is distributed, any combination of the tranches could be made commercial (Tranche 1 only; Tranche 1 and 2 only; or Tranche 1, 2, and 3).

The structure can be replicated for any index-based insurance product. For example, if a country offers drought insurance using local weather stations or even satellite data with models to estimate soil moisture, these index-based contracts could be organized with a structure similar to that presented for Mongolia. This structure is more rigid than many other forms of regulation as it both ring-fences this unique line of insurance from other areas of the insurer's business, and it completely protects all indemnity payments so that policyholders are not left unprotected if an insurance company fails and cannot pay indemnity obligations.[4]

Of more interest for this article, this structure develops clear rules for paying losses and clearly defines the financing for

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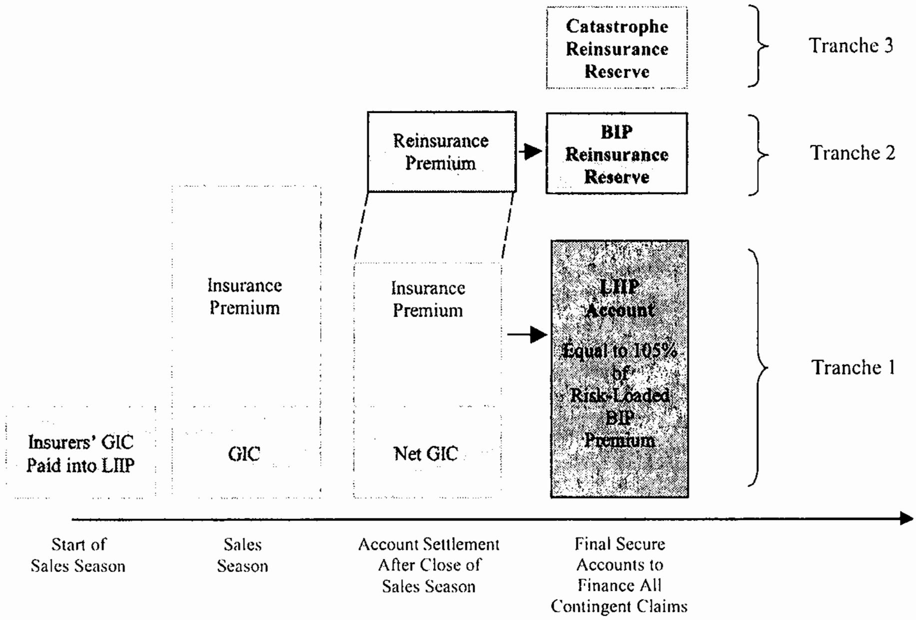
[4] The reader should bear in mind that this aspect of the project to protect the herders is unique. This may not be the best policy if one considers other individuals who have different types of insurance from the same company. They may need an equal claim to assets in the event the insurance company becomes insolvent.



Source: Authors' representation.

Figure 2. Financing Structure of the Index-Based Livestock Insurance (IBLI) in Mongolia

each tranche. In principle, each of these tranches could be securitized. Given the data and the portfolio model, a risk-rating entity could provide an initial rating for each tranche. At the outset, one could also provide market-based pricing for these debt instruments.

Each of the insurance companies own a share of Tranche 1 (the LIIP) based on their share of premium collected from herders. The LIIP can be thought of as an SPV (much like those used for CAT bonds or the securitization of loan portfolios), albeit organized and controlled by the government. The commitment of the government of Mongolia and the World Bank loan imposes significant discipline on the management of the LIIP account.

Given the structure of this unique SPV, it would be very straightforward to allow an insurance company to sell any portion of its LIIP share at any time, from the point of BIP sales to the settlement of payments. Of course, the value would be significantly driven down in a year of massive dzud.

There is no good reason to require the insurance company to continue to hold its share of the LIIP through the complete insurance cycle. This flexibility could easily allow the insurance company to remove its capital at any time. An insurance company could decide after the sales season that it has too much capital at risk in the LIIP, or the company could be in a position where it would like to liquidate part of its LIIP investment to use in alternative investments.

Given the experimental nature of the pilot, the Mongolian government and the World Bank currently hold the risk for Tranches 2 and 3. However, should the pilot prove successful (and with some minor modifications that clearly define the boundaries of each tranche), Tranches 2 and 3 could also be financed in the private sector through reinsurance or securitized instruments like CAT bonds. Given sufficient historical data and portfolio models that evaluate the spatial distribution of sales against the historical losses, one can estimate the risk profile for any one of the three tranches presented in Figure 1. As updated information regarding potential losses from the underlying index becomes available, the risk-return profile for each tranche could be dynamically recalculated, allowing for continuous trading of securities based on each tranche.

Marketing Tranches of Risks for Natural Disaster Risks in LICs

The structure presented in Figure 2 opens the way for micro-CAT bonds[5] that could also be used to transfer correlated, catastrophic risks out of LICs and into global capital markets. If such instruments can be established, this should help stimulate more risk transfer opportunities (e.g., insurance markets) within the country. For LICs, micro-CAT bonds could offer some important advantages relative to traditional reinsurance. Of course, the issue of who will pay the transaction costs of establishing and reviewing the type of structure presented in Figure 2 is a paramount consideration. Donors and LIC governments will likely have to incur these costs.

In considering a structure of the type illustrated in Figure 2, an important question is how to market this type of risk. As the scale of use and the comfort with this type of structure increases, one can expect global reinsurance markets to become involved. This section describes how individual and institutional investors could also become financially involved in experimental projects that develop natural disaster risk transfer markets in LICs. These investments offer the opportunity to support the emergence of insurance markets for natural disaster risks in LICs by easing a common constraint to market development—access to capital. This involvement could be structured with an institutional investor or it could be more direct as described below.

The challenge of attracting institutional investors remains the high transaction costs associated with the due diligence on structuring and rating the tranches to determine an appropriate return. More intriguing is the open question of how to involve the individual investor. However, regulation to protect individual investors may also be an insurmountable burden.

In any case, any one of the three tranches presented in Figure 2 offers the opportunity for investing in an instrument similar to a securitized loan portfolio or a CAT bond. The challenge is how would any of the micro-CAT bonds be marketed and how would one have some assurance that the proper structure is in place to package IBRTPs for natural disasters? Donors have demonstrated a willingness to incur the costs of developing pilot programs for the transfer of weather and natural disaster risks in LICs. Without such donor support, very little of the activity to date would have occurred. Public good arguments can be used to justify public or donor support targeted at facilitating the development of new natural disaster risk transfer markets for LICs.

To that end, the International Finance Corporation (IFC) of the World Bank Group has been working to become a share owner in a Global Index Reinsurance Facility (GIRIF). The GIRIF would consist of:

1. *a commercial risk-taking company to underwrite indexable weather and other indexable natural catastrophe risks in developing countries, and*
2. *a technical assistance/donor funding pool to develop the technical parameters of the business.*[6]

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[5] We use the term "micro-CAT bond" because investing is of such small volume that it may not be of interest to either the CAT bond market or to a global reinsurer. One should also recognize that the level of risk in Tranche 1 is actually not catastrophic.

[6] This information was taken from the IFC website on May 30, 2007 (http://www.ifc.org/ifcext/spiwebsite1.nsf/2bc34f011b50ff6e85256a550073ff1c/0c3c26c0a76328ec85257235005bad08?opendocument).

Given the use of reliable index-based contracts that are more likely to be free of moral hazard and adverse selection, these market developments may also attract more investors from the outside. It will be necessary for these markets to develop some level of scale before global reinsurance markets will be willing to fully participate. It is also extremely important that the regulatory environment is strong, to increase confidence both inside and outside the LIC about the sustainability of the emerging insurance markets for natural disaster risks. The financing structure for the IBLI offers one example for how to create an SPV-like structure that is needed to gain the confidence of outside investors.

Returning to how one might finance the LIIP account (Tranche 1) in the Mongolian project, it would be quite feasible to organize the sale of shares that are currently held by insurance companies. Consider simply organizing 100 certificates, each representing a 1% share of the proceeds from this SPV. It should be possible to allow anyone to purchase any of these shares at any point in time. Of course, there is no reason to restrict the ownership of shares to a fixed percentage (i.e., 1%); any fraction would be easy to implement. It would be important to track the total volume to make certain that a clearly defined business entity or individual owns every portion of the SPV.

Owners could include other investors in Mongolia, global reinsurers, or a broader global community of investors. Again, the shares could conceivably be sold at any time during the insurance cycle. The price would change based on the expectations regarding mortality in different regions of Mongolia. A more practical application would be a shorter period of sales that coincides with the sales closing period.

Institutional and Socially Responsible Investors

There are obvious questions and challenges to the ideas presented in this article. As was pointed out above, in the Mongolian case only Tranche 1 is commercial at this stage. Thus, any investors may be attracted to Tranche 1, which offers the potential for a positive return. Tranche 2 will grow into a more commercial venture if reserves are built over time and if there is imposed an upper limit for identifying when payments from this tranche stop and payments from Tranche 3 begin.

For those tranches that are not commercial, one can raise the question regarding how socially responsible investors might be willing to become involved. Perhaps some groups or individuals would be willing to invest in social tranches knowing that they would incur the risk of losses with a rate of return lower than market rates, simply for the sake of helping develop these markets. Another challenge is to ensure that the opportunity for investing in any of these tranches is made with the lowest transaction costs possible.

It is useful to review some of the progress made on other fronts to provide context for these ideas. Socially responsible investing that supports social, environmental, and corporate responsibility shows a growing interest, and in recent years new investment instruments have emerged, allowing investors to support the poor in LICs while still making a return. For example, the Calvert Group, Ltd. (www.calvert.com) offers socially responsible mutual funds made up of companies that have been selected according to various social criteria. Calvert also offers other unique online arrangements which direct socially responsible investors to community-based investments in development (http://www.calvertgiving.org/).

The securitization of microfinance portfolios also provides a venue for socially responsible investors to diversify their investment portfolio while simultaneously supporting development in LICs. There is a growing demand for capital in the microfinance markets of the world. Some argue that the demand is significantly greater than the supply. Microfinance institutions (MFIs) have learned that using capital markets rather than relying on donor grants and loans can be a more flexible and sustainable source of capital.

For example, Compartamos is one of the largest MFIs in Mexico. Compartamos first securitized a portion of its portfolio in local currency in 2002. That endeavor was well received by both individual and institutional investors and allowed the MFI to greatly expand its lending operations. In 2004, it issued a second bond (US$44 million) for institutional investors to further expand their capital and lending capability. The transactions were underwritten by Banamex, a Mexican subsidiary of Citigroup.

There are also a growing number of MFI investment funds that comprise a pool of smaller MFIs. Blue Orchard Microfinance Securities issued the first cross-border microfinance securitization in 2004, with a US$40 million bond issued to benefit a pool of MFIs in nine countries (Institute for Financial Management and Research, 2007; Meehan, 2004).

The largest securitization by an individual MFI took place in Bangladesh in 2006 with the Bangladesh Rural Advancement Committee (BRAC). BRAC has more than 5 million borrowers with an average loan size of US$162. BRAC has arranged to securitize US$180 million of its loan portfolio over six years in local currency at a cost of 12%, which is about 2% lower than could be achieved by borrowing that amount through commercial banks (Institute for Financial Management and Research, 2007).

A significant example in support of the ideas presented in this article is the use of the internet to attract individual investors. Kiva organizes peer-to-peer lending between socially responsible investors in higher income countries and individual entrepreneurs in LICs through web-based transactions. While there are important distinctions between this and what is being proposed here, Kiva is a noteworthy development. Kiva began in March 2005, and since then more than 60,000 people have lent over US$6 million to small businesses and entrepreneurs in LICs (http://www.kiva.org/). The growth of Kiva speaks to the willingness of people to make investments even without a financial gain since Kiva lenders receive no return on their loans and there is the risk of default (although repayment rates thus far are excellent).

In summary, the growing number of microfinance investment funds and securitizations as well as the activity that is emerging on the internet, like Kiva and some of the activity managed by Calvert (http://www.calvert.com), speak to the potential market for social investing in natural disasters given the right platform, infrastructure, credibility, and marketing.

Returning to the Mongolian structure presented in Figure 2, each of the three tranches represents a form of an SPV, albeit Tranche 1 is the only commercial tranche at this point. To the extent the control of each tranche is placed in a stronger legal and regulatory framework, such as under the control of the state bank of the LIC, this may increase the confidence of investors. The CAT bond element, which may be missing in the short term, must be rated by a financial rating institution. Portfolio software developed by a third party can provide indicative pricing; still, it would require some faith on the part of the socially responsible investors that the project and the structure are sound.

Evidence from the investment activity presented above gives some indication of the willingness of socially responsible investors to use their money based upon a large degree of faith. Thus, one can consider that the tranches presented in Figure 2 could be sold as micro-CAT bonds marketed to either institutional or individual investors. Again, each of these tranches can be developed with more or less commercial versus social objectives. To the extent they are clearly commercial, they could attract both reinsurers and institutional investors.

As Kiva, Calvert, and others have demonstrated, the proper presentation can attract socially responsible investors. If socially responsible investors gain confidence that the investments satisfy their desire to contribute to development in LICs and, in the case of the Calvert offerings, to diversify their investment portfolios, there could be a strong market for these activities. The individual integrity of projects having strong accountability and transparency should be of the most interest to this class of investor. This feedback should also enhance the incentives for those working on these types of projects to ensure they are developed in a sustainable fashion.

As an extension of the ideas presented here, securitization of natural disaster risks in LICs could also offer a different approach for people to give money for natural disaster relief. While the idea of providing disaster relief with these types of index-based weather insurance is also being tested (as in the Ethiopia World Food Program and with the Mexican FONDEN program), it is useful to consider how individuals may be willing to "lend" money via structures similar to those presented in this article. Many concerned citizens provide contributions after natural disasters occur in LICs. These post hoc responses, while well-intentioned, are provided without the benefit of ex ante rules and structure, increasing the likelihood of such funds being used inappropriately.

These same individuals may be persuaded that their good intentions could also be served by investing in the early development phases of an insurance project targeted at transferring natural disaster risks from the poor. Such a project would have predefined rules about how funds are distributed after the disaster. These instruments must have clear rules regarding who will receive the benefits.

The transparency of when and how funds would be used when a disaster strikes provides a strong incentive for those who are concerned about what happens to any charitable donations for disaster relief after a major event has occurred. Micro-CAT bonds linked to products that use a parametric index should be more attractive to a broader class of investors as these instruments are less prone to moral hazard and adverse selection problems. Additionally, many of the parametric indexes are likely to trigger payments more rapidly than numerous other systems designed to deliver cash after a disaster to those who lose crops, livestock, or assets (Goes and Skees, 2003).

Conclusion

Progress has been made in the development and use of CAT bonds in higher income countries, which allow equity investors to prefinance the losses from major catastrophes. In the most extreme cases, money invested in a CAT bond will only be used to cover catastrophic losses, and investors forfeit their capital. If there is no catastrophe, investors receive the principle and a high rate of interest. Extending these ideas, we introduce the potential for micro-CAT bonds to prefinance losses from natural disasters in LICs. The increased activity using IBRTPs for natural disaster risks in LICs opens the way for this approach. Such index insurance is less prone to the traditional problems of adverse selection and moral hazard. To the extent that the transaction costs are lower, aggregate indexes for weather, earthquakes, and even hurricanes and typhoons could offer a feasible path to a new generation of micro-CAT bond products in LICs.

This article uses the structure of the Mongolian IBLI project to demonstrate how a pool of index insurance products could be carefully regulated while also developing the needed structure to introduce micro-CAT bonds. While CAT bonds have high transaction costs in setting up the SPVs and developing the rating as a means of determining the price, it is argued that micro-CAT bonds could be marketed to both institutional investors and a broad class of socially responsible investors under a project structure similar to that of the Mongolian IBLI project and employing an internet platform similar to that used by Calvert and Kiva.

Finally, these ideas are presented to spur new thinking about how to facilitate insurance markets for natural disaster risks in LICs. The use of micro-CAT bonds is unlikely to provide large capacity as the market grows. That is not the intent. Rather, the intent is to provide nascent insurance markets in LICs with access to capital. In LICs, the lack of access to global reinsurers and capital markets is a constraint to insuring against natural disaster risk. Micro-CAT bonds could crowd-in a capital market in such a fashion whereby the more developed and much larger reinsurance market would become significantly involved. Micro-CAT bonds provide the opportunity to get limited venture capital of a broad class of investors into well-structured pilot tests that use index-based insurance to transfer extreme weather and natural disaster risk in LICs.

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Improving Humanitarian Response to Slow-Onset Disasters Using Famine-Indexed Weather Derivatives

Sommarat Chantarat, Calum G. Turvey, Andrew G. Mude, and Christopher B. Barrett

Abstract

This paper illustrates how weather derivatives indexed to forecasts of famine can be designed and used by operational agencies and donors to facilitate timely and reliable financing for effective emergency response to climate-based, slow-onset disasters such as drought. We provide a general framework for derivative contracts, especially in the context of index insurance and famine catastrophe bonds, and show how they can be used to complement existing tools and facilities in drought risk financing through a risk-layering strategy. We use the case of arid lands of northern Kenya, where rainfall proves a strong predictor of widespread and severe child wasting, to provide a simple empirical illustration of the potential contract designs.

Key words: catastrophe bond, covariate risk, famine relief, food aid, food insecurity, Kenya, pastoralists, weather derivatives

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Climate variability and extreme weather events are among the main risks affecting the livelihoods and well-being of poor populations. In sub-Saharan Africa, around 140 million people are exposed to the constant threat of famine induced by natural disasters such as droughts and floods. The capacities of communities, social networks, or families to buffer members' welfare are, however, insufficient to prevent widespread hunger and severe human suffering when covariate shocks hit. Due to limited insurance against covariate weather risks, short duration but highly catastrophic shocks can have serious long-term consequences for children's development, household productivity, asset accumulation, and income growth (Dercon and Krishnan, 2000; Hoddinott and Kinsey, 2001; Dercon and Hoddinott, 2005; Hoddinott, 2006).

Governments, external relief organizations, and players in the international aid community commonly step in as insurance providers of last resort for vulnerable populations, providing emergency response to humanitarian crises in the wake of extreme weather shocks. Their commitment to humanitarian relief exposes operational agencies and donors financially to catastrophic weather risks in developing countries worldwide. As the frequency and intensity of natural disasters and food emergencies have increased in recent decades (Munich Re, 2006), so has the number of people needing humanitarian assistance, requiring more resources from external agencies and donors. With limited available funds to support emergencies, rigorous tools for efficient planning and prioritization of interventions and resource allocation become crucial to enhance the humanitarian and economic value of emergency operations.

