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Weather Risk Management in Light of Climate Change Using Financial Derivatives

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Abstract

Accumulating scientific evidence demonstrates that climate change causes higher agricultural production risk – even when the potential for on-site risk mitigation is exploited. Climate change reduces average crop yields, and causes an increase in weather and yield variability. Faced with higher weather-related production risks, the demand by agribusiness stakeholders for effective weather risk management solutions is expected to increase. Suitable weather risk transfer products are needed to cope with the adverse financial consequences of climate change. An overview of the latest scientific findings on this subject is provided in **chapter 1**.

The main objective of this dissertation is to propose a method for structuring index-based weather insurance such that it yields optimal hedging effectiveness for the insured. In **chapter 2**, for a given weather index and an actuarially fair premium, the optimal payoff structure is derived (in an expected utility framework) taking the non-linear relationship between weather and yields into account. The optimal index-based insurance contract solves a constrained, stochastic optimization problem that models the insured's trade-off between the costs of obtaining a weather hedge (insurance premium) and the benefits (risk reduction) without imposing functional form assumptions on the relationship between crop yields and weather, using a fully non-parametric approach. In addition, to account for transaction costs, a weather contract is derived that maximizes an insurer's profits such that the insured still considers the loaded contract as a viable purchase (for a given level of risk aversion). A computer-based algorithm is implemented (in MATLAB) in order to derive the optimal index-based weather insurance contract (as well as the profit-maximizing counterpart) for given yield and weather data. Since the provision of agriculture-specific weather risk transfer products is still in its infancy, the proposed structuring methodology contributes to the development of weather risk transfer products that account for the agronomy-specific weather characteristics in crop yield losses. Due to its generality, the structuring method can be applied to any crop and in any location for which sufficient weather and yield data is available.

The model is then used to shed light on a number of timely questions. For that purpose, simulated weather and crop yield data is used, which represents a maize-growing region in Switzerland, and is derived from a process-based crop simulation model in combination with a weather generator. In light of climate change, the potential of hedging weather risk with index-based weather insurance is evaluated. In **chapter 3**, simulated crop yield and weather data representing today's climatic conditions and a climate scenario is used to assess the hedging benefits (for the insured) and the expected profits (for

the insurer) from buying, respectively selling, optimal index-based weather insurance under both climatic conditions. Adjusted insurance contracts are simulated that account for the changing distribution of weather and yields due to climate change. For the underlying location, crop and climate scenario, I find that the benefits of hedging weather with adjusted contracts almost triple for the insured, and insurers' expected profits increase by about 240% when offering adjusted contracts.

With climate change putting an end to stationarity of weather and yield time series, a fundamental assumption underlying risk management is undermined. Climate change thus challenges the insurance industry's practice of using historical data for structuring and pricing weather insurance products. The effect of this practice on risk reduction and profits from hedging future weather risks with non-adjusted contracts, which are based on historical weather and yield data, is evaluated. I find that when insurers continue to rely on using backward-looking data for the contract design, the climate change induced increase in the risk reduction and expected profits (from offering adjusted contracts) is eroded. Thus, in times of climate change, the payoff structure of index-based weather insurance requires regular updating to guarantee that the insured's future weather risk is reduced efficiently.

In the Over-the-Counter (OTC) weather derivative market, generic weather derivatives are offered that possess a linear payoff structure in contrast to the non-linear contracts considered here. In **chapter 4**, the loss in risk reduction from hedging agricultural weather risk with linear derivatives is therefore evaluated. For insurers, the expected profits from offering linear contracts to agricultural growers are compared to the profits from selling an optimal non-linear contract that reflects the agronomic relationship between weather and yield. For that purpose, the contract parameters (strike, exit, cap, and ticksize) needed to purchase a generic weather derivative in the OTC market are derived from the optimal and profit-maximizing contracts. For the case study, I find that hedging weather risk with linear contracts decreases the insured's hedging benefits, as well as the insurer's profits, by about 20 to 24% compared to the optimal non-linear contracts. By deriving the contract parameters from the optimal contracts, a decision-support tool is proposed, which facilitates the structuring process for entrepreneurs in weather-dependent sectors wishing to buy linear weather derivatives in the OTC market.