Recent innovations in weather derivatives[1] and the booming market for transferring covariate weather risks provide considerable promise to mitigate weather-related catastrophic shocks that threaten humanitarian crises. Improved early warning systems and emergency needs assessment practices have used timely monitoring and analysis of situations in vulnerable areas to significantly improve humanitarian response in recent decades (Barrett and Maxwell, 2005).

The goal of this paper is to show how weather derivatives can be designed and used by governments and operational agencies to improve humanitarian response to slow-onset disasters, especially drought. The contracts we propose, "famine-indexed weather derivatives" (FIWDs), comprise two main characteristics. First, the weather variables used to trigger contract payouts need to be indexed to some indicators of forecasted prevalence and severity of food insecurity conditions in the targeted areas, and second, the timing and frequency of the cash payouts need to facilitate potential early interventions.

We motivate this idea by briefly reviewing current innovations in the weather derivatives market and its potential in developing countries. The rationale for FIWDs and the contracts' main characteristics are then described. We provide a general framework for two distinct contract structures—weather index insurance and a famine catastrophe bond—and explain how developing country governments and international organizations might combine these derivative products with other funding opportunities (e.g., contingent grant or debt from international development banks) to enhance catastrophic risk transfer opportunities and to obtain cost-effective catastrophic risk financing (Hess, Wiseman, and Robertson, 2006; Syroka and Wilcox, 2006; Hess and Syroka, 2005). Finally, we illustrate the possibilities with an application to the arid lands of northern Kenya, an area that suffers recurring, severe droughts often requiring a massive international humanitarian response to avert famine.

Weather Derivatives and Their Potential in Developing Countries

A weather derivative is a type of parametric contingent claim contract whose payoff schedule depends on a measure of meteorological outcomes, such as inches of rainfall, at a certain location during the contract period (Chicago Mercantile Exchange, 2002). The weather derivative contract specifies a specific event or threshold that triggers payments and a payment schedule as either a lump-sum payment or a function of index values beyond that threshold. A variety of derivatives can be issued on well-specified weather variables or a single- or multiple-specific weather event (Dischel, 2002; Turvey, 2001). The most common types of contracts are put and call options, mostly seen in the form of weather-indexed insurance—swaps and collars.

If weather variables are highly correlated with covariate economic loss, derivatives on appropriate weather variables can be used to effectively hedge against such loss. The contracts can be written on various weather risks, and traded like financial assets. The weather derivatives market therefore provides opportunities for covariate weather risks to be transferred and managed either as part of a diversified global weather risk portfolio (weather risks in Kenya, for example, are potentially uncorrelated with those in other geographic areas) or as part of a diversified

[1] We refer to weather derivatives loosely as financial contracts that derive values from weather variables. In this context, weather derivatives may thus refer to weather index insurance offered by reinsurers, weather indices, or weather-related contracts traded in the exchange.

capital market portfolio (Hommel and Ritter, 2005; Froot, 1999). The weather derivatives market has grown dramatically, to the notional value of US$19.2 billion in 2006/07, from US$2.5 billion in 2001/02.[2] To date, the market has expanded to cover weather risks outside the United States, Europe, and Japan.

Among the popular products, catastrophe (cat) bonds are weather derivatives that have been issued primarily by reinsurance companies to facilitate transfer of the risk of highly catastrophic events with very low annual loss probabilities (mostly less than 1% per annum) to capital markets. Cat bonds are typically high-yield derivatives with the return conditional on well-defined weather conditions indicating the occurrence of a catastrophic event. From the perspective of the investor, cat bonds yield above-market rates [typically a 3%–5% spread over LIBOR (Banks, 2004; Bantwal and Kunreuther, 2000)] encompassing various compensating premiums,[3] while offering diversification. Consequently, there is an increasing appetite for these products in the market. Hedge funds, institutional money managers, commercial banks, pension funds, and insurance companies are regularly investing in cat bonds. The market to date is concentrated in reinsurance of U.S. hurricane and Japanese earthquake risk, but has been extended beyond natural perils to provide risk coverage against epidemics and manmade disasters.

The total cat bond market size grew to almost US$5 billion in 2005 (Guy Carpenter and Co., 2006), and it is expected to continue trending upward as the cost of issuing declines with the development of more standardized bond structures and as the investor base expands and becomes more knowledgeable (Bowers, 2004). Recently, there has been an attempt to design cat bonds to securitize systemic risks in agriculture (Vedenov, Epperson, and Barnett, 2006). Cat bonds—or at least the principles that underpin them—might serve as a means to transfer highly catastrophic but low probability weather risks from developing countries to the global capital market (Hofman and Brukoff, 2006).

The weather risk market also facilitates reinsurance opportunities. For example, Indian weather risks are currently reinsured in the weather derivatives market, allowing local insurance companies to sell weather insurance against drought to small farmers since 2002. The Mexican public reinsurance company Agroasemex has similarly provided weather index insurance to state governments to protect farmers against drought in most of the dryland areas since 2001. Weather insurance contracts are also currently sold in Malawi, Tanzania, and Thailand as part of pilot programs.[4]

The market also facilitates transfer of highly catastrophic weather risks that can trigger emergency needs by governments, donors, or international humanitarian organizations (Hess et al., 2005; Alderman and Haque, 2007). The United Nations World Food Programme (WFP) successfully took out US$930,000 in drought insurance from an international reinsurer, AXA Re, for Ethiopia's 2006 agricultural season covering 17 million people at risk of livelihood loss (WFP, 2005). In December 2007, the WFP announced it was expanding "the first humanitarian insurance policy" in Ethiopia, hoping to raise US$230 million in insurance and contingency funds to cover 6.7 million

[2] The survey has been conducted yearly by the Weather Risk Management Association (WRMA) and PriceWaterhouseCoopers. (For further detail see http://www.wrma.org.)

[3] Apart from the risk premium on comparably rated corporate bonds, premiums are needed to compensate for ambiguity about the probability of rare catastrophic events, costs of the learning curve for a complex product and market, and loss aversion which results in overvaluation of loss probability (Banks, 2004; Bantwal and Kunreuther, 2000; Nell and Richter, 2004).

[4] Various weather index insurance products are currently being developed in Bangladesh, Honduras, Kazakhstan, Morocco, Nicaragua, Peru, Senegal, Vietnam, and several of the Caribbean islands (Barnett and Mahul, 2007).

people if there is a drought comparable to the one in 2002/03 (IRIN Africa, 2007). In addition, the Mexican government issued a US$160 million cat bond in 2006 to insure its National Fund for Natural Disasters (FONDEN) against the risk of a major earthquake (Hofman and Brukoff, 2006; Guy Carpenter and Co., 2006).

Similar products currently being explored include a Caribbean Catastrophe Risk Insurance Facility aimed at allowing Caribbean countries to pool and transfer natural disaster risks to the capital market (World Bank, 2006), and multinational insurance pools for the Southern African Development Community (SADC) that can facilitate transferring catastrophic weather risk as part of a regional strategy to obtain reinsurance cost reduction (Hess and Syroka, 2005). The World Bank is also currently establishing a new reinsurance vehicle, the Global Index Insurance Facility (GIIF), as a risk-taking entity to originate, intermediate, and underwrite indexable weather, disaster, and commodity price risks in developing countries (World Bank, 2006).

Using Weather Derivatives to Improve Emergency Response to Droughts[5]

Rationale

While weather shocks are neither necessary nor sufficient to induce widespread humanitarian crises, there is a strong historical correlation (Dilley et al., 2005; Ó Gráda, 2007) that potentially can be exploited. The effectiveness of humanitarian response to weather-induced crises depends not only on the quantity of aid provided but when and how assistance is provided. Timely delivery of food, medicine, and other essential supplies is crucial to effective emergency response.

[5] This section draws extensively on ideas and texts from Chantarat et al. (2007).

Since slow-onset disasters such as droughts exhibit foreseeable patterns, drought-induced humanitarian crises may be somewhat predictable. When seasonal rains fail to arrive, agricultural production generally deteriorates, leading to increasing food shortages and prices, depressed rural livelihoods, and acute food insecurity. Progress has been made by local governments and operational agencies (e.g., United Nations agencies such as the WFP and FAO) in developing credible emergency needs assessments and reasonably accurate early warning systems[6] for identifying where and when to intervene, and at what scale. However, resources are limited in part by a general lack of timely and reliable funding to respond to emergency needs.

At present, the main mechanism for financing emergency operations is through the appeal process, where early warning systems trigger a field emergency needs assessment that leads to an international appeal for appropriate funding. The main problem with this approach is that donor funding is unreliable and often quite delayed, with actual humanitarian delivery taking as long as four to eight months (Morris, 2005; Haile, 2005). Delays are costly. As an emergency progresses, unit costs per beneficiary increase sharply as more expensive, processed commodities become increasingly needed for therapeutic feeding, donors pay premia for faster transport (including airlift), and populations migrate to camps where broader support costs (e.g., shelter, water, medical care) become essential. In the 2004/05 Niger emergency, for example, the cost for WFP's deliveries increased from $7 to $23 per beneficiary due to a six-month delayed response.

[6] Programs such as the Global Information and Early Warning System (GIEWS), WFP's Vulnerability Analysis and Mapping (VAM), the Strengthening Emergency Needs Assessment Capacity (SENAC) project, and USAID's Famine Early Warning Systems Network (FEWS-NET) currently collaborate and facilitate early warning and emergency needs assessment capacity.

Famine-Indexed Weather Derivatives

The most crucial attribute of weather derivatives for any humanitarian response system is the capacity to make immediate cash payouts for timely emergency intervention. The key to designing weather derivatives to improve emergency response to slow-onset disasters such as droughts is a well-established correlation between the specific event weather variable (s) and estimated humanitarian needs, and an appropriate contractual payout structure.

Humanitarian crises often result from successive drought episodes, late arrival of the main rains, or discontinuous rainfall patterns within the season, occurring in spatially widespread locations. Although simple rainfall volume matters, so does the temporal and spatial distribution of rainfall within seasons. Therefore, an appropriate weather derivative contract to properly hedge against widespread suffering should take into account these rainfall variables and events. Such patterns can be clearly observed in the case of arid pastoral areas of northern Kenya, discussed in more detail in our illustration provided later. Mude et al. (2006) show that drought episodes are strongly associated with sharply higher prevalence of severe child wasting.[7]

Formally, weather variables and other weather-related covariates (W)—rainfall volume, distribution, multiple rainfall events, etc.—may be indexed to some indicator of severe and widespread human suffering from food crises (F) by an established empirical forecasting model:

$$(1) \quad F = f(W) + \varepsilon,$$

where $f(\cdot)$ is a general function and ε is a standard mean zero disturbance term. The value of this pure reduced-form estimation is that the forecasted human impact conditional on observed weather depends solely on observed weather and immutable or exogenous covariates (e.g., location or seasonal dummy variables). It is objective, verifiable, and extremely difficult to manipulate. Therefore, $f(W)$ can serve as a parametric "famine index" that forecasts the risk of widespread, severe undernutrition associated with observed weather events.

New forecasts may be generated in near-real time based on the arrival of new weather data, so the famine index can evolve over time throughout the contract coverage. Hence, this may better capture not only the impact of shortfalls in rainfall quantity in a specific time or season, but also the timing and distribution of rainfall within a season or across seasons. Finally, assuming $f(\cdot)$ is invertible, one can recover an extreme weather trigger W^* corresponding to an appropriate critical threshold of forecasted degree of human suffering, F^*, which triggers emergency response intervention such that $W^* = f^{-1}(F^*)$ (Turvey, 2001).

Establishing Appropriate Contractual Payout Structures

Since timely financing for effective early intervention is a goal, weather derivative contracts derived through the forecast-based famine index, $f(W)$, should trigger indemnity payouts as soon as the famine index meets or exceeds the prespecified thresholds, or allow multiple triggered payouts within the contract term, rather than paying out only at the end of the contract term. Response delays can be costly and even deadly. Thus, if the seasonal rains failed badly and widely, the contract might trigger indemnity payments well before the end of the contract so as to allow more effective and lower cost intervention. In the following section, we

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[7] Among the covariates used in Mude et al.'s (2006) forecasting model are various autoregressive lags of prevalence of severe child wasting, herd dynamics, food aid, and forage availability, some of which are not objectively measured. Thus, they may be prone to moral hazard if directly used as triggers for derivative contracts. To further develop these measures as triggers for weather derivative contracts, slight modifications are needed to ensure that the covariates used are transparent and free from tampering.

provide a general framework for such contracts that can be designed and used to improve emergency response to drought.

Structure and General Framework

Generally, contingent debt or grant facilities offered by the World Bank and other international financial institutions on concessionary terms to developing countries affected by either natural or manmade disasters may be used to support countries' early intervention in response to drought. The catastrophic layer of drought risk, where such facilities are no longer available or suitable to accommodate the emergency need, then can be managed through global financial market mechanisms. For this purpose, weather index insurance or catastrophe bonds may facilitate transfer of extreme drought-induced famine risk to market players willing to accept the risk at some cost. We now consider these two forms of famine-indexed weather derivatives, which can complement other available financing facilities to hedge against various layers of drought-induced famine risk.

Weather Index Insurance

Weather index insurance can allow governments and/or international aid agencies to transfer drought-induced famine risk to international insurers or reinsurers, most likely with the donor community funding the insurance premium ex ante. A well-designed contract can be beneficial to both beneficiary and donors alike. On the one hand, if the insurance is triggered, the indemnity payout will be released to a government and/or nongovernmental operational agencies to finance effective emergency response. On the other hand, pre-financing humanitarian aid allows donors to hedge against the risk of volatile demand for overseas development assistance (Skees, 2002; Syroka and Wilcox, 2006).

We refer to $\Pi_T(W, W^*)$ as the total payoff at the terminal period T of a famine-indexed insurance contract[8] covering a vulnerable period $[0, T]$ and based on the observed specific weather event (W), the famine index function $f(W)$, and a prespecified anthropometric trigger F^*. It is F^* that determines the index trigger $W^* = f^{-1}(F^*)$. Depending on the nature of drought risk and financial exposure of organizations in the affected countries, various index and payout structures can be considered.

Famine-indexed insurance can be in the form of a simple put option, establishing payout at the end of the contract T. Thus,

$$(2)\quad \Pi_T(W, W^*) = \text{Max}[C(W^* - W_T), 0],$$

where $C(\cdot)$ is some function that maps the severity of weather shortfalls relative to the extreme weather threshold to the associated funds required for immediate humanitarian assistance. For example, $C(\cdot)$ might be defined by $(W^* - W_T)^x$, where $x \geq 1$, which captures the intensity of the famine index relative to the weather event, especially if the extent of potential suffering is nonlinearly related to precipitation shortfalls. The required funds can be estimated from past emergency operations or can be based on the drought contingency planning system a developing country might already have in place.

To ensure timely funding, weather-linked famine insurance can also be designed to make a payout at any first time t within the vulnerable period coverage, $[0, T]$, if the weather index W reaches the threshold W^*. The payoff at terminal period T can be written as:

$$(3)\quad \Pi_T(W, W^*) = e^{r(T-t)} C(W^* - W_t) * 1_{t(W, W^*) < T},$$

where r is a required rate of return, which, for simplicity, is assumed to be

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[8] Alternatively, the insurance payoff also can be structured in terms of a direct famine index $f(W)$ relative to the anthropometric famine trigger F^*. Thus, the payoff $g_T'(f(W), F^*) = \text{Max}[C(f(W) - F^*), 0]$.

deterministic;[9] 1_A is an indicator function of an event A; $t(W, W^*)$ is the first time passage of W to reach the threshold W^*; and $1_{t(W,W^*)<T} = 1$ is an indicator function designed to capture a trigger at any period t within [0, T] and 0 otherwise.

The insurance coverage [0, T] can be chosen so that it covers the entire period each year when people are vulnerable to extreme weather, e.g., the whole rainfall season. Finally, the function $C(\cdot)$ in this digital, down-and-in option may simply represent a lump sum of required funding released to finance baseline early intervention to the forecasted drought event triggered.

Famine-indexed insurance also can be designed to cover multiple drought events (usually multiple years (N) with one event in a vulnerable period [0, T] each year) and thus to establish multiple triggered payouts at any year n within the N-year coverage. The total payoff realized at the end of the contract at year N can be represented by:

$$(4) \quad \Pi_N(W, W^*) = \sum_{n=1}^{N} e^{r(N-n)} \Pi_n(W, W_n^*),$$

where $\Pi_n(W, W_n^*)$ represents insurance payoff at the terminal date of any year n within the N-year coverage.[10] For example, $\Pi_n(W, W_n^*) = \text{Max}[C(W_n^* - W_n), 0]$ if a yearly contract is a simple put option. Moreover, a cap of $\overline{\Pi}_n$ can be applied to limit the insurer's maximum loss each year, thereby potentially increasing market supply. The total payoff at the end of this contract is written as:

$$(5) \quad \Pi_N(W, W^*) = \sum_{n=1}^{N} e^{r(N-n)} \text{Min}\left[\Pi_n(W, W_n^*), \overline{\Pi}_n\right].$$

Furthermore, W_n^* and $\overline{\Pi}_n$ are subscripted, indicating the trigger and the cap can change over time. If the trigger and the cap are the same in all periods, then (4) and (5) can be converted to simple annuities.

The actuarially fair premium for the insurance contract is calculated by taking the expectation of the insurance payoff with respect to the underlying distribution or process of weather variable W, and discounting the term with the appropriate discount rate.[11] Hence, the actuarially fair premium for a famine-indexed insurance covering N years of drought events (with one event in a vulnerable period [0, T] each year) can be expressed as:

$$(6) \quad Premium = e^{-rN} E^{\omega}\left[\Pi_N(W, W^*)\right],$$

where E^{ω} indicates expectation at the beginning of the contract with respect to a state variable ω that pertains to some catastrophic weather risk governed by the underlying distribution of weather variable W. To this fair rate, a loading factor $m > 1$ is usually added to capture insurers' attitudes toward ambiguity of the underlying weather, their opinions about weather forecast, and their aversion toward catastrophic risks.

Catastrophe Bonds: Famine Bonds

While weather index insurance contracts can facilitate the transfer of drought risks to international insurers or reinsurers, the extreme layer of the catastrophic weather risks may not feasibly and/or

[9] A stochastic required rate of return may be applied as it captures interest rate risk under a variety of assumptions (Heath, Jarrow, and Morton, 1992) and other related risks due to factors other than a catastrophic event. The adjusted discount rate with stochastic required rate of return can be designated by

$$r(t) = \int_0^t r(s)\,ds.$$

[10] Since the coverage period of [0, T] is fixed across years, for simplicity, the yearly contract can be designed such that the terminal coverage period T is also the terminal period of a year. Hence, the period between the end of year 1 and the start of the contract, year $T_1 - T_0 = 1$ year, and the period between the end of the contract and the end of any year n, $T_N - T_n = N - n$ years. Therefore, subscript T is dropped from the yearly terminal payoff $\Pi_n(W, W_n^*)$ of any year n.

[11] If a stochastic discount rate is considered, the premium will have to be calculated based on the joint distribution of weather variable W and the appropriate term structure of interest rate.

cost-effectively be absorbed by a single or a small number of insurers or reinsurers. Extreme drought risks that cannot be absorbed through the reinsurance market using weather index insurance potentially can be securitized and transferred to the capital market in the form of catastrophe (cat) bonds—or simply "famine bonds" in this setting.

Catastrophe bonds are typically engineered as follows. The hedger (e.g., governments, agencies) pays a premium in exchange for a prespecified coverage if an extreme weather event occurs; investors purchase cat bonds for cash. The premium plus cash proceeds are directed to a special-purpose company, generally an investment bank, which then invests in risk-free assets (e.g., treasury bonds) and issues cat bonds to investors. Investors then hold cat bonds whose cash flows (principal and/or coupon) are contingent on the risk occurrence. If the covered event takes place during the coverage period, the special-purpose company compensates the hedger and there is full or partial forgiveness of the repayment of principal and/or interest to investors. Otherwise, the investors receive their principal plus interest, which incorporates the associated risk premium.

Conceptually, governments or international organizations can initiate the issuance of zero-coupon or coupon catastrophe bonds, for which principal and/or interest payments to bondholders are conditional on the occurrence of extreme drought-induced famine identified by the constructed famine index relative to a specified threshold. For government or humanitarian agencies, famine bonds simply offer an insurance function just like weather index insurance for the highly catastrophic layer of drought risk by releasing immediate cash payment for emergency operations once the famine index is triggered. Thus, government and operational agencies finance famine bonds similarly to paying index insurance premiums. They can appeal to the donor community for premium contributions in advance, i.e., in the form of disaster pre-financing (Goes and Skees, 2003).

Generally, the price of a famine cat bond issued at time 0 with face value P, annual coupon payments c, and time to maturity of N years, at which the bondholder agrees to forfeit a fraction of the principal payment P by the total insurance payoff $\Pi_n(W, W_n^*)$ at maturity, can be written as:

$$(7)\quad B(0, N) = e^{-rN}E^{\omega}\left[P - \text{Min}\left[\sum_{n=1}^{N} e^{r(N-n)}\Pi_n(W, W_n^*), \overline{\Pi}\right]\right] + \frac{c}{r}(1 - e^{-rN}),$$

where $\overline{\Pi} < P$. A famine bond therefore can be structured as a coupon bond that is embedded with a short position on a weather-linked option based on a trigger established by the famine index—specifically, famine-indexed insurance. Equation (7) is a multi-year bond issue that deducts from principal the indemnity in each year compounded to year N at the continuous compounding rate r and subject to a cap $\overline{\Pi}$ that cannot exceed principal. Like typical bonds, famine bonds are valued by taking the discounted expectation of the coupon and principal payments under the underlying distribution of the weather index and the required rate of return on investment.[12] Alternatively, if the coupon $c = 0$, the bond will be issued as a discount bond, and if $N = 1$, a one-year bond.

The main advantage of securitizing and managing famine risk using cat bonds over index insurance is the potential to avoid default or credit risk with respect to catastrophe reinsurance. The threat of widespread catastrophic losses imposes a significant insolvency risk for reinsurance

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[12] A stochastic rate

$$r(t) = \int_0^t r(s)\,ds$$

may be used as the adjusted required return representing interest rate risk under a variety of assumptions (Heath, Jarrow, and Morton, 1992) and other related risks due to factors other than a catastrophic event, which can be incorporated into the bond pricing by setting the discount rate $r(t)$ equal to the rate of return required by investors in general bonds of comparable risk.

companies, and hence for their capacity to compensate such losses. In contrast, cat bonds permit division and distribution of highly catastrophic risk among many investors in the capital market, and so may allow greater diffusion of the extreme weather risk. Moreover, funds invested in a cat bond are collected ex ante, which implies that such credit/default risk is minimized to the default risk connected with the investments made by the special-purpose vehicle. Comparing the premium costs between the two requires further investigation of market capacity and opportunity.

Empirical pricing of the weather index insurance and famine bonds based on the framework provided above can be done in various ways, depending largely on assumptions, model specifications, and the methodology used to derive or calibrate the empirical distribution of the famine index, $f(W)$, and the term structure of interest rates. A variety of such models applied to credit instruments are presented in Turvey and Chantarat (2006) and Turvey (2007).

It is arguable that various option valuation models (e.g., Black and Scholes, 1973) widely used in finance are inappropriate in this context. The extreme weather events characterized in the constructed index tend not to follow geometric Brownian motion, thus violating the underlying assumption of the models, as weather patterns tend to be autocorrelated, mean-reverting, and exhibit seasonal trends (Dischel, 1998; Martin, Barnett, and Coble, 2001; Richards, Manfredo, and Sanders, 2004; see Turvey, 2005, for an exception). Moreover, because a weather index does not have a traded underlying asset, and unlike a financial index, there is no spot market or price for weather events, then applying the principle of risk-neutral valuation or a replicating portfolio to the value of weather options is inappropriate (Davis, 2001; Martin, Barnett, and Coble, 2001; Hull, 2002).

Weather derivatives are frequently priced using actuarial methods (Turvey, 2001, 2005). This approach to empirical pricing of index insurance and cat bonds may involve two general steps: (*a*) estimating the distribution of the weather index and thus the probabilities of triggering the payout, and (*b*) incorporating the estimated probability distribution and the required rate of return into the actuarially fair pricing framework provided above.

We illustrate these concepts by pricing the illustrative famine-indexed weather derivatives for northern Kenya using the comparable historical burn rate, which assumes that variability of past weather reflects the expected variability of future weather, and therefore uses the observed historical distribution of the weather variable in calculating actuarially fair prices. We also employ Monte Carlo simulation, which simulates the probability distribution of the weather variable using a sufficiently long time series of available weather data and an assumed structure of randomness as the main inputs. Further explorations are needed to allow for price discovery of these innovative weather derivatives in the market.

Incorporating FIWDs to Enhance Effective Drought Risk Financing Strategies

The famine index could be used to layer drought-induced famine risks such that financial tools and facilities appropriate for each layer can be applied cooperatively. One possible example, considered also by Hess, Wiseman, and Robertson (2006) and Hess and Syroka (2005), combines international development banks' debt/grant facilities, index-based risk-transfer products, and the traditional donor appeals process in drought emergency response financing.

Beyond the nation's self-retention layer (i.e., interventions in response to frequent, local, and low-loss drought events can be managed using national resources), a famine index could be used as a trigger for the release of contingent grants and/or debt with fixed and preestablished terms to governments or operational agencies for early intervention in emergency response.[13] Combinations of weather index insurance and catastrophe bonds then can be used to transfer the catastrophic layer of drought risks beyond the capacities of the institutional grants/debt facilities.

All in all, a risk manager's decision on an effective risk-layering strategy, as well as optimal risk allocation arrangements among available strategies and instruments within each layer of risk, becomes a problem of minimizing risk financing costs—financially and economically—with respect to resource availability and market prices for FIWDs. But timely and predictable payouts from FIWDs now replace delayed and unreliable humanitarian aid in response to severe drought events when FIWDs are used to complement traditional donor appeal processes.

Potential for Famine-Indexed Weather Derivatives in Northern Kenya

The arid areas of northern Kenya are largely inhabited by marginalized pastoral and agro-pastoral populations that traditionally rely on extensive livestock production for their livelihood, and consequently are particularly vulnerable to covariate shocks in the form of drought and flood. To address the vulnerability of its populations and to improve their ability to manage risks, the Government of Kenya's Arid Lands Resources Management Project (ALRMP) has been funded by the World Bank since 1996, aiming to develop and implement a community-based drought management system. A community-based early warning system based on monthly household and environmental surveys that collect detailed information on livelihoods, livestock production, prices, and the nutritional status of children is currently used to signal various stages of drought and food insecurity situations, and thus to help government and operational agencies manage droughts.

In the context of FIWD design, these survey-based variables may not all be suitable as a direct index to hedge against famine risk, because they may be manipulable by prospective beneficiaries. However, since drought episodes are strongly associated with sharply higher food insecurity in the pastoral communities (WFP, 2001–2006), the predictive relationship between rainfall variables associated with extreme rainfall events and available food insecurity indicators such as nutritional status of children, levels of exogenous food availability (e.g., existing food aid pipeline commitments), real prices of key staple crops, etc., could be used in a parametric famine index for various derivative contracts.

For illustrative purposes, the relationship between rainfall variability and the directly observed proxy of prevalence and severity of child undernutrition is used to develop a famine index for FIWDs for the study areas.[14] Specifically, we obtained sample readings of the mid-upper arm circumference (MUAC) for children aged 6–59 months in each of 44 communities in three arid districts—Turkana, Samburu, and Marsabit—for which sufficient continuous monthly observations from 2000–2005 were available.[15] These three districts are rated most vulnerable to food

[13] Further, the debt triggered may be attached with the index insurance (Turvey and Chantarat, 2006) whereby the debt repayment is contingent upon the occurrence of disaster (i.e., when $W^* > W$).

[14] Other factors, such as domestic and international policies or other economic criteria, may influence pricing variables, and so their capacities to truly reflect the needs of the affected population.

[15] Theoretically, 30 households are randomly selected per community, and they are revisited each month. However, because of incompleteness due to poor data organization and storage of these repeated cross-sectional household data (described in detail in Mude et al., 2006), a subset of suitable data, for which a sufficient number of continuous observations were available, was chosen for the analysis of community-level impact of covariate shocks.

insecurity, and thus their populations are among the majority of Kenyan populations to receive yearly food assistance, making these areas very suitable as an illustrated case for our study.[16]

As a measure of wasting, MUAC reflects short-term fluctuations in nutritional stress and is typically easier and less costly to collect than weight-for-height data, the most commonly used and most documented anthropometric measure of wasting. Furthermore, several studies have found MUAC to be a far better predictor of child mortality than weight-for-height (Alam, Wojtyniac, and Rahaman, 1989; Vella et al., 1994). We calculate the proportion of children in each community with a MUAC *z*-score of –2 or lower[17] and use this as a proxy for widespread acute food insecurity. This coincides with other measures used among operational agencies and in anthropometric research in various disciplines—for example, Howe and Devereux's (2004) definition of "famine" as a condition where 20% or more of children in a specified area are severely wasted (i.e., with *z*-score of an anthropometric measure of malnutrition < –2) and "severe famine" when 40% or more of children in a specified area are severely wasted. This MUAC measure of the prevalence of severe child wasting can be used to quantify the level of drought-induced famine risks and thus to establish appropriate thresholds that trigger weather derivative payout for emergency response.

These data are then matched with the 1961–2006 rainfall series, comprised of 1961–1996 CHARM historical rainfall data estimated from historical satellite imagery (Funk et al., 2003) and 1996–2006 METEOSAT-based daily rainfall estimates.

Rainfall Variability and Food Insecurity in Northern Kenya

The pastoral areas examined here are generally characterized by bimodal rainfall with short rains falling October-December, followed by a short dry period (January-February), and long rains in March-May followed by a long dry season from June-September. This pattern is shown in Figure 1, which plots kernel density estimation of yearly rainfall patterns in the three northern Kenyan districts we study. Pastoralists rely both on rains for water and pasture for their animals, as well as occasional dryland cropping. Dry seasons are typically hunger periods in these pastoral communities.

In a normal year, water availability suffices to ensure adequate yields of milk, meat, and blood, most of which is consumed within pastoral households, with the remainder sold in order to purchase grains and nonfood necessities. While localized rain failures may occur, migratory herders commonly are able to adapt to spatiotemporal variability in forage and water availability. But when the rains fail across a wide area, especially if short and long rains both fail in succession, catastrophic herd losses often occur and bring with them severe human deprivation.

Chantarat et al. (2007) report that the major recent droughts with dire humanitarian consequences—1997/98, 2000/01, and 2005/06—were all years in which not only was aggregate rainfall low, but it was also spatially widespread and continued across multiple seasons. Moreover, evidence of the effect of variability in seasonal rainfall on the prevalence and severity of malnourished children can be clearly observed in the following dry season, as shown in Figure 2, which plots the dynamics of rainfall and nutritional status characterized by the

[16] These three pastoral districts also share similar socioeconomic characteristics, climate patterns, natural resource endowments, and livelihood portfolios according to the WFP's 2001 Vulnerability Analysis and Mapping (VAM) pilot study on chronic vulnerability to food insecurity, allowing the application of similar concepts and tools to drought response across this vast area.

[17] MUAC data are standardized using the internationally recognized 1978 CDC/WHO growth chart. The threshold $z < -2$ is consistent with the benchmark often employed by emergency relief agencies to define famine (Howe and Devereux, 2004; World Food Programme, 2000).

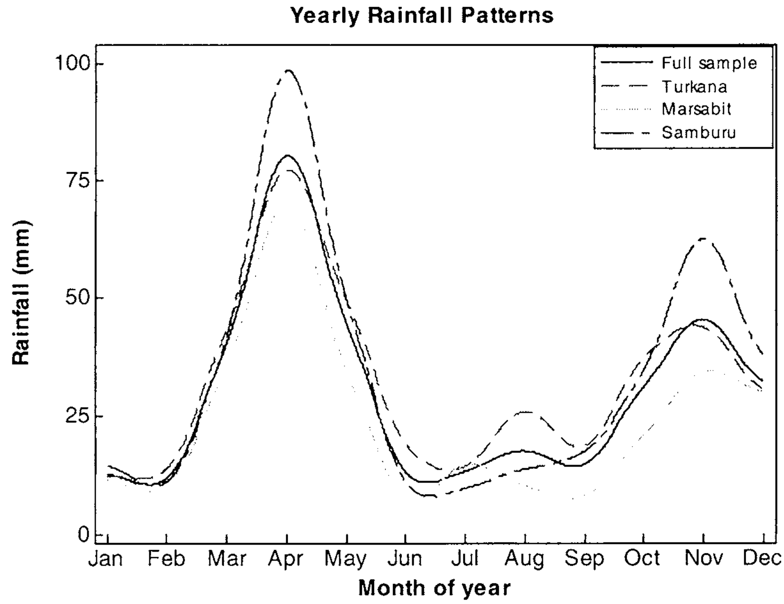


Figure 1. Kernel Density Estimation of Yearly Rainfall Pattern in Three Pastoral Districts of Northern Kenya, 1961–2006

proportion of severely wasted children in a community from 2000–2005 in the three districts of our study. The impact of 2000's failed long rains resulted in a larger proportion of malnourished children in the following long dry season, whereas the localized failure of the 2003 short rains resulted in a temporary peak in proportion of malnourished children in the following short dry season at the start of 2004.

Kenya's current drought response system is illustrated in Figure 3. Seasonal rain forecasts are conducted two months before the start of the seasonal rains with the goal of producing early warning to help herders improve their livelihood decisions as well as to facilitate drought response planning among agencies. Approximately two-month-long seasonal rain assessments then take place after the end of the seasonal rains. These result in estimates of the affected populations and the associated funding needs, information which is then used in the donor funding appeals. It usually takes at least five months from the end of each rainy season until the newly programmed humanitarian aid is actually delivered. Consequently, aid delivery under the current response system might fail to preserve livelihoods or even the lives of some affected populations.

Predictive Relationship Between Rainfall and Humanitarian Needs

To assess how FIWDs can be designed to hedge against drought-induced famine risks in northern Kenya, we explore the predictive relationship between seasonal rains and the prevalence of severely wasted children in each subsequent dry season. For illustrative purposes, we use the cumulative long rains (mm, from March to May) and short rains (mm, from October to December) to characterize seasonal rains in each community. The area average of each of these two seasonal rains is constructed by weighted averaging across 44 communities using communities' mean proportion of severely wasted children as weights. These weighted long rains and short rains represent overall exposure to drought risk in these northern Kenya communities.

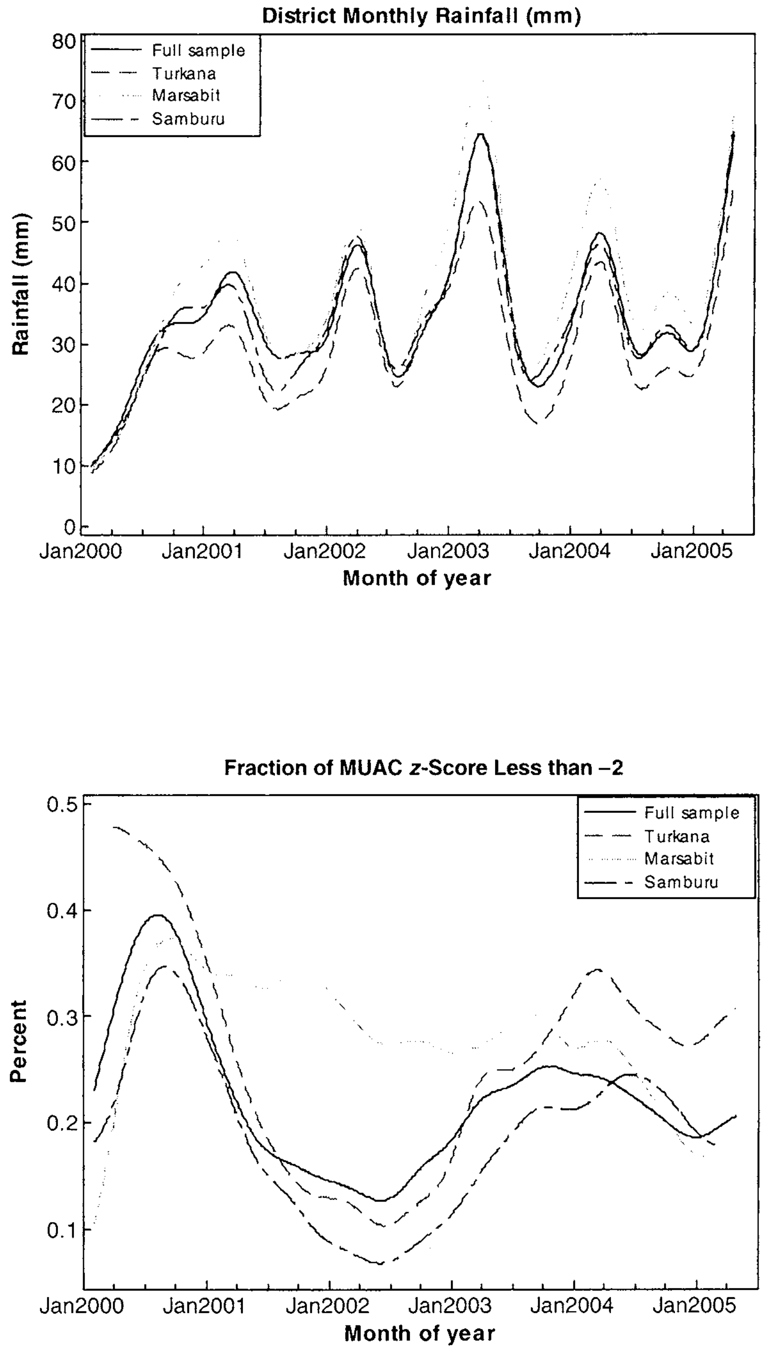


Figure 2. Kernel Density Estimations of Monthly Rainfall and Proportion of Severely Wasted Children, 2000–2005

Season	Long Dry (Hunger Period)	Short Rains	Short Dry (Hunger Period)	Long Rains	Long Dry (Hunger Period)	Short Rains	Short Dry (Hunger Period)
Month	Jun - Sep	Oct - Dec	Jan - Feb	Mar - May	Jun - Jul Aug - Sep	Oct - Dec	Jan - Feb
Current System	Short rains forecast		Short rains assessment Long rains forecast	Appeal	Donor Response → Aid delivery Long rains assessment Appeal	Donor Response	→ Aid delivery
System with FIWDs	Establish FIWD contract to hedge against risk of widespread acute food insecurity during the following short and long dry seasons		First payout triggered at the end of short rains after the realization of cumulative short rains → Funding available for early intervention		Second payout triggered at the end of long rains after the realization of both cumulative long rains and preceding cumulative short rains → Funding available for early intervention		

Figure 3. Kenya's Current Drought Emergency Response System

This area average is the appropriate measure to use to hedge against drought-induced risk since localized droughts can be managed by transferring resources from unaffected areas, and so only catastrophic droughts that affect most of the areas need to be transferred.[18]

Table 1 reports sample district-level and overall (basket weighted)-level statistics of the proportion (%) of severely wasted children averaged over short dry (January-February) and long dry (June-September) periods, cumulative long rains (mm), cumulative short rains (mm), monthly average normalized vegetative index (NDVI, a measure of forage availability for herds), and percentage of communities experiencing failed long rains or short rains, where "failure" reflects cumulative seasonal rainfall more than one standard deviation below the community-specific long-term mean.