Closing remarks are offered in **Chapter 5**, where the challenges for weather-dependent industries and the benefits for weather market participants in light of climate change are discussed.

Zusammenfassung

Wissenschaftliche Erkenntnisse zeigen, dass der Klimawandel zu einer Zunahme von landwirtschaftlichen Produktionsrisiken führt – selbst unter Ausschöpfung des Potenzials zur Risikominderung. Mit dem Klimawandel reduzieren sich die durchschnittlichen Ernteerträge und die Variabilität des Wetters und der Erträge nimmt zu. In Anbetracht der gestiegenen wetter-bedingten Produktionsrisiken steigt die Nachfrage im Agrarbereich nach effektiven Lösungen, um Wetterrisiken abzusichern. Geeignete Risikotransferprodukte werden benötigt, um die negativen finanziellen Auswirkungen des Klimawandels abzumindern. **Kapitel 1** bietet einen Überblick über die neusten wissenschaftlichen Ergebnisse auf diesem Gebiet.

In dieser Dissertation wird eine Methode vorgestellt, mit der der Versicherungsauszahlungsverlauf einer index-basierten Wetterversicherung hergeleitet werden kann, so dass eine optimale Absicherungseffektivität für den Versicherten erzielt wird. In **Kapitel 2** wird für einen zugrundeliegenden Wetterindex und eine aktuarisch faire Versicherungsprämie die optimale Auszahlungsstruktur (im Rahmen eines Erwartungsnutzenmodells) unter Berücksichtigung des nicht-linearen Zusammenhangs zwischen Wetter und Erträgen hergeleitet. Der optimale index-basierte Versicherungsvertrag stellt die Lösung eines beschränkten, stochastischen Optimierungsproblems dar, anhand dessen die Abwägung des Versicherungsnehmers zwischen den Kosten zum Erwerb einer Wetterabsicherung (Versicherungsprämie) und dem Nutzen (Risikoreduzierung) modelliert wird, ohne einen bestimmten Funktionsverlauf für die Beziehung zwischen Ernteerträgen und Wetter anzunehmen und unter Verwendung eines gänzlich nicht-parametrischen Ansatzes.

Um Transaktionskosten zu berücksichtigen, wird darüber hinaus eine Wetterabsicherung strukturiert, die die Gewinne des Versicherers maximiert, so dass der Versicherungsnehmer (für gegebene Risikoaversion) den um eine Gewinnmarge bereicherten Vertrag gerade noch gewillt ist zu kaufen. Um die optimale index-basierte Wetterabsicherung, sowie das gewinnmaximierende Pendant, für gegebene Ertrags- und Wetterindexdaten herzuleiten, wurde ein Computergestützter Algorithmus (in MATLAB) implementiert. Da sich das Angebot an agrarspezifischen Wetterrisiko-Transferprodukten noch in den Anfängen befindet, trägt die hier vorgestellte Strukturierungsmethode zur Weiterentwicklung von solchen Produkten bei, die die agronomiespezifischen Wettereigenschaften von Ackerfrüchten berücksichtigen. Aufgrund seiner Allgemeingültigkeit kann die Strukturierungsmethode auf jede Kultur und an jedem Standort angewendet werden, für die ausreichende Wetter- und Ertragsdaten vorhanden sind.