On average, the proportion of severely wasted children is higher in the long dry period than in the short dry period (Table 1). Marsabit experienced the highest proportion of wasted children despite its more favorable rainfall. Turkana is typically the most arid district with the lowest mean cumulative short rain and the lowest monthly NDVI. Years when 100% of communities faced failed long rains are observed in all three districts. A high percentage of communities with failed short rains are also observed. On average, 26% of children are severely wasted during long dry seasons and 21% during short dry periods, with mean cumulative long rain and short rain volumes of 218 mm and 136 mm, respectively.

Taking the observed rainfall volume and temporal and spatial effects of rainfall into account, we use two consecutive preceding seasonal rains in predicting the prevalence of severely wasted children in each of the two dry seasons. Seemingly unrelated regression is applied in fitting these two relationships using six years of 44 community basket-weighted variables available from the 2000–2005 ALRMP data.

[18] Correlation coefficients of seasonal rains across these 44 communities vary from 0.16 to 0.98 for long rains and 0.33 to 0.99 for short rains.

Table 1. Sample Statistics of Weather and Proportion of Severely Wasted Children

District	Statistics	Short Dry (% MUAC z < -2)	Long Dry (% MUAC z < -2)	Long Rain (mm)	Short Rain (mm)	Percent Failed LR (%)	Percent Failed SR (%)	NDVI
Marsabit	Mean	0.20	0.29	233	162	14	15	0.32
9 communities	Std. Dev.	0.11	0.04	86	70	30	27	0.15
	Minimum	0.00	0.24	53	8	0	0	0.09
	Maximum	0.31	0.35	454	327	100	100	0.69
Samburu	Mean	0.16	0.22	214	144	15	15	0.29
14 communities	Std. Dev.	0.07	0.11	84	68	27	27	0.12
	Minimum	0.09	0.07	62	12	0	0	0.05
	Maximum	0.26	0.38	417	313	100	93	0.64
Turkana	Mean	0.25	0.26	217	119	16	10	0.22
21 communities	Std. Dev.	0.09	0.12	59	66	26	17	0.12
	Minimum	0.14	0.10	78	20	0	0	0.05
	Maximum	0.34	0.46	317	395	100	67	0.62
All (weighted) [a]	Mean	0.21	0.26	218	136	15	13	0.26
44 communities	Std. Dev.	0.09	0.10	69	62	25	21	0.14
	Minimum	0.00	0.07	66	15	0	0	0.05
	Maximum	0.34	0.46	371	344	100	82	0.69

Notes: Proportion of severely wasted children (% MUAC z < -2) statistics are from 2000–2005, rainfall statistics are from 1961–2006, and normalized vegetative index (NDVI) statistics are from 1990–2005.

[a] Forty-four communities are weighted using their mean proportion of children with MUAC z < -2 in dry seasons.

The estimated forecasting model of basket-weighted proportion of severely wasted children in the long dry season is written as:

$$(8)\quad \ln(F_{LD})_t = \underset{(2.34)}{3.607} - \underset{(0.13)}{0.619}\ln(LR)_t - \underset{(0.35)}{0.177}\ln(SR_{-1})_t - \underset{(0.07)}{0.224}\ln(AID_{LD})_t + \varepsilon_t,$$

$$R^2 = 0.753.$$

Standard errors are reported in parentheses, F_{LD} is the proportion (%) of severely wasted children averaged over the long dry season (June-September), LR denotes the cumulative long rains (mm), SR_{-1} represents the immediate leading cumulative short rains (mm) of the preceding year, AID_{LD} is the basket-weighted average of communities' mean quantity of food aid (kg) received per household per year calculated from October of the preceding year to September (the end of the long dry period), and t represents time in years.

Similarly, the forecasting model for proportion of severely wasted children in the short dry period is expressed as:

$$(9)\quad \ln(F_{SD})_t = \underset{(2.60)}{5.28} - \underset{(0.247)}{0.248}\ln(LR_{-1})_t - \underset{(0.52)}{1.113}\ln(SR_{-1})_t - \underset{(0.15)}{0.119}\ln(AID_{SD})_t + \varepsilon_t,$$

$$R^2 = 0.563.$$

Standard errors are given in parentheses, F_{SD} is the proportion (%) of severely malnourished children averaged over the short dry season (January-February), LR_{-1} represents the cumulative long rains (mm) of the preceding year, and AID_{SD} is the mean quantity of food aid (kg) received per household per year calculated from March of the preceding year to February (the end of the short dry period).

The above model specifications were used in this illustrative case for a variety of reasons. First, the basket-weighted average covariates represent the weighted aggregate of the overall exposure to drought-induced famine risks in the communities under study. Second, the coefficients are consistent with our priors about the relationship between rainfall and malnutrition. Third, the estimated parameters showed reasonable statistical significance, even though the number of observations was very low. Fourth, the model selected was the best of many models examined. Finally, although our data were obtained from a large number of monthly observations, we were limited in time to annual counts of the proportion of wasted community children to six annual measures. This is a data limitation that will be overcome in time,[19] but for the purely illustrative purposes of this paper and the FIWD concepts and pricing methods it introduces, there is no better measure to directly predict prevalence and degree of food insecurity, and we would rather err on the side of precision.

We should also explain that food aid variables were included in these forecasting models purely to control for (*a*) non-weather effects (e.g., disease, conflict) that matter to the variability of the proportion of severely wasted community children, and (*b*) pre-programmed food aid flows (e.g., school feeding and other non-emergency food aid as well as food aid resulting from prior years' appeals).[20] The predictive relationships between the two preceding seasonal rains and the prevalence of severely wasted children conditional on an ex ante expectation of a food aid pipeline now can be used to develop a parametric famine index for FIWDs.

According to (8), a 1% increase in the basket-weighted long rains will decrease the overall proportion of severely wasted children by 0.619%, whereas a 1% increase in short rains will decrease the malnutrition proportion by 0.177%. Clearly, the influence of the long rains is more indicative of wasting in the long dry season than the prior fall short rains. And as expected, (9) also suggests that the preceding short rains seem to have a more significant impact on malnutrition status in the short dry period compared to the preceding long rains. Nonetheless, with significantly different impacts, two preceding seasonal rains are both critical predictors of short dry seasons' prevalence of severely wasted children. The combination of these two rain events characterizes a joint weather-event trigger for derivative contracts.

Designing Famine-Indexed Weather Derivatives for Northern Kenya

Using the forecasted proportion of severely wasted children as an indicator of acute food insecurity, the famine index derived from the predictive relationship in (8) for the long dry season is thus $F_{LD} = 36.845 LR^{-0.619} SR_{-1}^{-0.177} AID_{LD}^{-0.224}$. Holding the prevalence of child malnutrition constant at F_{LD}^{*}, and incorporating the food aid variable based on ex ante expectation of $\overline{AID}_{LD}$ (40 kg/household food aid in the preexisting pipeline)[21] into the intercept, we use:

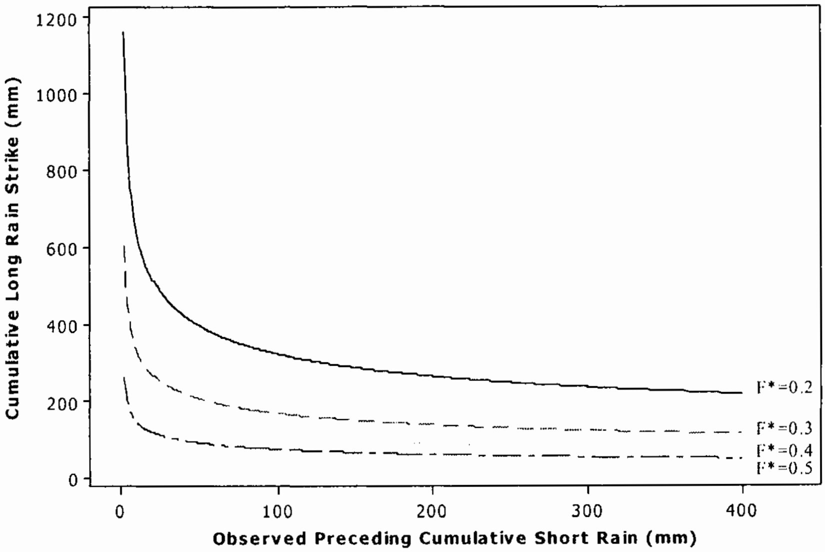
$$(10)\quad LR^{*}\left(SR_{-1}(F_{LD}^{*})\right) = \left[\frac{36.845\overline{AID}_{LD}^{-0.224} SR_{-1}^{-0.177}}{F_{LD}^{*}}\right]^{1/0.619}$$

to obtain the conditional trigger of cumulative long rains contingent upon the already observed outcome of the preceding cumulative short rains. Critically important is the inclusion of the famine index, in terms of proportion of wasted children (F_{LD}^{*}), not as an outcome, but as a policy variable. Here (10) represents what we will refer to as an iso-food insecurity index curve, as depicted in Figure 4.

[19] Phase two of the ALRMP project from 2005 onward continues to collect data from these communities.

[20] The weighted average yearly food aid variables used are not statistically determined by the prevalence of severely malnourished children in dry seasons. Thus, reverse causality does not appear to be an issue in these data.

[21] The level of food aid at 40 kg/household/year, used here for illustrative purpose, is approximately a 75% standard deviation below the 2000–2005 mean.



Note: Calculations are based on ex ante expectation of food aid delivery of 40 kilograms per household per year.

Figure 4. Iso-Food Insecurity Index Relations for Hedging Against Levels of Prevalence of Severely Wasted Children (F^*)

This is similar to an isoquant in classical production economics. At a particular level of expected aid delivery, this curve shows the loci of strike or trigger long rain levels, $LR^*(SR_{-1}(F^*_{LD}))$, given an observed preceding SR_{-1} that probabilistically leads to a level of prevalence of severely wasted children F^*_{LD} in the long dry season. It can therefore serve as an early warning mechanism for slow-onset food crises.

The critical calculus is

$$\frac{\partial LR^*(SR_{-1}(F^*_{LD}))}{\partial F^*_{LD}} < 0,$$

and so as the chosen level of prevalence of severely wasted children to hedge against (F^*_{LD}) increases, the long rain trigger decreases. This is depicted in Figure 4 as a downward shift in the iso-food insecurity index curve. In addition,

$$\frac{\partial LR^*(SR_{-1}(F^*_{LD}))}{\partial SR_{-1}} < 0$$

indicates that as the observed preceding short rain increases, the long rain strike required to hedge against a given level of prevalence of severely wasted children (F^*_{LD}) is lower. Thus, the long rain strike $LR^*(SR_{-1}(F^*_{LD}))$ is determined jointly by the random outcome in the preceding short rains and the chosen level of F^*_{LD}.

The meaning of F^*_{LD} is critical. Like a deductible in conventional insurance, the choice of F^*_{LD} represents the level of food insecurity for which the government or operational agencies can provide assistance using existing resources (food and cash) but above which additional resources will be needed. Hence, if $F^*_{LD} = 0.3$, the iso-food insecurity index curve determines the boundary of short and long rain combinations, below which prevalence of wasted children $F^*_{LD} > 0.3$ could arise probabilistically. In other words, to ensure that cash for emergency food relief is available for early prevention of the predicted prevalence of severe child malnutrition beyond a prespecified level F^*_{LD} in the long dry season, this model is equivalent to a random strike model, with the indemnity payout at the end of the long rain established by $\Pi = \text{Max}[C(LR^*(SR_{-1}(F^*_{LD})) - LR), 0]$.

Here, $C(\cdot)$ links the particular prevalence and severity of child wasting resulting from a long rain shortfall to the appropriate dollar amount of humanitarian assistance needs and the long rain strike $LR^*(SR_{-1}(F^*_{LD}))$ below which the contract triggers a payout. Importantly, its determination is based on the realization of the preceding cumulative short rain.[22,23]

For illustrative purposes, we consider a derivative contract written before the short rain period (in September) to hedge against the potential widespread food insecurity event in the short dry season (during January-February of the following year) as well as the long dry (June-September of the following year) season. The specific instruments we investigate first are index insurance contracts with:

(11) $\Pi_{SD(t)} = \$1{,}000{,}000 * 1_{(SR \leq 65\,mm)}$,

(12) $\Pi_{LD(T)} = \$1{,}000{,}000 * \mathrm{Max}\left[\left(LR^*(SR_{-1}(F^*_{LD})) - LR\right)^x, 0\right]$,

(13) $\Pi_T = e^{r(T-t)} * \Pi_{SD(t)} + \Pi_{LD(T)}$,

where (11) is a binary option with an indemnity paid out at the end of the short rain season (in January) if there is a severe shortfall in the cumulative short rain below 65 mm. This indemnity structure takes into account the need for an immediate cash payout to finance early intervention should weak short rains lead to a catastrophic food crisis in the short dry period.[24]

Equation (12) is the main indemnity structure and the primary vehicle for the famine insurance product for hedging widespread food crisis in the critical long dry season. It holds a tick of \$1 million for every millimeter of long rain falling below the strike, $LR^*(SR_{-1}(F^*_{LD}))$. The payoff may be raised to the power x, which increases this payoff fractionally as the long rain shortfall increases. The idea here is that there is a nonlinear relationship between drought and prevalence of child malnutrition, with the risk of famine increasing convexly with respect to decreases in rainfall.

The total indemnity payoff at the end of the contract is thus provided in (13) by adding the value of the short dry indemnity paid immediately after the short rain season adjusted for time value by discount factor r, and the long dry indemnity paid at the end of the long rain season, which is assumed to be the end of the contract. A cap ($\overline{\Pi} \geq 0$) on the maximum indemnity payout can be applied in order to limit the insurer's losses so that the total payout at the end of the contract (T) becomes:

(14) $\Pi_{capped} = \mathrm{Min}\left[e^{r(T-t)} * \Pi_{SD(t)} + \Pi_{LD(T)}, \overline{\Pi}\right]$.

Next, we consider the simple one-year, zero-coupon famine bond with principal P, rate of required return r, and an indemnity payout structure Π_{capped} described in (14) and capped at δ% of the principal. We then price this based on:

(15) $B(0, T) = e^{-rT} * [P - \Pi_{capped}]$,

where $\overline{\Pi} = \delta P$.

The famine bond is initially sold at a discount. The bondholder's realized annual return if the insurance indemnity is not triggered is therefore the difference

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[22] Random strike models are useful when there is a causal intertemporal relationship between one weather event and a subsequent event on a particular outcome. See Turvey, Weersink, and Chiang (2006) for an example of a random strike price in a different context.

[23] A similar procedure could be used to derive an indemnity structure for hedging against prevalence of widespread child wasting in the short dry season based on a random short rain strike conditional on the observed preceding long rain. However, our investigation indicates that prevalence is established relative to the short rains.

[24] The short rain strike of 65 mm is obtained in similar fashion to that of $LR^*(SR_{-1}(F^*_{LD}))$. Specifically, the short rain strike conditional on the preceding long rain outcome observed before the start of the contract can be written as follows:

$$SR^*(LR_{-1}(F^*_{SD})) = \left[\frac{196.429\,\overline{AID}_{SD}^{-0.119}\,LR_{-1}^{-0.248}}{F^*_{SD}}\right]^{1/1.113}.$$

The strike $SR^*(LR_{-1}(F^*_{SD})) = 65$ mm is based on the expectation of $\overline{AID}_{SD} = 75$ kilograms per household per year, $F^*_{SD} = 0.3$, and an average long rain of 210 mm.

between the principal and the purchased bond price. The structure of these famine-indexed weather derivative contracts is shown in Figure 3. The next section analyzes the expected payoffs from contracts with various combinations of these factors.

Famine-Indexed Weather Derivatives Pricing

We present the pricing results from the insurance product first and the famine bond second. As discussed previously, the two are related in that it is the indemnity structure of the weather insurance product which determines the discount on the famine bond.

Two methods are used for purposes of comparison. In the top panels of Tables 2, 3, and 5, the results are derived using a burn rate approach, which is based on the actual historical outcomes from 46 years of rainfall data. The bottom panels are based on 50,000 Monte Carlo simulations using the best fit distributions for basket-weighted cumulative short rain (gamma(8.0525, 21.279)) and cumulative long rain (lognormal(3,357.6, 68.56)).[25]

The long rain strike used throughout these results is based on a minimal level of food aid delivery of 40 kilograms per household per year, about a 75% standard deviation below its 2000–2005 mean. The insurance indemnity payouts are based simply on the parameter $x = 1$, so payouts are linearly related to rain shortfall relative to the trigger level. The tables present the expected indemnity payoff for index insurance contracts in order to reflect the value of the products as determined by the distribution of short and then long precipitation risk. Actuarially fair premiums can be derived easily by discounting these expected payoffs with an appropriate discount rate.