Das entworfene Strukturierungsmodell wird dann dazu verwendet, um einige aktuell relevante Fragen zu beantworten. Dazu werden simulierte Wetter- und Ernteertragsdaten verwendet, die mittels eines biophysikalischen Modells in Kombination mit einem Wettergenerator hergeleitet werden, und die die Maisanbaubedingungen einer Region in der Schweiz abbilden. In Anbetracht von Klimawandel, wird das Potenzial von Index-basierter Wetterversicherung zur Reduzierung von Wetterrisiken bewertet. In **Kapitel 3** werden simulierte Wetter- und Ertragsdaten, die die heutigen klimatischen Bedingungen und ein Klimawandelszenario darstellen, verwendet, um die Absicherungsvorteile (für den Versicherungsnehmer) und die zu erwartenden Gewinne (für die Versicherung) bei Absicherung mit, bzw. Verkauf von, optimalen index-basierten Wetterversicherungen in beiden Klimaszenarien zu bewerten. Dazu werden Versicherungsverträge simuliert, die der durch den Klimawandel hervorgerufenen Veränderung der Wetter- und Ertragsverteilungsfunktionen Rechnung tragen. Für den zugrunde-liegenden Standort, die Kultur, und das Klimawandelszenario, zeigt sich, dass sich die Vorteile der Wetterabsicherung für den Versicherungsnehmer verdreifachen, und die zu erwartenden Gewinne der Versicherer um beinahe 240% ansteigen, wenn an den Klimawandel angepasste Verträge angeboten werden.

Da sich mit dem Klimawandel die Annahme der Stationarität von Wetter- und Ertragsdaten nicht länger aufrechterhalten lässt, wird damit eine grundlegende Annahme im herkömmlichen Risikomanagement ungültig. Der Klimawandel stellt die Versicherungsbranche somit vor eine Herausforderung, da die gängige Praxis, historische Daten für das Strukturieren und die Festsetzung der Prämien zu verwenden, nicht länger fortgesetzt werden kann. Deshalb werden die Auswirkungen auf Risikoreduzierung und Gewinne ermittelt, sollte die Branche an dieser Praxis festhalten und künftige Wetterrisiken mit nicht-angepassten Verträgen absichern, welche auf historischen Wetter- und Ertragsdaten basieren. Es zeigt sich, dass sich die durch den Klimawandel herbeigeführte Zunahme in Risikoreduzierung und Gewinnen, die durch angepasste Verträge erzielt werden könnten, verringert. In Zeiten von Klimawandel muss die Auszahlungsstruktur von index-basierten Wetterversicherungen regelmässig angepasst werden, um das künftige Wetterrisiko der Versicherungsnehmer effizient zu reduzieren.

Im Markt für ausserbörslich gehandelte Wetterderivate besitzen typische Wetterderivate eine lineare Auszahlungsstruktur im Gegensatz zu den hier betrachteten nicht-linearen Verträgen. In **Kapitel 4** wird deshalb die Risikoreduktionseinbusse ermittelt, die entsteht, wenn Wetterrisiken im Agrarbereich mit linearen Derivaten abgesichert werden. Die Gewinne der Versicherer, die Erzeugern im Agrarbereich lineare Verträge anbieten, werden mit den Gewinnen beim Vertrieb von nicht-linearen Verträgen verglichen, welche die agronomische Beziehung von Wetter und Erträgen widerspiegeln. Zu diesem Zweck werden die Vertragsparameter (Ausübungshürde, Ausstiegshürde, maximale Auszahlung und Ticksize), die benötigt werden, um ein typisches ausserbörslich gehandeltes Wetterderivat zu kaufen, vom optimalen bzw. gewinnmaximierenden Vertrag abgeleitet. Für die Fallstudie zeigt sich, dass die Absicherungsvorteile des Versicherungsnehmers bei Verwendung eines linearen Vertrages (und die Gewinne des Versicherers) um 20 bis 24% sinken im Vergleich zur Absicherung mit optimalen nicht-linearen Verträgen. Durch das Ableiten der Vertragsparameter von optimalen Verträgen wird ein Modell zur Entscheidungsfindung vorgeschlagen, das den Strukturierungsprozess für Unternehmer in wetterabhängigen Branchen, die ein lineares ausserbörslich gehandeltes Derivat kaufen wollen, erleichtert.