[25] Distributions are written as gamma(α, β), where $\alpha > 0$ determines shape or skewness and $\beta > 0$ determines scale or width of the distribution, and lognormal(μ, σ) with parameters for mean and variance, respectively.

For the insurance contracts for hedging against a given level of child wasting prevalence F^* defined from 0.2 to 0.5 for each column, the expected long rain strike decreases from 308.6 to 70.2 millimeters (Tables 2 and 3). Specifically, the higher the level of malnutrition prevalence one wants to hedge against, the lower is the likelihood and magnitude of contract payout. The expected payoffs in the long dry season (contingent on conditional long rain strike) therefore decrease substantially as the level of F^* increases. These values range from about \$97.2 million and \$95.6 million for $F^* = 0.2$, to \$3,532 and \$388,426 for the burn and Monte Carlo estimates, respectively, at the higher level of $F^* = 0.5$ with much rarer trigger probability (Table 2).

According to the 46-year historical data, the contract covering $F^* = 0.5$ made one payout in the year 2000, the worst drought in the past 40 years in Kenya. In contrast, the fact that the contract covering $F^* = 0.2$ triggered payouts in 39 out of 46 years is expected, as the average proportion of severely wasted community children in these particular districts of Kenya is already as high as 0.26 in the long dry season. Two payouts were made (in 1997 and 2000) at $F^* = 0.45$ and $F^* = 0.4$, implying a frequency of one in 23 years.

The contingent claim on short rains failure occurs only under severe conditions (specifically in 1970, 1997, and 2005, coinciding with the historical record of devastating droughts due to short rains failure). The payoff of \$65,217 based on historical measures compares to \$102,780 using the Monte Carlo simulation, suggesting the best fit distribution is skewed more negatively than history might have recorded. The total expected payoffs from contingencies on both short and long rains range from \$97.3 million to \$70,929 using the burn approach and \$95.7 million to \$494,634 using the Monte Carlo approach (Table 2).

The range of payoffs is much higher using the Monte Carlo approach. The differences between the burn approach and the Monte

Table 2. Weather Index Insurance Expected Payoff Statistics, 1961–2006

	Famine Trigger (F^*), where Strike SR^* = 65 mm						
Pricing Method	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**
Historical Burn Rate [a]							
Expected Strike LR^* (mm)	308.61	215.21	160.30	124.96	100.72	83.26	70.23
Expected *SD* Payoff ($)	65,217	65,217	65,217	65,217	65,217	65,217	65,217
Expected *LD* Payoff ($)	97,220,597	29,505,197	10,353,626	4,055,296	1,425,886	600,631	3,532
Expected Total Payoff ($)	97,287,994	29,572,594	10,421,023	4,122,693	1,493,283	668,028	70,929
Std. Dev. Total Payoff ($)	81,419,233	49,554,422	27,145,007	13,906,329	6,969,875	3,023,025	272,219
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	374,106,609	205,193,020	113,205,263	69,259,487	39,104,762	17,402,449	1,195,889
SD Triggered Years	3	3	3	3	3	3	3
LD Triggered Years	39	23	10	5	2	2	1
Monte Carlo Simulation [b]							
Expected Strike LR^* (mm)	308.16	214.90	160.07	124.77	100.58	83.15	70.13
Expected *SD* Payoff ($)	102,780	102,780	102,780	102,780	102,780	102,780	102,780
Expected *LD* Payoff ($)	95,571,430	28,752,950	8,916,012	3,218,886	1,350,931	690,477	388,426
Expected Total Payoff ($)	95,677,680	28,859,160	9,022,220	3,325,094	1,457,118	796,706	494,634
Std. Dev. Total Payoff ($)	76,621,900	45,106,260	24,514,640	14,297,660	8,521,659	5,823,947	4,233,706
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	996,512,400	648,651,000	542,513,000	599,369,000	432,394,500	194,205,900	116,622,200

Notes: The expected total payoffs are calculated at the end of the contract, where the expected *SD* payoffs are brought forward using an 8% rate of return. The actuarial fair premium can be calculated by discounting the expected total payoff with the appropriate discount rate.

[a] The historical burn rate is based on actual historical outcomes from 46 years of rainfall data.

[b] The Monte Carlo simulation is based on 50,000 simulations using the best fit distributions.

Carlo approach are due to the sampling frame. The burn approach assumes that all possible outcomes are contained within the history of the sample, while the Monte Carlo approach, driven by a defined distribution, assumes the existence of rarer events on the downside which were not realized during the historical period strata. Especially at $F^* = 0.5$, with only one payout triggered historically, the 50,000-iteration Monte Carlo approach would have sampled more possible severe outcomes, as rare as they might be.

The capped insurance results are reported in Table 3. The caps—ceiling of covering insurance payout that limits the insurer's loss—used were approximately 70% of the largest historical payoff. The capped products are remarkably similar, with expected payoffs (and standard deviations) between the burn and Monte Carlo approaches very close. Under the Monte Carlo approach, the effects of the caps reduced total expected payoffs from \$95.7 million to \$94.2 million for $F^*= 0.2$, and from \$494,634 to \$93,282 for $F^* = 0.5$. More generally, as the cap increases, so too would the range of payouts and hence the cost of the insurance.

The one-year catastrophe bond discounts are provided in Table 4 for various combinations of caps as a percentage of principal and various required rates of return, where the difference from the risk-free rate represents risk premiums investors required. These rates are chosen such that they reasonably represent spreads required by investors in the existing cat bond markets (according to Froot, 1999). The values in Table 4 indicate the retail price of a bond per dollar of principal. The total annual return realized by the bondholder will always be higher than the required rate of return if the triggering widespread acute food insecurity event does not occur. The difference between the two therefore represents an additional premium required associated with the catastrophic famine risk.

For example, a famine bond covering prevalence of severe wasting of $F^* = 0.3$ with a required rate of return of 8% and cap at 30% is priced at \$0.8787 and will pay \$1 principal one year later should the famine condition not be triggered. Thus the total return realized by the investor if a critical drought event is not triggered[26] is 12.13%, which can be interpreted as an additional 4.13% premium associated with the famine risk contingency and above the risk premium required for other sources of risk (e.g., default risk, interest rate term structure risk, etc.). However, if triggered, principal payment decreases to as little as \$0.3 for a loss of 57.8%.

In general, for a given cap level and required rate of return, the famine bond prices decrease with the level of malnutrition prevalence to be insured against, since the lower F^* trigger means that the bond has a higher probability of triggering payout and hence is more risky. Similarly, famine bond prices decrease as the cap level increases, because the smaller proportion of repaid principal if the bond triggers translates into the higher risk of loss. And finally, it is straightforward to observe that the bond prices decrease as the required rates of return increase.

Using Famine-Indexed Weather Derivatives to Improve Drought Emergency Response

The risk-transferring potential of the FIWD contracts proposed here vary greatly with the frequency of the extreme events as well as their degree of catastrophe. For example, as shown in Table 3, capped weather index insurance covering severe wasting prevalence $F^* = 0.2$ results in a prohibitive premium with expected payoff of \$93.9 million. The contract triggers payout in 39 of 46 years due to the fact that the average proportion of severely wasting condition in northern Kenya is already as high as 0.26 in the long dry season.

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[26] Equivalently, the total return of a famine bond can be interpreted as a 7.18% spread over the one-year LIBOR rate of 5.12%. The LIBOR rate is as of September 11, 2007.

Table 3. Capped Weather Index Insurance Expected Payoff Statistics, 1961–2006

Pricing Method	Famine Trigger (F^*), where Strike SR^* = 65 mm / ($ Cap at 70% of historical maximum) 0.2 ($260,000,000)	0.25 ($140,000,000)	0.3 ($80,000,000)	0.35 ($50,000,000)	0.4 ($28,000,000)	0.45 ($10,000,000)	0.5 ($800,000)
Historical Burn Rate							
Expected Strike LR^* (mm)	308.61	215.21	160.30	124.96	100.72	83.26	70.23
Expected Total Payoff ($)	93,989,039	27,253,505	9,070,036	3,701,586	1,251,876	479,714	52,174
Std. Dev. Total Payoff ($)	72,109,066	42,354,305	22,431,866	12,060,865	5,718,127	2,063,170	199,710
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	260,000,000	140,000,000	80,000,000	50,000,000	28,000,000	10,000,000	800,000
Monte Carlo Simulation							
Expected Strike LR^* (mm)	308.16	214.90	160.07	124.77	100.58	83.15	70.13
Expected Total Payoff ($)	94,215,120	27,636,790	8,035,131	2,673,187	972,646	321,917	93,282
Std. Dev. Total Payoff ($)	71,489,720	40,392,290	19,479,810	9,651,412	4,457,400	1,445,366	256,701
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	260,000,000	140,000,000	80,000,000	50,000,000	28,000,000	10,000,000	800,000

Table 4. Zero-Coupon Famine Bond Prices for Different Bond Specifications ($)

Required Return	Cap (% Face)	Famine Trigger (F^*) 0.2	0.25	0.3	0.35	0.4	0.45	0.5
6%	30%	0.7083	0.8262	0.8959	0.9218	0.9325	0.9367	0.9382
	50%	0.5707	0.7752	0.8791	0.9160	0.9306	0.9358	0.9376
	70%	0.4502	0.7395	0.8697	0.9134	0.9296	0.9354	0.9374
8%	30%	0.6956	0.8120	0.8787	0.9040	0.9139	0.9179	0.9196
	50%	0.5611	0.7605	0.8621	0.8983	0.9118	0.9170	0.9191
	70%	0.4429	0.7238	0.8527	0.8952	0.9109	0.9166	0.9188
10%	30%	0.6819	0.7959	0.8613	0.8861	0.8958	0.8998	0.9014
	50%	0.5499	0.7454	0.8451	0.8805	0.8937	0.8988	0.9009
	70%	0.4341	0.7094	0.8358	0.8775	0.8928	0.8985	0.9006
12%	30%	0.6684	0.7802	0.8442	0.8686	0.8780	0.8819	0.8835
	50%	0.5391	0.7307	0.8283	0.8630	0.8760	0.8810	0.8830
	70%	0.4255	0.6954	0.8192	0.8601	0.8751	0.8807	0.8828

Note: Prices are based on 50,000 Monte Carlo simulations using best fit distributions.

But the results in Table 3 further suggest that early intervention at $F^* = 0.3$ or higher (with the frequency of 10 in 46 years) may feasibly be financed using famine index insurance. The insurance contract that covers up to \$80 million requires a premium with expected payoff of approximately \$8 million. Alternatively, intervention triggered by $F^* = 0.4$ or more (occurring in 1–2 of 46 years) also may be feasibly financed using famine bonds. At the required rate of return of 8% and with a 50% cap, famine bonds covering $F^* = 0.4$, 0.45, or 0.5 can be issued at the total rate of return of 8.82%, 8.3%, and 8.09%, respectively.

While these derivative products can be used to finance emergency response to catastrophic drought risk, coordinating them with other sources of humanitarian funding and the country's existing drought contingency resources may further enhance the potential and cost-effectiveness of the early intervention. Integrated risk financing ideas proposed by Hess, Wiseman, and Robertson (2006) and Hess and Syroka (2005) for Ethiopia and Malawi can be similarly illustrated in the context of drought emergency response financing for arid northern Kenya. Suppose early emergency response is crucial if $F^* = 0.25$. The financial exposure associated with the emergency intervention costs can be first layered by their frequency and level of catastrophe. The instruments covering various layers of these exposures, characterized by different conditional long rains strike and cap levels, are derived and reported in Table 5.

For illustrative purposes, financial exposure can be disaggregated into four layers and then can be managed sequentially by (*a*) government reserves or preestablished contingency funds, (*b*) contingent debt/grants, (*c*) famine-indexed insurance, and (*d*) famine bonds—which now becomes feasible for the layer of a 4-in-46-year loss event (or with approximately 8.7% probability of occurrence per year). The first layer covers the most frequent loss exposure (a 23-in-46-year loss event) and up to \$30 million. This layer covers the operational costs on the most recurrent but relatively minor losses, e.g., local droughts occurring almost every two years, which lead to an expected loss as high as \$11.67 million. The second contract covers the loss beyond the first contingency layer, up to another \$30 million. Since this layer of loss still occurs with relatively high probability, it may be too costly for any commercial risk transfer products and thus may be appropriately financed by a contingent debt or grant from development facilities available from many international financial institutions (e.g., World Bank). The expected loss of \$7.1 million will be financed in this layer.

The major catastrophic losses requiring an extensive emergency response then can be financed using index insurance or a famine (cat) bond. However, the probability of occurrence of the next layer of risk still may be too high (an 8-in-46-year loss event) to be appropriate for a cat bond. A weather index insurance contract may first be used to cover this immediate layer of losses up to \$60 million, with a premium representing expected payoff of \$7.3 million. Finally, a famine bond contract can be designed for the last, low-probability/catastrophic-loss layer, up to \$100 million in humanitarian budgetary needs.

The donor appeals process can then resume for any remaining costs not covered by these financing mechanisms (e.g., costs exceeding \$100 million or extra costs not fully captured in the derivative contracts). But with an initial, substantial funding layer in place and available for immediate payout, both the overall costs and the time pressures should be reduced, making the appeals process a viable vehicle for topping up pipelines begun through these other risk management instruments.

It is worth noting that the total drought risk financing costs will vary with the layering strategy as well as with the combinations of instruments used.

Table 5. Layering Financial Exposure in Providing Emergency Intervention to Drought Events Using Triggering Level of Prevalence of Child Malnutrition of $F^* = 0.25$ and Strike $SR^* = 65$ mm

	Layering Strike LR^* / ($ Cap for *LR* Payoff)			
Pricing Method	LR^* ($30,000,000)	LR^*-30 ($30,000,000)	LR^*-60 ($60,000,000)	LR^*-120 ($100,000,000)
Historical Burn Rate				
Expected Strike LR^* (mm)	215.21	185.21	155.21	95.21
Expected Total Payoff ($)	11,671,814	7,146,556	7,301,997	3,519,623
Std. Dev. Total Payoff ($)	13,576,351	12,150,113	18,276,614	15,399,052
Minimum Payoff ($)	0	0	0	0
Maximum Payoff ($)	30,000,000	30,000,000	60,000,000	85,193,020
Monte Carlo Simulation				
Expected Strike LR^* (mm)	214.93	184.90	154.90	94.93
Expected Total Payoff ($)	12,049,830	7,849,441	6,994,606	1,995,035
Std. Dev. Total Payoff ($)	13,838,810	12,357,140	16,692,620	10,344,390
Minimum Payoff ($)	0	0	0	0
Maximum Payoff ($)	30,000,000	30,000,000	60,000,000	100,000,000

The main idea, therefore, is that contracts based on forecasted prevalence and severity of food insecurity can be designed and used as a trigger mechanism to coordinate multiple prospective sources of emergency funding in order to increase cost-effectiveness and timely response to drought-induced humanitarian disasters.

Discussion and Implications

There is no general approach for the design and pricing of famine-indexed weather derivative contracts. This paper presents the first attempt. The results from our illustrative northern Kenya case are of course specific to the assumptions we made and replicable only over the equivalent distributions of climate and human ecology. Accordingly, it is best to focus on the principles involved and not on the specific numerical estimates. These principles and their numerical illustrations are nonetheless both important and exciting.

Our objective was to develop a weather-based famine insurance product that could be used by governments, operational agencies, or NGOs to enhance the timeliness and reliability of funding for emergency intervention to catastrophic but slow-onset droughts. We proposed a general structure for famine-indexed weather derivatives, but emphasize two common yet critical characteristics.

- First, weather variables or event trigger(s) need to be indexed to a forecasted degree of prevalence and severity of food crisis so that they can serve as both an early warning to trigger early intervention and to provide the cash necessary for such intervention.
- Second, as delayed humanitarian assistance is costly, even deadly, contractual payouts need to be structured to cover potential emergency response over all possible vulnerable periods in the year.

FIWDs with these two features can be integrated with existing humanitarian funding facilities.

Though using the best measures available given the problem identified, the FIWDs designed for northern Kenya should be taken as an illustrative case only and, for a variety of reasons, require further investigation if considered for real applications. First, though derivative prices are based on 46 years of high-quality rainfall data, the predictive relationship between weather and food insecurity is derived from only six years of available household data. It is therefore critical to reestimate the relationships with additional data in order to minimize potential basis risk. Second, the suitability of communities' proportion of severely wasted children (measured by MUAC *z*-score < -2) as a proxy for severe human suffering relies on an accurate and continued data collection process at the community level. The principles and results generated in this study emphasize the importance of and the need for improving data collection and standardization, which can strengthen the potential and feasibility of famine-indexed weather derivatives in the near future.

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Challenges for Use of Index-Based Weather Insurance in Lower Income Countries

Jerry R. Skees

Abstract

This article offers some perspective on the progress and challenges of managing catastrophic weather risk in lower income countries through the use of index insurance. Innovations in insurance for natural disaster risk are critically important to help the rural poor improve their lives and to contribute to the overall economic growth in lower income countries. By reviewing lessons learned from various index insurance projects, several conclusions are made about how best to approach weather risk management to benefit the livelihoods of the rural poor. It is important to recognize the limitations of index insurance and that it is not a substitute for crop insurance. However, using index insurance to address catastrophic risk can serve as the foundation for the development of broader financial services by removing one of the major constraints to market development. This in turn can offer households more effective strategies for consumption smoothing in the face of different sources and magnitudes of risk.

Key words: ex ante risk management, index insurance, risk transfer, rural development, weather risk

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This article provides a perspective on the progress and challenges associated with index-based risk transfer products (IBRTPs)[1] in lower income countries. Effectively, IBRTPs are a proxy for loss and a vehicle to transfer risk to insurance or capital markets. These products are designed to pay out when an independent physical measure of a loss event (such as extreme weather, area yields, or even complex process models that use satellite images) crosses a threshold value of the index, indicating catastrophic conditions are creating serious problems for clients.

The concept of creating an index to proxy losses is not new. Indian scholars were writing about the merits of these ideas in the early 1900s (Chakravati, 1920), and in the 1940s at the University of Chicago, Professor Harold Halcrow completed a Ph.D. dissertation on area-yield crop insurance (Halcrow, 1949).

The interest in using a variety of IBRTPs in lower income countries has grown in recent years. A major objective of this article is to share a vision for what is possible to achieve and highlight important policy and market issues that merit serious academic attention.

[1] Rather than simply referring to these products as index-based weather insurance, Skees and Barnett (2006) began referring to them as IBRTPs to communicate that structurally they are open-ended. In the economic literature, they take the form of contingent claims. However, in the legal and regulatory environment, they can be structured either as insurance or derivatives. For lower income countries, where derivative markets are unlikely to be properly regulated, it is highly recommended that these products be structured as insurance products.

There are cautions to be raised. While there are enough pilot projects to begin assessing significant product design and project implementation issues, important behavioral outcomes from firm-level decision makers cannot yet be assessed due to the limited experience with these products. These efforts in lower income countries must also be placed in a larger economic and public policy context.

Underlying all of our[2] academic and practical efforts in recent years is the critical question of what are the most appropriate market and institutional arrangements that allow smallholder and mostly farm-based rural households to effectively and efficiently smooth consumption over time. This article brings together some of our current thinking.

I begin by reviewing why this special class of insurance products has captured the attention of the donor and development practitioner community and then presenting reasons for the importance of insurance access in lower income countries. The framework for the economic considerations of agricultural insurance for smallholder households is focused on getting the "big risk" out of the way first. This is done in the context of the development literature (Barnett, Barrett, and Skees, forthcoming). Within the policy context, one must also address the issue of subsidizing these products since subsidies in agricultural insurance are prevalent in developed countries, but for the most part are impractical in lower income countries. Next, a few case studies are used to highlight some important lessons learned about designing index-based weather insurance for smallholder households. Finally, in the context of past experiences with index insurance projects, I share my views about how IBRTPs can be used to "create a market" for more sophisticated agricultural insurance products.

[2] I would like to acknowledge the great number of professionals with whom I have worked over the years on these topics. This list is too long and the risk of omitting someone is too high to name these individuals here.

Abbreviated History and Background

Agricultural insurance continues to capture the attention of policy markers, donors, and a large number of stakeholders in lower income countries around the world. The current agricultural economics literature is filled with articles examining various aspects of agricultural insurance as governments in developed countries have increased their support for this risk management tool.

While I have worked on agricultural insurance issues for 25 years, my focus during the past 10 years of researching and developing agricultural insurance products has turned from developed countries to lower income and developing countries. Previous work with the U.S. crop insurance program has shown that government support for agricultural insurance is more about political economy and income enhancement than about risk management (Skees, 1999, 2001).

My experience with the Congressional Commission for the Improvement of the Federal Corp Insurance Program in 1989 led to a rediscovery of research on the potential merits of area-yield insurance (Halcrow, 1949), and, in turn, to the development of the Group Risk Plan (GRP) (Barnaby and Skees, 1990; Miranda, 1991; Glauber, Harwood, and Skees, 1993; Baquet and Skees, 1994; Skees, Black, and Barnett, 1997). The GRP is an index-based insurance product that uses county yields as the mechanism for calculating indemnities for insured farmers. As such, the GRP is less prone to asymmetric information, and consequently less prone to the same levels of adverse selection and moral hazard that plague traditional crop insurance products.

Work on GRP motivated Peter Hazell, who had long worked on crop insurance for developing countries (Hazell, Pomareda, and Valdés, 1986), to revisit his thinking about developing rainfall insurance products. The Skees, Hazell, and Miranda

(1999) article emerged from our joint efforts to advance rainfall insurance in Nicaragua with a 1998 World Bank project. In 1999, a group inside the World Bank was awarded a Development Marketplace Contract to advance these ideas in Nicaragua, Morocco, Tunisia, and Ethiopia. A number of articles emerged from these efforts (Skees et al., 2001; Skees and Varangis, 2002; Varangis, Skees, and Barnett, 2002; Skees et al., 2005).

Since that time, there has been a proliferation of interest and involvement in index-based weather insurance products for lower income countries (Barnett, Barrett, and Skees, forthcoming; Hartell et al., 2006; Hazell and Skees, 2006; Hess et al., 2005; Hess and Syroka, 2005; Manuamorn, 2007; McCarthy, 2003; Molini et al., 2007; Shynkarenko, 2007; Skees, 2003; Syroka, 2007; Turvey, 2001, 2005). The workshop that resulted in the articles published in this special issue is evidence of the continued and growing interest in the subject.

To a great extent, donor interest in IBRTPs has been driven by the need to find more cost-effective and efficient instruments to transfer weather risks that impact the livelihoods of millions of poor farm households who operate on extremely small parcels of land. The literature and experience with traditional crop insurance in developing countries have been extremely negative. By the 1970s and 1980s, most donors and development practitioners had discounted the possibility of agricultural insurance contributing to the development process, and attempts to foster such insurance were largely halted (Hazell, Pomareda, and Valdés, 1986).

Because IBRTPs address many of the problems with traditional crop insurance, there has been a renewed interest in weather insurance for developing countries. Index-based products do not require costly claims adjustments, which are simply not practical for small parcels of land. To the extent that the index is measured by an independent third party, these products also are largely free of adverse selection and moral hazard problems. Nonetheless, no one should conclude that these products are going to be the final answer to transferring weather risks for smallholder farm households in lower income countries. To be sure, our own work has involved the constant reshaping and revisiting of the basic premises that led us to pursue this class of products for lower income countries.

Insurance Is Important for Lower Income Countries

There is a significant need for effective and efficient mechanisms for transferring natural disaster risks that negatively impact the livelihoods and assets of small-unit farming households in lower income countries (Barnett, Barrett, and Skees, forthcoming). In the event of a shock such as extreme weather, those households without risk-transfer mechanisms are more likely to be thrust into permanent poverty (Barrett and McPeak, 2005; Barrett and Swallow, 2006; Carter and Barrett, 2006; Carter et al., 2007). In that situation, poor households must choose between depleting assets, pushing themselves further below the poverty line, or reducing consumption, which often has long-term health and developmental consequences.

Beyond the risk of poverty traps, the economic development literature also clearly demonstrates that when risk-transfer instruments are unavailable to them, the poor pay more for risks as a result of their management decisions (see Dercon, 1996, 1998, 2004, 2005). For example, Rosenzweig and Binswanger (1993) examine the portfolio choices for farmers in India. Their work suggests the poor are paying implicit premium rates in excess of 30% based on the low-risk/low-return choices they make. This form of extreme risk-averse behavior among the poor is understandable when considering riskier choices such as adopting advanced technologies, moving to the city for new employment, renting land rather than crop sharing, etc. Of particular note, these very decisions by the poor are also costly for other levels of society as they lead to more inefficient economic outcomes and slowed economic growth.

Understanding these microeconomic underpinnings is important because a growing body of evidence indicates that lower income countries with both banking and insurance markets experience the greatest economic growth [U.S. Agency for International Development (USAID), 2006]. Insurance, savings, and credit can be used to smooth consumption during difficult times. Each is important for protecting against different types of risk. Savings and credit can be a very efficient means of smoothing consumption over low-magnitude loss events (e.g., temporary unemployment) but may not be adequate when high-magnitude loss events occur (e.g., natural disaster, or death of the family breadwinner). For infrequent high-magnitude loss events, insurance is generally a more efficient mechanism than savings and credit for facilitating consumption smoothing. If households can smooth consumption using a combination of insurance, savings, and credit instruments, they tend to be more willing to invest in higher-risk, higher-return activities.

The vulnerability of the rural poor in lower income countries is particularly acute because they typically lack access to these financial mechanisms to efficiently manage production uncertainties. Households in rural regions tend to have few livelihood choices, limited availability of financial services, and even less access to insurance products. In the absence of effective insurance markets that transfer risk out of a community or region, households remain vulnerable to the financial consequences of high-magnitude loss events, the kind of loss events capable of inflicting total financial ruin. This vulnerability further constrains a household's access to other financial instruments. Creditors are understandably reluctant to make unsecured loans to highly vulnerable households. And when an entire region is susceptible to a natural disaster such as drought or flooding, lenders are especially reluctant to extend credit (de Janvry et al., 2003). They fear that following a natural disaster many loans will go into default while at the same time deposits will be depleted. Lenders may also be subject to political risk as governments pressure lenders to forgive even secured debt in the event of a regional agricultural production crisis.

Innovations in providing insurance for natural disaster risk to rural areas and to poor households are critically important to help the poor improve their lives and to contribute to the overall economic growth in lower income countries. The risk of these events negatively impacts production decisions and constrains capital flows into the region. It is important to note that the instruments needed to cover weather and natural disaster risk must be structured differently than traditional insurance products designed to transfer uncorrelated risks such as automobile accidents, death, and disability. Uncorrelated risks can be pooled locally within an insurance portfolio. In the case of correlated risks due to extreme weather or other natural disasters, domestic insurance companies are reluctant to offer insurance against these risks as they gain little from pooling these policies within the region unless they are able to sufficiently diversify or transfer their risk to a facility that can diversify, such as a global reinsurance company.

Innovative insurance mechanisms for transferring correlated weather and natural disaster risks out of rural areas of lower income countries are an important component to addressing the many risks faced by poor households and a vital component to the synergy among insurance, savings, and credit markets. This synergy cannot be captured by interventions focusing on only one financial service (e.g., interventions to increase credit availability). By transferring risk out of the community and region, these insurance mechanisms lower the risk exposure of poor households and local lenders, and as a result, the poor also gain access to broader financial services often at better terms. In Mongolia, for example, lenders have provided both better access to credit and lower interest rates to herders purchasing index-based livestock insurance.

An approach is required that more fully considers this functional relationship among diverse financial services to facilitate the development of savings and credit mechanisms for financing investment and smoothing consumption over low-magnitude loss events, but also to facilitate the transfer of high-magnitude risks via insurance markets. A strategy that addresses all of these issues provides a more comprehensive risk management approach for poor households and has the potential to initiate a virtuous cycle of increased local reinvestment, increased capital flow into the region, and improved economic growth.

Economic Considerations for Agricultural Insurance for Smallholder Households

In recent years, our focus has been on first removing catastrophic risks as part of the development process for agricultural insurance. This effectively turns the development process on its head: Insurers typically begin with individual products for smallholder households and then concern themselves with how to finance the catastrophic risks. However, once effective risk transfer for the biggest risks (the most catastrophic events, which are also more likely to be more highly correlated) has been organized, development of a broader range of financial services, including more advanced forms of agricultural insurance specifically targeted to individuals, can emerge.

Part of the development process for agricultural insurance also involves recognizing that individual households should consider layering risks as part of an optimal risk management strategy. A large aspect of layering risks involves development of the most effective and efficient mechanisms for getting the big risk out of the way first. For risks that are near the median of a loss profile, self-retention is usually optimal; for risks at lower or intermediate levels, a blend of borrowing, saving, and insurance is optimal; for the most extreme, catastrophic risks, some blend of insurance and government ex ante financing (e.g., serving as reinsurance for the most catastrophic risk) may be optimal (Skees, Barnett, and Hartell, 2005). The relative price of borrowing versus insurance generally reinforces these arguments. Still, our profession needs to dig deeper into these important economic questions and use the insights gained from more formal and realistic models of the household production and consumption process to give further foundation for the types of IBRTPs that should be supported.

At least part of the confusion about the value of agricultural insurance and the type of policy prescription that emerges when governments intervene to promote these markets is due to the way agricultural economists have approached the problem of agricultural insurance research and risk management. Very much consistent with our thinking about how agricultural insurance fits into a broader economic development and poverty household production and consumption framework, Wright (2006) provides one of the most significant challenges to the way agricultural economists model agricultural insurance. Wright recast the challenge of risk management to how to smooth household consumption over time rather than how to optimize farm income from a single crop in a single crop year given certain assumptions about risk aversion.

Anyone understanding the complex production choices facing rural households and the many risk management and risk coping strategies used by these households will appreciate the challenges Wright brings to these discussions. These issues speak to the need to layer risk management and to consider which choices will be more optimal for smoothing consumption over time. To the point, how does the value of crop insurance change when examining the entire portfolio of household choices, which includes farm enterprises, off-farm income choices, and formal and informal risk management mechanisms such as savings, lending, and various forms of insurance? Of course, the answer depends on the variance-covariance matrix of the activities in the portfolio. However, even when the returns from activity choices are correlated, but not perfectly correlated, the value of individual crop insurance is lessened.

This becomes even more evident when one considers how savings and borrowing can help smooth consumption when specific weather events create small to moderate losses in the portfolio. Portfolio models assume that the correlation among the returns from the different activity choices is unchanged given different random outcomes. But an interesting puzzle emerges: What if the correlation of returns among the activity choices is greater when the weather events are the most extreme? If so, then a simple drought index to indemnify when severe droughts occur may be highly effective insurance for the portfolio and, in fact, superior to having individual crop insurance for only a few, or even all, of the activities in the portfolio. Interestingly, development economists who work on household production and consumption models and poverty dynamics have understood this for some time. However, most of our colleagues in development economics have not performed research on agricultural insurance markets.

Catastrophe Insurance Helps Lessen the Effects of Activities of the Poor That Become More Correlated in a Catastrophe!

I am extending the argument for catastrophe insurance by stating that there are likely many regions of the world where the correlation among activities may be greater during extremely catastrophic weather events. The correlation of returns among the activity choices may in fact increase during a catastrophic weather event and the benefits of diversification disappear.

Even if the correlation among activities of a portfolio is unchanged for enterprise choices when there are low returns, responding to the challenge from Wright (2006) and putting insurance into a larger portfolio context where other arrangements for smoothing consumption are considered will lead to the conclusion that insurance for modest or even intermediate losses for a single portfolio activity is likely not optimal. Insurance against catastrophic losses likely fits better.

For example, consider a rural community where the majority of households depend on the outcome from agricultural production. Smallholder farm households grow crops, have livestock as a form of savings, and receive off-farm income from harvesting the crops from larger households or working in post-harvest processing facilities. At the household level, a major drought destroys their crops, motivates them to sell the livestock to generate cash for current consumption, and leaves them without off-farm income as there are no crops to harvest. Because markets are not well integrated (i.e., this community is isolated from communities that are not experiencing the drought problem), many households are selling livestock at the same time and depressing local prices, while experiencing higher prices for food and animal fodder. In fact, the very actions these smallholder households have taken to manage risk—a well-diversified portfolio of activities—do little or nothing to help them withstand a catastrophic drought. In this case, the addition of another activity, the purchase of catastrophic drought insurance, can provide significant transfer of high-consequence risk for the household.

Extending this scenario to the broader community heightens the argument for getting insurance focused on the most extreme events. Because the catastrophe is also impacting a large geographic area, both formal and informal mechanisms for pooling and sharing risk begin to break down. We have argued that, in some regions, this is a significant constraint to the development of broader financial services (Skees and Barnett, 2006; Skees, Hartell, and Murphy, 2007).

The nature of weather risk in some regions of the world, where the correlation may indeed change as extreme drought or flooding occurs, raises new questions about how to frame the issue of what type of insurance may be most effective. If the propositions presented above are correct—(*a*) that the correlation among activities meant to diversify risk for smallholder households may change to the detriment of the household during the most extreme events, and (*b*) that a large number of households suffering at the same time and in the same region becomes a constraint to offering other financial services—then the case for developing index insurance that focuses only on catastrophic risk is stronger.

Of more significance, the basic economic models used to examine the value of agricultural insurance can lead to the wrong answers. Even modeling basis risk for weather insurance products must be revisited in a world where the correlation among activities in a portfolio changes as the severity of weather events changes. In other words, if extreme events impact large numbers of households in the same location, then basis risk also should be lower for catastrophic loss events.

Insurance Supply, Demand, and Subsidies

Nonetheless, if one concludes that catastrophic events are indeed the right focus for introducing insurance products for smallholder farmers in lower income countries, it still begs the question of whether individuals will purchase such products. There is significant cognitive failure literature on natural disasters that suggests individuals forget or underestimate bad events (Kunreuther, 1979; Skees, Hartell, and Hao, 2006; Hogarth and Kunreuther, 1989). Thus, there may be a disconnect between what must be charged to insure low-probability, high-consequence events and the willingness of households to pay for insurance products designed to protect against losses caused by these events.

Is this a market failure that justifies some role for government? If so, what role should the government take? We have argued that the government should be cautious about simplistic approaches to subsidizing agricultural insurance premiums. Rather, if the government is to take some risk sharing, the focus should be on financing the more extreme catastrophic risks. Government programs targeting catastrophic risk are largely limited. Mexico and Mongolia are exceptions (AGROASEMEX, 2006; Mahul and Skees, 2007).

It is largely due to the numerous problems plaguing farm-level crop insurance that many government programs involve subsidies for multiple peril crop insurance (MPCI). Providing farm-level MPCI is problematic for any country. The problems of adverse selection, moral hazard, high transaction costs, and financing of correlated risks are well documented (Knight and Coble, 1997; Skees, 2001; Glauber, 2007). After considering actuarial problems, administrative costs, and subsidies, crop insurance programs with loss ratios exceeding 2-to-1 or even 4-to-1 (as in the United States) cannot be justified using any reasonable economic criteria (Skees, Hazell, and Miranda, 1999).

These problems are exacerbated in lower income countries as it is simply out of the question to envision traditional approaches to crop insurance in a country dominated by small farms. The administrative costs of obtaining needed farm-level information and conducting farm-level loss adjustment make this type of insurance prohibitively expensive for insurance companies to offer and smallholder farmers to buy.

During a 2005 workshop on the topic of delivery costs, a manager of a Mexican crop insurance company publicly stated that his company would not consider selling crop insurance to anyone who was farming less than 25 hectares.[3] Clearly, there are few farmers in lower income countries farming on 25 hectares or more.

To add to the challenge of providing subsidies, lower income countries with a large percentage of their populations engaged in some level of the agricultural production chain cannot afford the fiscal strain that would be imposed if they chose to subsidize agricultural insurance. The role of government in developed countries with agricultural insurance has led to considerable confusion among donors, policy makers, and practitioners about how to introduce agricultural insurance without subsidy in lower income countries. Wright (2006) also raises his own set of concerns about the subsidies that have gone into agricultural insurance and properly asks why those public dollars are not being used to support investments that have clear social returns, like research.

This is not to suggest that government and donors do not have an important role in supporting the development of markets for agricultural insurance. We have written about this previously, emphasizing the role of government in supporting data and information gathering and sharing, product development, establishing an enabling legal and regulatory environment, ex ante catastrophic risk financing (removing the most extreme risk only), and appropriate social response policies (Skees et al., 2005). These investments can be significant expenditures designed to "crowd-in" markets. Such investments can be fundamental and much better than simplistic approaches offering to provide premium subsidies as a percentage of total premium. These simplistic approaches invite further rent seeking from the market (Skees, 2001) and a likely outcome that the better-off segments of society will receive most of the benefit by the significant inefficiencies and programs.