Abschliessend werden in **Kapitel 5** die sich durch den Klimawandel ergebenden wirtschaftlichen Herausforderungen für wetterabhängige Industrien und die Vorteile für die Teilnehmer am Wettertransfermarkt diskutiert.

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Contents

Chapter 1

Introduction

Weather patterns affect economic activity in many industries. Production as well as consumption are directly and indirectly influenced by the prevailing weather conditions. Depending on the nature of the business, anomalies of meteorological conditions such as temperature, precipitation, frost, drought, snowfall or wind causes uncertainty in cash flows and revenues. Entrepreneurs faced with weather risk, that is the sensitivity of revenues to the vagaries of the weather, experience fluctuations in production or sales volume over time that are caused by fluctuations in weather events. In contrast to floods, storms, and hurricanes, most of these weather events are considered non-catastrophic. Nevertheless, non-catastrophic weather risks can have an enormous impact on the financial stability of companies. Managing weather risk is therefore of fundamental importance for entrepreneurs generating revenues in weather-dependent industries, and will become even more important in a changing climate with an increasing number of extreme weather events. Insurance has been an integral part in dealing with weather risk, as it helps reduce the residual risk that cannot be prevented through cost-effective risk mitigation strategies. The provision of proper weather insurance solutions to hedge the volume risk caused by weather variability is one important step towards mitigating the effects of climate change, and the subject of this dissertation.

1.1 Climate Change, Variability, and Changes in Agricultural Production

Accumulating scientific evidence demonstrates that climate change is having an impact on the frequency, intensity and geographic distribution of extreme weather events as a result of rising atmospheric concentrations of greenhouse gases.[1] These trends are expected to continue as the world warms, leading to, for example, more intense heat waves (Stott et al., 2004), heavy precipitation events, and droughts (Easterling et al., 2000; Beniston et al., 2007). Such changes in climatic conditions pose concerns for all industrial activities, and in particular agricultural production (Lazo et al., 2011). Agriculture is extremely vulnerable to climate change as the weather is the primary determinant of production.

Crop yields respond to climate change through the direct effect of weather, atmospheric CO_2 concentration, and water availability. Changes in average temperature conditions and increased climatic variability alter the prevailing growing conditions of plants. In particular, within-season and inter-annual variability of precipitation, episodes of drought conditions, and heat stress, especially during critical development stages, negatively affect biomass accumulation and cause variation in crop yields. Moreover, changes in weather conditions impact the incidence and severity of pests and diseases, which then indirectly affect the quantity, and quality of crop yields (Adams et al., 1998). An increase in greenhouse gases such as carbon dioxide may positively affect the physiology of crop growth by increasing biomass production (Tubiello et al., 2002; Rosenzweig and Iglesias, 1994), but is insufficient to offset the negative impacts.

The influence of climate change on agricultural crop yields has been widely studied (Adams et al., 1998; Reilly and Schimmelpfennig, 1999; Mendelson, 2001; Olesen and Bindi, 2002, 2004; Tubiello et al., 2002; Reilly et al., 2003; IPCC, 2007; Iglesias et al., 2009; Bindi and Olesen, 2010). The general agreement is that some crops in some regions of the world will benefit, while the overall impacts of climate change on agriculture are expected to be negative, thus threatening global food security (Rosenzweig and Parry, 1994; Parry et al., 2004; Lobell et al., 2008; Brown and Funk, 2008). The disparities in climate change vulnerabilities of crops and regions is a result of differences in crop sensitivities to climate change and in water availability.