Learning from Case Studies

The advent of a number of pilot projects designed around index-based weather insurance products in lower income countries is notable (Table 1). Still, the history for these products is very limited. This section is not intended to be a detailed accounting of the ongoing activity. Rather, a few case studies illustrate how index-based weather insurance products are designed for farm and rural households.

It is worth noting that weather insurance products have been used in the United States for a number of years, with most noteworthy success among specialty crops where other forms of agricultural insurance may be limited (e.g., high-valued citrus crops vulnerable to freeze). Beyond that, the use of index-based weather insurance in the United States is limited and may have been hindered by early mistakes in implementing these programs.

In 1988, a major insurance provider introduced drought insurance for farmers in the Midwest, which failed in the first year due to poor underwriting decisions. The sales for the product were increasing rapidly as the sales closing date approached. Rather than consider that the farmers knew what the insurance company did not (farmers clearly understood that a major drought was emerging), the insurance provider, encouraged by the demand for the product, extended the sales closing beyond the dates set in the original contract. As demonstrated by the growing interest in the product, farmers knew the probability of a payout was greater than implied in the contract. The painful lesson was that farmers, once again, had information superior to the insurance provider.

[3] Author's personal notes from the workshop, "Innovations in Agricultural Production Risk Management in Central America: Challenges and Opportunities to Reach the Rural Poor," Antigua, Guatemala, May 9–12, 2005.

Table 1. Summary of Index-Based Risk Transfer Products in Lower Income Countries

Country	Risk Event	Contract Structure	Index Measure	Target User	Status
Bangladesh	Flood	Index insurance for disaster relief			In development
Caribbean Catastrophe Risk Insurance Facility	Hurricanes and earthquakes	Index insurance contracts with risk pooling for reinsurance coverage	Indexed data from NOAA and USGS	Caribbean countries' governments	Implemented in 2007
Ethiopia	Drought	Index insurance	Rainfall	World Food Programme operations in Ethiopia	$7 million insured for 2006; policy not renewed for 2007
Mexico	Natural disasters impacting smallholder farmers, primarily drought	Index insurance	Rainfall, wind speed, and temperature	State governments for disaster relief; supports the Fondo por Desastres Naturales (FONDEN) program	Began in 2001; available in 26 of 32 states; currently 28% (2.3 mil. ha) of dryland cropland is covered; expansion limited by data availability
Mexico	Major earthquakes	CAT bond and index insurance contracts	Richter scale readings	Mexican government to support FONDEN	Introduced in 2006; CAT bond provides up to $160 million; index insurance provides additional funding up to $290 million
Mexico	Insufficient irrigation supply	Index insurance	Reservoir levels	Water user groups in the Rio Mayo area	Proposed
Bangladesh	Drought	Index insurance linked to lending	Rainfall	Smallholder rice farmers	In development; pilot launch planned for 2008
Honduras	Drought		Rainfall		In development
India	Drought and flood	Index insurance linked to lending and offered direct to farmers	Rainfall	Smallholder farmers	Began with pilot in 2003; now index insurance products are being offered by the private sector and the government with an estimated 300,000 policies sold in 2006

(continued . . .)

Table 1. Continued

Country	Risk Event	Contract Structure	Index Measure	Target User	Status
Malawi	Drought	Index insurance linked to lending	Rainfall	Groundnut farmers who are members of National Smallholder Farmers' Assn. of Malawi (NASFAM)	Pilot began in 2005; 2,500 policies sold in 2006 pilot season; $7,000 in premium volume
Mongolia	Large livestock losses due to severe weather	Index insurance with direct sales to herders	Area livestock mortality rate	Nomadic herders	Second sales season of pilot completed in 2007; offered in 3 provinces; 14% of eligible herders are participating
Morocco	Drought		Rainfall		No interest from market due to declining trend in rainfall
Nicaragua	Drought and excess rain during production; excess rain during harvest period	Index insurance	Rainfall	Groundnut farmers	Launched in 3 departments in 2006
Peru	Flooding, torrential rainfall from El Niño	Index insurance	ENSO anomalies in Pacific Ocean	Rural financial institutions	Proposed
Peru	Drought	Index insurance linked to lending	Area-yield production index	Cotton farmers	Proposed
Senegal	Drought	Index insurance linked to area-yield insurance	Rainfall and crop yield	Smallholder farmers	Proposed
Tanzania	Drought	Index insurance linked to lending	Rainfall	Smallholder maize farmers	Pilot implementation in 2007
Thailand	Drought	Index insurance linked to lending	Rainfall	Smallholder farmers	Pilot implementation in 2007
Vietnam	Flooding during rice harvest	Index insurance linked to lending	River level	Smallholder rice farmers	In development
Kazakhstan	Drought	Index insurance linked to MPCI	Rainfall	Medium and large farms	In development

Source: Author (also see Barnett, Barrett, and Skees, forthcoming).

The insurance provider did not have adequate resources to pay the massive losses resulting from the 1988 drought. The issue was settled in the courts. Rainfall insurance has not been offered to Midwestern farmers since that time. This event was a major setback to what could have emerged in the U.S. markets and is a reminder that mistakes in the development of these products can easily destroy or delay future opportunities.

Among lower income countries, India has the longest running programs for selling weather insurance. From my review, the Indian weather insurance program may encounter the same intertemporal adverse selection problem as did the sales of the 1988 U.S. Midwestern rainfall insurance product. Many of the weather insurance products are being sold after crops are planted when farmers will have more knowledge about the likelihood of drought or floods. Sales closing dates must be set well in advance of when information starts to emerge about the likelihood of a problem.

Rainfall insurance in India began with technical assistance from the World Bank working with ICICI Lombard and BASIX, which is a livelihood promotion group working directly with the poor and providing a wide range of services including technical expertise, microfinance, and insurance products (Hess, 2003). In the first year of the pilot, the insurance was sold to more than 200 groundnut and castor farmers in the coastal district of Mahahbubnagar in Andhra Pradesh to protect against drought.

I was fortunate in being able to visit a group of these farmers in 2003 and provide some limited advice about the project as it was beginning. I returned to the area in 2006 and visited a village that had obtained a payment for severe drought losses. This visit reinforced that, while the contract was promoted as a groundnut and castor contract, the problems in the 2005 drought for the village were much more serious: The riverbed dried up, creating severe shortages of drinking water for livestock and the villagers, stopping any fishing, and preventing planting of rice along the river.

Index-based weather insurance in India is highly noteworthy, as currently it is being run without government subsidies, and smallholder farmers are paying the full price of these products. Anecdotes abound about the successes or failures associated with the program. A large number of farmers have purchased the products (some reports suggest more than a half million farmers over the program's first four years). Most of the products have been purchased via the government crop insurance provider that began weather insurance sales in response to the introduction of these products from the private sector.

In 2004, the Agricultural Insurance Company of India (AICI), the administrator of the government crop insurance program, began selling unsubsidized rainfall insurance products in the khariff (the season from June to September). In 2005, the AICI sold 125,000 rainfall insurance policies in different regions of India. The ICICI Lombard-BASIX product continues to compete side by side with these new products from the government. The rainfall insurance products offered by both groups are directly linked to lending.

During 2004 and 2005, other institutions began expanding the market for weather insurance in India. It is estimated that at least 300,000 weather insurance contracts were sold in 2006. Weather insurance policies are now sold to smallholder farm households by both AICI and private-sector insurance companies, IFCCO-Tokyo, HDFC-Chubb, and ICICI Lombard (World Bank, 2007). Weather insurance is also being marketed to nonfarm enterprises that are affected by weather risks, such as salt processors and brick makers.

However, there have been reports of protests by farmers who had significant crop losses due to extreme rainfall when they had purchased a drought policy.

Such problems are to be expected as many different weather and pest problems can impact crop yields. Nonetheless, if index-based weather insurance is sold as crop insurance, farmers who have losses from that crop and do not receive payments are bound to be disgruntled. If the educational efforts to explain these products are not significant, these types of problems can easily create enough discontent to destroy further efforts to develop weather insurance markets.

There are over 100 million smallholder farmers in India. To get a better picture of the uptake of these products, it would be useful to have more information about the percentage of eligible farmers in the market who are buying the insurance. Of course, this is difficult given the vast number of farmers in India and the expansion of the market. In Mongolia, these estimates are easier to make within the limited scale of the index-based livestock insurance pilot. Some 3,400 herders purchased insurance in 2007, representing about 14% of the eligible herders in the second year of this pilot program (Mahul and Skees, 2007).

Nevertheless, the large number of farmers purchasing weather insurance products in India and the growth of companies offering these products in such a short time are impressive. The expansion of rainfall insurance products can be greatly attributed to the effort of ICICI-Lombard and BASIX to modify and improve the product according to field staff and client feedback. They have invested in improving the accessibility of the product by simplifying the delivery system, training agents, and incorporating new technology (Manuamorn, 2007). For example, their contract was simplified to make it more straightforward for customers, many of whom may be uneducated or illiterate. They abandoned a more complex payout structure in favor of a simple contract covering up to three growing phases. A farmer can choose to cover any or all of the phases. Their rainfall contracts are generic in that they are no longer designed for specific crops, but only insure against rainfall levels for three specified time periods, beginning with the onset of the monsoon season (Figure 1).

Incorporating client feedback, ICICI Lombard and BASIX lowered the minimum liability allowed on a policy as most insureds wanted a small amount of coverage for a smaller premium. A similar behavior is being exhibited in Mongolia where herders are given a choice of insuring between 30% and 100% of the value of their herds. The vast majority of herders select 30%, again, to lower the premium costs.

As the sample contract for Indian rainfall shows (Figure 1), farmers can purchase insurance for one, two, or three phases of the growing season. The first phase is timed with the onset of the rainy season (planting). The index insurance covers drought risk for the first two phases, the sowing and growing periods, and covers excess rain for the third phase, the harvest period. The premium is 90 INR (US$2) for each of the first two phases for a sum insured of 1,000 INR. The premium for the third phase is 110 INR for a sum insured of 1,000 INR.

The brief review provided above highlights several lessons that merit further reflection:

- Sound underwriting (including appropriate sales closing dates) is critical.
- The poor are selecting liability levels that are relatively low.
- Simple weather contracts may be preferred to more complex contracts.

These three points are examined more fully below.

Sound Underwriting—Setting Appropriate Sales Closing Dates

The first issue presents an interesting and important aspect of any of these products—various sources of forecasting

TERMSHEET FOR WEATHER INDEX INSURANCE

Product Reference	NA06		
Crops	Any crop in the district		
Reference Weather Station	Nalgonda		
Index	Aggregate rainfall during the cover phases in mm. If rainfall on a day is < 2 mm, it is not counted in the aggregate rainfall. If rainfall on a day is > 60 mm, it is not counted in the aggregate rainfall. The above condition is applicable only for deficit rainfall cover and not for excess rainfall cover.		
Definition of Day 1	Month of June at reference station is observed >= 50 mm. If above condition is not met in June, the policy invariably starts on July 1.		
Policy Duration	**110 days**		
Cover Phase	**I**	**II**	**III**
Duration	**35 days**	**35 days**	**40 days**
PUT			
Strike (mm) <	**60**	**80**	—
Exit (mm) <	**10**	**10**	—
Notional (Rs / mm)	10.00	10.00	—
Policy Limit (Rs)	1,000	1,000	—
Phase Premium (Rs)	**90**	**90**	—
CALL			
Strike (mm) >	—	—	**240**
Exit (mm) >	—	—	**340**
Notional (Rs / mm)	—	—	10.00
Policy Limit (Rs)	—	—	1,000
Phase Premium (Rs)	—	—	**110**
Combined Premium (Rs)	**280**		
Combined Policy Limit (Rs)	3,000		
Data Source	Indian Meteorological Department		
Settlement Date	Thirty days after the data release by IMD and verified by insurer		

Source: BASIX of India (a similar contract appears in Manuamorn, 2007).

Figure 1. A Sample Termsheet for Weather Index Insurance in India

information can create problems for insurance products which are not properly designed. Many indigenous populations have their own systems to forecast the weather. However, beyond that, more sophisticated forecasting procedures are being developed.

In our work on El Niño, it became clear that the sea surface temperature provided information about emerging problems as early as 7–8 months before the actual event (Khalil et al., 2007). Furthermore, we learned that lenders felt they could control loan default problems by using this information to restrict lending to farmers if there were indications of an impending El Niño. The same issue emerged in Mongolia where lenders revealed they stopped making loans to herders in areas that were experiencing drought because they knew very well that the probability of having high mortality rates during the subsequent winter would result in higher loan defaults. If lenders exhibit this behavior, one would certainly expect insurers must do the same.

Again, the most direct way to control this type of intertemporal adverse selection involves setting sales closing dates early enough whereby available information does not give someone an advantage in knowing the insurance product is underpriced. Doing this in some regions of the world will undoubtedly mean the sales closing date must be set so far in advance that it will reduce demand for the product. Dynamically pricing weather insurance products based upon emerging forecast information is another option. In part, this is why agricultural economists have been attracted to the use of weather derivatives. With effective exchange markets that have many buyers and sellers taking opposite positions on the weather, prices would change as weather conditions and forecasts change.

Weather markets in the United States began around 1997 following the deregulation of the energy markets. These markets were established within the energy sector to protect against swings in temperature that have direct impacts on the demand for energy. Most of these trades were done over-the-counter (OTC).

From 2001 to 2003, I did some work with some of these emerging markets to scope out the possibilities for using OTC trading for agricultural risk. When the weather products must be specifically tailored, as they typically are for agricultural applications, the preconditions for active trading and effective price discovery are unlikely to be met (Odening, Musshoff, and Xu, 2007; Richards, Manfredo, and Sanders, 2004). Indicative of this is that nearly all of the professionals I interacted with during these early years of the market left the weather trading desk to work in the insurance and reinsurance sector. In short, active trading to dynamically price weather insurance is not practical for many of the highly tailored products developed to transfer special forms of weather risk. At this point, insurance markets seem better suited for index-based weather insurance products.

Two alternatives to having early sales closing dates could be: (*a*) the sale of options to purchase insurance, and (*b*) multiple-year contracts. Both of these alternatives merit further research. Selling an option to give the buyer the right but not the obligation to purchase the insurance would still require advanced purchase decisions. Of course, this type of option would be less costly than the full premium costs, but it would still require an early commitment of funds and it is not very practical as an alternative for smallholder households given the high delivery costs. The second alternative would involve rolling the premiums forward with an annual payment for a multi-year contract. Again, this alternative is not practical for smallholder households. Both of these options are more likely to be successfully implemented for a risk aggregator like a microfinance institution.

The Poor Select Low Liability Levels for Insurance

Within the development community an interesting question has been raised: Following a major disaster, how might a massive influx of indemnity payments influence inflation in the local economy? The emerging evidence regarding the levels of insurance that are being purchased should ease these fears. If operators of smallholder households are purchasing such limited liability, the influx of funds following a major disaster will only partially compensate for their losses.

Of more concern is whether there will be bad publicity or negative reactions from the insured if a catastrophe occurs and they find that the indemnities they receive are less than they expected or needed. Fundamental educational efforts are needed. In part, this was the reason for the introduction of two different levels of index insurance for the 2007 sales season of the index-based livestock insurance pilot in Mongolia. One product pays for livestock mortality levels above the 6% threshold and the other pays when levels exceed 10%. In the educational efforts, it was explained that herders would have better catastrophe protection if they used the same premium currency needed to purchase the 6% threshold policy at 30% of the value of their animals, to purchase higher levels of liability on the 10% threshold policy for the same amount of premium. This strategy would ensure a greater payment in the most catastrophic years. However, sales information from 2007 indicates that herders overwhelmingly selected the policy at the 6% threshold and with policies at the lowest level of liability. This suggests herders were much more concerned about more frequent risks, and with limited options for managing their risk this is a rational choice.

Simple Contracts May Be Preferred to More Complex Contracts

The type of generic weather insurance contract that has emerged in India has some significant advantages over more complex contracts attempting to fit weather data to crop growth models. Basis risk is always going to be an issue with weather insurance contracts. Complex scientific models that "overfit" weather data to crop yields can give the wrong impression, implying basis risk is lower than is likely the case.

While I highly value the science that goes into understanding crop growth processes and attempting to create the ideal weather index that will capture variations in yields, these models fail to capture the rich diversity of individual farm-yield risk that will almost always be present within a local community. Basis risk comes from a wide range of sources: (*a*) the weather station being used for the contract may be too far from the insured, (*b*) the insured may be farming soils which are different than those used in a crop growth model for designing a rainfall insurance contract, and (*c*) management by the individual farm operator can be significantly different than the conditions imposed in a crop growth model.[4]

Each of these variables can result in a significant loss for an individual farmer even when a complex weather index suggests no loss should have occurred. This becomes more likely when the weather index being created is attempting to protect against relatively common losses that are near the mean values, and again, is less likely when insuring against extreme, catastrophic events that affect an entire community. Still, in areas of the world where microclimates dominate, index-based weather insurance simply does not make economic sense. In areas where weather events are not correlated across a large geographical area, attempts

[4] The very fact that management is not included is, of course, one of the advantages of index-based weather insurance. Management can be the source of adverse selection and moral hazard. Nonetheless, the poor may not have the resources to apply the same standard management practices that were assumed in the crop growth simulation models used to design the contract. Thus, the opportunity still exists for misunderstanding how well an index insurance contract will capture farm-level losses.

to populate the area with enough weather stations to reduce the basis risk to an acceptable level can easily negate the cost advantage of index-based weather insurance over traditional loss-adjusted insurance.

Overpromoting index-based weather insurance as the solution to individual crop-yield problems may be the largest risk faced by this innovation. If efforts to match individual crop yields to weather events are presented in such a fashion that the insured believe they have better insurance protection than they do, misunderstandings are to be expected. This does not negate the importance of using crop modeling efforts to design the most appropriate generic weather insurance products. Such efforts can be used to design the thresholds and the most critical time periods. Still, every caution should be taken in the educational and sales efforts that follow. Presenting the contract as a seasonal weather contract designed to compensate when severe weather events create a wide range of problems will be less likely to invite challenges and misunderstandings when farmers have losses on specific crops.

Selling a generic weather insurance contract similar to the one presented in Figure 1 has many advantages:

- Misunderstanding about protection for a specific crop yield is reduced.
- There are many regions of the world where inter-cropping is the dominant farming system, and contracts that cover major weather events within the cropping season should fit better for those farming systems.
- Giving farmers a choice about which periods of the growing season concern them most is a good marketing strategy.
- These products can allow for more flexible farming systems as the farm plan can change due to changing weather conditions once a farmer has this generic contract.
- These contracts can be purchased for any other activity that could negatively impact rural households due to extreme weather events in one or all of the specified periods.

Summary and Conclusions—A Framework for Insurance Development

This article raises a number of important conceptual and product design issues regarding the development of agricultural insurance in lower income countries. Primarily, starting with the development of mechanisms to transfer the big risks—spatially correlated, high-impact events that overwhelm even well-diversified farm activity portfolios—is arguably key for easing many of the constraints to the development of rural financial markets. Giving explicit consideration to the most appropriate mechanisms for addressing the characteristics of different risk layers is part of the development of broader financial services for the poor. The task now becomes one of framing a model for the systematic development of market-based weather risk transfer products.

The observations shared in this paper lead to several important conclusions:

- When agricultural insurance is placed into a broader framework motivated by helping smallholder households smooth consumption over time, focusing on catastrophe insurance is likely to be considered more optimal.
- When one considers how households can use different risk management mechanisms for different layers of risks, catastrophe insurance is likely to be more optimal than insurance for less severe events.
- When insurance against natural disaster risks is considered within a larger institutional setting that includes consideration for how to develop financial services for the poor, catastrophe insurance markets are also likely to be more optimal.

- When considering the development of index-based weather insurance products, generic index-based weather insurance that protects against catastrophic events is again likely to be more optimal and less likely to create misunderstandings about the nature of the index insurance product.

A focus on, and richer understanding of the role that catastrophic weather insurance can play in markets also causes us to consider how the development process for agricultural insurance might be reversed for lower income countries. Rather than starting with products targeted at low-impact, high-probability risks, there is a need to start with products that get the "big risk" out of the way first, even for those index-based weather insurance products targeted to smallholder households.

In large part, the enthusiasm for using IBRTPs to transfer weather risk in lower income countries is motivated by a clear need for identifying new approaches to developing sustainable financial markets for the rural poor. Scaling up[5] financial services for the rural poor can only be achieved by adapting services and products to match the risk profile of this market demographic: smallholder farmers with few assets and uncertain and/or seasonal cash flow. The approach must also address the concerns of lending institutions and other businesses that limit or ration their services to smallholder farmers as a strategy to reduce their own risk exposure indirectly tied via their clients to correlated weather events. And finally, the approach should display some semblance of economic efficiency tempered by equity considerations.

Our approach has been to first design a financially sustainable index-based product that will transfer the most severe segment of risk. In many cases the most efficient way to introduce IBRTPs is to begin with a product that transfers the portfolio risk of rural lenders who have exposure to natural hazards impacting agricultural and other rural enterprises, such as drought and flood (Skees and Barnett, 2006; Skees, Hartell, and Murphy, 2007).

By targeting the aggregate portfolio of an MFI, lower administrative and product delivery costs are achieved than by providing direct coverage to smallholder households. The transaction costs associated with providing insurance services to smallholder households can be prohibitive. Reducing the portfolio risk of MFIs is one way to ease the constraints to greater and more efficient complementary rural financial services.

In the future, once mechanisms are in place to transfer catastrophic risk, it becomes possible to envision several types of subsequent insurance product developments. Future products could include insurance that is more closely linked to agricultural credit and/or individual, farm-level insurance for independent risks. Other secondary products could include individual products that would reduce the basis risk of index insurance by using ground-level data to assess losses for larger farms. In short, introducing index-based weather insurance products that get the big risk out of the way first can facilitate other market developments resulting in more appropriate products being targeted to users operating different size farms.

This strategy, reinforced by our work and observations of similar work around the globe, suggests a somewhat different process for developing index-based insurance that begins with a linkage to lending. The model consists of three sequential development stages that correspond to increasingly greater direct individual loss indemnification:

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[5] Scaling up in this context refers to improving the availability and accessibility of financial services (banking and insurance) for the rural poor.

- Stage 1. This is the first generation of insurance sold to MFIs and other risk aggregators by global reinsurance markets to offset the default risk linked to natural disaster and the liquidity risk in lending or revolving credit portfolios (Skees and Barnett, 2006; Skees, Hartell, and Murphy, 2007).

- Stage 2. This stage more directly confronts the household-level factors contributing to default risk by linking index insurance to lending and provides a direct benefit to borrowers. The benefit could extend beyond the "credit insurance" aspect and include some level of payment for coping with and recovery from catastrophic loss.

- Stage 3. Basic index insurance products are used as a form of reinsurance for more traditional farm-level crop insurance linked to loans for larger farms in a lower income country. Indemnities paid would be based upon estimates of farm-level losses rather than the index insurance. In this case, the MFI or other ground-level rural network serves as an insurance delivery mechanism.

Despite my earlier concerns about traditional agricultural insurance for weather and crop insurance, index insurance and traditional insurance are not by definition mutually exclusive—a point that is often lost in articles seeking to compare the relative farm-level benefits of these two risk management tools. These different forms of insurance can coexist and complement one another since they are really designed to target different layers of risk and, frankly, different levels of administrative capabilities. Nevertheless, advances in technology that lower delivery costs and loss adjustment for traditional agricultural insurance will be needed to better cope with the problems of traditional forms of agricultural insurance.

In general, however, the introduction of a mechanism to clear the most catastrophic risk should precede traditional forms of insurance that cover less severe risks. Separating the layers of catastrophic risk can improve the performance and affordability of traditional insurance approaches and coverage for more frequent risks. With careful development, properly designed and targeted index-based weather insurance products can become a first step to facilitating the broader development of robust rural financial markets that serve the needs of the poor in lower income countries.

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Using Participating and Financial Contracts to Insure Catastrophe Risk: Implications for Crop Risk Management: *Abstract*

Geoffroy Enjolras and Robert Kast

High losses generated by natural catastrophes reduce the availability of insurance. As their effects are more and more frequent and violent, there are new needs in insurance for innovative products, especially in the agricultural sector. Many developed countries have already modernized their crop insurance system, e.g., the USA, Spain, and France. Global funds are progressively suppressed and the development of (subsidized) private insurance is encouraged.

These reforms are globally a success, but in fact at least a third of the agricultural surfaces is still not covered, even in the most developed systems (Spain). Moreover, the States' intervention remains compulsory and at a high level (USA). Last but not least, reinsurances face a risk because there exists a possible correlation of world losses as a result of global warming.

Facing these constraints, we propose to cover the whole risk by introducing two innovative contracts: participating policies and financial contracts. Participating policies are already developed in life insurance. The principle is the following: the policyholders pay an extra premium compared to standard insurance contracts. In counterpart, they can be refunded depending on the individual behavior of the stakeholder and on the overall performance of the insurance company. One can easily understand this tool is a persuasive way for the insurance companies to reduce informational asymmetries and for the insured to receive coverage.

Weather-risk contracts are now exchanged on financial markets. They are characterized by an underlying asset that is not traded, e.g., temperature or rain. They take the form of weather options and futures, as well as Cat bonds. Although this kind of market is quite marginal at the moment, its growth is consistent. Thus, potential applications to the agricultural sector are very promising. The main question concerns the correlation between meteorological indexes and financial ones. An imperfect correlation may attract investors seeking to diversify their portfolios. In counterpart, the subscriber is directly exposed to a basis risk, which reduces the coverage's efficiency. Our model takes into account this noisy parameter.

We then develop a formulation that proposes to manage catastrophic risk assuming it can be decomposed into an individual (or idiosyncratic) component and a collective (or systemic) one. According to Raviv (1979), the set of participating and nonparticipating policies allows implementing the two major principles of risk allocation: the mutuality and the transfer principles. In our analysis, we substitute a financial policy for the standard nonparticipating one. Moreover, we measure the impact of unfair premia (i.e., with deductibles and transaction costs) on the coverage level.

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Our model is based on the framework of the expected utility theory. We maximize the expected final wealth of an insured subscribing to both participating and financial policies, with respect to their corresponding premia and indemnities. Then we can formulate some conclusions.

Optimizing the expected wealth of the insured, we first determine the optimal design of insurance policies, with the calculus of the optimal indemnities and premia of both participating and financial contracts. Assuming participating policies exist, we also define the optimal level of deductibility. As we consider unfair contracts, we introduce deductibles and loading ratios into our formulation.

Next, we show that participating contracts hedge the individual losses under a variable premium subject to transaction costs and risk premia. We also find that the loss after the subscription of a participating contract is equivalent to the purchase of call options indexed on a weather-based financial index but subject to a basis risk and unfair premia. Finally, the combination of the two policies leads to an expected loss equal to the sale of futures contracts indexed on a weather-based financial index. The basis risk is deleted while the existence of unfair premia reduces the coverage efficiency.

Direct applications of our formulation to crop risk management are plentiful. Such a combination of contracts provides advantages to all insurance actors. The policyholders may insure their global risk with an integrated product. As shown in the paper, the insurers are the only ones able to design the contracts; thus, the greater will be the market and the better will be the pricing of the contracts. Moreover, the States may encourage the development of such products, as the model suggests their intervention should be focused on the subsidization of the contracts. Such an involvement may reduce the negative impact of unfair pricing for the insured. In terms of public policies, our formulation offers substantial advantages.

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Indifference Pricing of Weather Insurance: *Abstract*

Wei Xu, Martin Odening, and Oliver Musshoff

Weather derivatives are difficult to price because weather cannot be traded, i.e., the market for weather risk is incomplete. Hence, a straightforward application of standard pricing models for financial derivatives is impossible. Actually, the poor transparency of pricing algorithms employed by sellers is considered a major cause of the slow development of weather markets.

We seek to contribute to the ongoing discussion on pricing of weather derivatives by introducing a new approach—indifference pricing. Indifference pricing starts with the appealing notion that the amount of money at which a potential buyer (or seller) of weather insurance is indifferent, in terms of expected utility between buying (or selling) and not buying (selling), constitutes an upper (lower) limit for the contract price. Such an approach can take into account the particular economic situation of individual buyers (sellers). However, compared with other approaches, indifference pricing is less ambitious since it does not attempt to predict a unique market price or even an equilibrium price. Instead, it calculates price boundaries for sellers and buyers and simply states whether or not transactions are likely to occur. Nevertheless, the approach circumvents the determination of the market price of risk. Clearly, along with this comes the cost of specifying a utility function, but this is unavoidable whenever no-arbitrage arguments are insufficient to determine a unique price. Furthermore, a nice property of indifference prices is that they recover familiar Black-Scholes prices in the case of complete markets. An additional advantage of indifference pricing is that it does not require the assumption of continuous trading which is at the heart of modern financial economics. It can also be applied in a discrete time setting where buying and selling positions are retained once they have been realized.

Taking up the general idea of indifference pricing, we develop a model that can be used to calculate the willingness to pay for weather insurance in an agricultural context. Then we apply this model to crop farms in Germany. First, we calculate indifference prices for wheat producers in northeast Germany and compare them with other pricing methods. Second, we ask for the willingness to pay for weather insurance in other regions and for other farm types.

Our findings show that under moderate risk aversion maximal bid prices of the grain producers exceed the minimal selling prices of insurers only for a few regions and crops. The basis risk that is inherent to a weather derivative, which has been optimized for a particular crop and a particular region, makes it less attractive for farmers in other regions. In other words, our calculations confirm results of previous studies, showing a considerable magnitude of basis risk inherent to index-based weather insurance in the agribusiness sector. Another finding is the considerable differences that may occur between indifference prices and the actuarial "fair price."

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Creating Safety Nets Through Semi-parametric Index-Based Insurance: A Simulation for Northern Ghana: *Abstract*

Vasco Molini, Michiel Keyzer, Bart van den Boom, and Wouter Zant

Our paper considers past and present social safety net arrangements in Northern Ghana, where village communities are poor and tend to face risks that affect virtually all members, and consequently call for safety net arrangements beyond individual and mutual insurance. Following a brief historical review, we assess the possible contribution of index-based crop insurance to such arrangements. This recently developed type of insurance bases its indemnification on objectively and easily measurable variables, such as rainfall data and prices at major markets, unlike standard insurance contracts which are individualized and have much higher transaction costs.

After noting that safety net arrangements should be effective, timely, and well-coordinated in securing (*a*) entitlements (in kind, cash, or as indemnification payments from insurance) for the poor, (*b*) funding (through taxes or private contributions, possibly insurance premiums), and (*c*) delivery of necessities such as staples to all households, we observe that index-based insurance could play a useful role in entitlement, and to a lesser extent in funding. However, index-based insurance does not in itself provide for adequate delivery, meaning that under supply shocks such as droughts the indemnity payments could cause prices to rise and channel away scarce food from the uninsured to the insured. This is particularly relevant in Northern Ghana, where rainfall varies strongly, subsistence farming is dominant, and few remittances flow in.

Turning to the modalities of index-based insurance, we seek to improve on existing indemnification schedules that are commonly specified synthetically or estimated in a simple parametric form. Via an adaptation of available kernel learning techniques, we can estimate a schedule that minimizes farmers' risk of falling below the poverty line. This schedule depends on selected index variables through a perfectly flexible functional form that maintains self-financing up to a prespecified subsidy. We test the scheme's performance as a safety net for Northern Ghana based on the size of its basis risk and its capacity to reduce poverty through full sample estimation as well as bagging. Although our schedule reduces by 20 percentage points the poverty incidence from an initial level of 63%, and proves to be quite robust under bagging, basis risk and associated poverty remain considerable, reflecting the limited capacity of the variables selected to eliminate it.

In the empirical section of the paper we compute the self-financing premium and the indemnification needed to avoid all income shortfalls below the poverty line over a historical record of 26 years, for hypothetical contributor pools consisting of all farmers in Northern Ghana. Under this scheme, we calculated different premiums for different poverty lines. The more the poverty line increases, the more additional

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resources are needed to bring all farmers above it. Actually, as shown by Figure 1, the per hectare premium as a percentage of average income ranges from about 5% with a poverty line of 500,000 cedi to approximately 17% with a poverty line of 600,000 cedi, and finally to 50% for the official poverty line of 700,000 cedi (about US$1 per capita per day).

Figure 2 shows the simulation results from comparison of the case without safety net to the (kernel-smoothed) income distribution under two index-based safety nets targeted at a poverty line of 700,000 cedi (the dotted line) and 600,000 cedi (the continuous line), respectively. Some interesting results emerge. Comparing the uninsured case with the two index-based insurances, we observe a tendency for shortfalls to diminish significantly. The poverty prevalence decreases and the depth of poverty is reduced as well, as can be seen from the narrowing of the right-hand-side tails. Indeed, the safety net targeted at the 600,000 cedi line is much less capable of redistributing income since, by construction, it pays out less frequently, but has a less prohibitive premium (17% of the average income).

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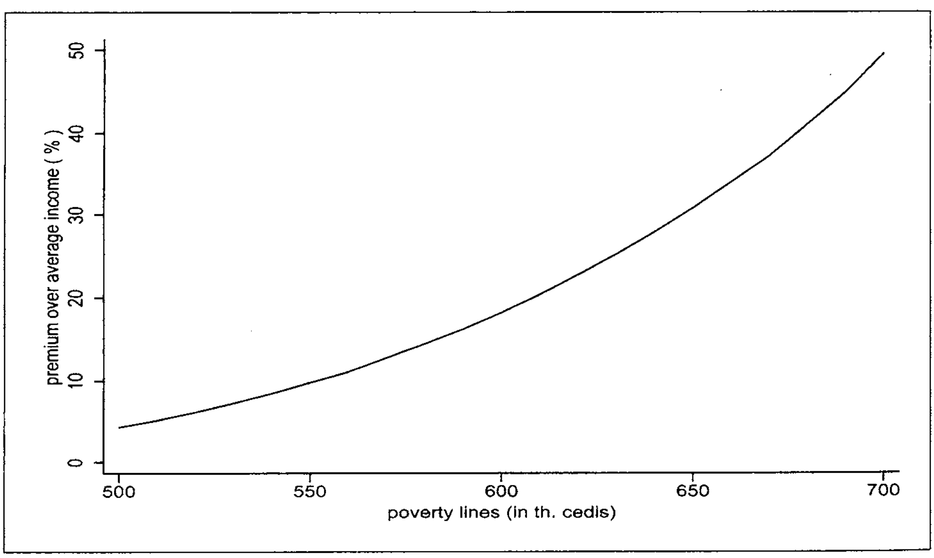
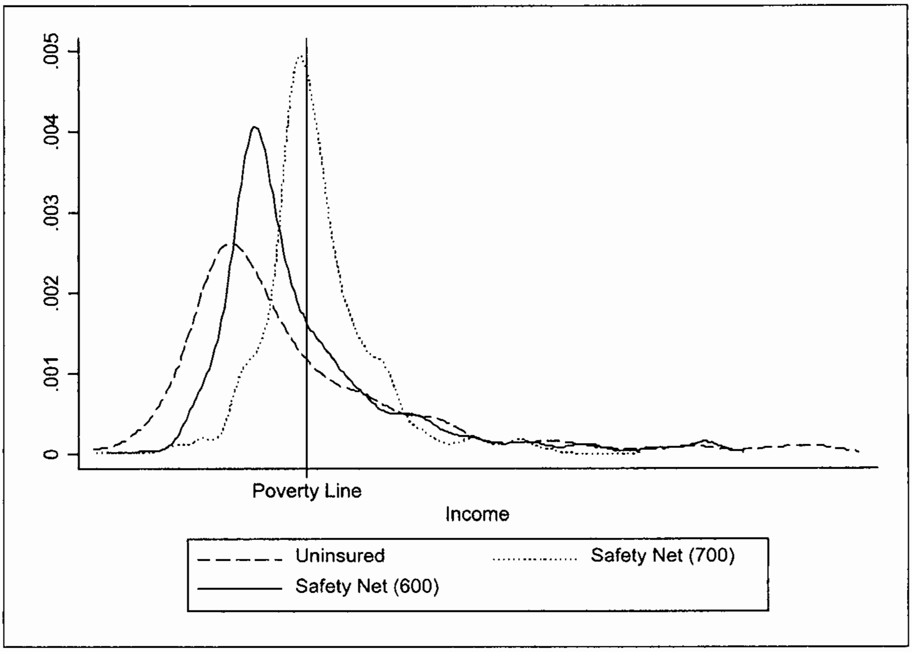


Source: Keyzer, Molini, and van den Boom (2007).

Figure 1. Premium Variation as a Function of Insurable Poverty Lines



Source: Molini et al. (2007).

Figure 2. Income Distribution Before and After the Index-Based Indemnification: Safety Nets with Poverty Lines at 700,000 and 600,000 Cedis

Announcement of The W.I. Myers Prize in Agricultural Finance

To encourage the publication of peer-reviewed research, Myers Endowment funds will be used to support two awards starting with the Spring 2006 issue of ***Agricultural Finance Review***. The prizes will include a monetary award as well as a certificate. Selected by the editors and on nomination by subscribers to *AFR*, the two awards will be for:

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- *Best Journal Article Authored by a Student.*

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