Many studies indicate that climate change alters mean yields (Reilly et al., 2002; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Lobell and Field, 2007; Lobell et al., 2008). In addition to the mean yield reduction, climate change contributes to a change in crop yield variability (Mearns et al., 1992; Olesen and Bindi, 2002; Chen et al., 2004; Isik

[1] Although the IPCC, in their 2001 report, still presented no clear proof of the correlation between global warming and the increased frequency and intensity of extreme atmospheric events, recent studies have provided a good deal of evidence that the probabilities of various meteorological parameters reaching extreme values are changing (Schär et al., 2004). The IPCC's fourth assessment report in 2007 confirmed that natural disasters have been occurring more frequently, with the number of extreme events expected to rise each year owing to anthropogenic climate change (IPCC 2007). A new report "Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation" (SREX) on extreme events and climate change, expected to be published in February 2012, will shed more light on this question.

and Devadoss, 2006; McCarl et al., 2008; Bindi and Olesen, 2010). With climate change, crop yields and weather time series are no longer stationary. The assumption of stationarity has historically facilitated the management of risk since historic weather and yield data could be used to derive probabilities of future weather-related yield losses. Climate change thus undermines the insurance industry's practice of relying on historical data to design and price weather risk transfer products.

Risk mitigation strategies, such as the adaptation in planting and harvesting dates, installation of irrigation systems, alteration of fertilizer and tillage practices, and the usage of new crop varieties, help to reduce some adverse effects (Smit et al., 2002; Finger et al., 2011). The effectiveness and benefits of agricultural risk mitigation strategies will depend on the severity of climate change (Howden et al., 2007). Even if farmers utilize all available risk mitigation practices, however, it is expected that the weather risk exposure increases with climate change (Ibarra and Skees, 2007; Trnka et al., 2011). To sum up, agricultural production is becoming more risky with climate change and additional risk transfer strategies are therefore needed to address the retained weather risk.

1.2 Weather Risk Management in Agriculture

1.2.1 Damage-based Insurance Products

Even in the absence of climate change, weather risk constitutes serious business risks for many industrial sectors including agriculture. Agricultural insurance in the form of crop or revenue insurance has therefore a long-standing tradition in developed countries, notably the United States, Canada, and Europe (Glauber, 2004; Barnett et al., 2005, Bielza et al., 2008). In its most fundamental form, an insurer will pay producers an indemnity in the event that their yields fall below a pre-determined level. With damage-based insurance, the claim is determined by measuring the percentage damage in the field soon after the damage occurs, and applying it to a pre-agreed sum insured. The sum insured is determined by the farmer based on his historical farm yields or expected revenues. Yield or revenue insurance can be obtained to cover single-peril or multiple-peril weather events.[2] The provision of farm-level yield (or revenue) insurance has, however, proven to be difficult for a number of reasons.

Farmers always know more about their risk exposure and their behavioral responses

[2]Damage-based insurance is best known for hail, but is also used for other named-peril insurance products (such as frost and excessive rainfall). Hail insurance and other named-peril insurance products have been offered for many years without any public subsidies (Mahul and Stutley, 2010).

to insurance purchasing than will the insurer (Barnett et al., 2005). This information asymmetry creates both risk classification and moral hazard problems (Skees and Reed, 1986; Coble et al., 1997; Hazell, 1992; Just et al., 1999). Efforts to address this information asymmetry are quite expensive (Miranda, 1991). In the U.S., adverse selection and moral hazard problems have contributed to actuarial under-performance with excess losses (Hazell and Skees, 1995) and consequently the introduction of government support (Skees, 2001). Premium subsidies are the most common form of public intervention in agricultural insurance. Almost all industrialized countries, and some developing countries, provide premium subsidies in the order of $50-300\%$ of the original gross premium paid by the farmer (Bielza et al., 2008; Mahul and Stutley, 2010). An alternative to damage-based insurance products, are index-based insurance products, which rely on a proxy for yield losses, instead of actual farm-level yields.

1.2.2 Index-based Insurance Products

Index-based insurance products base their coverage on some aggregate index that conveys information about the (individual) losses. Unlike traditional crop insurance that attempts to measure individual farm yields or revenues, index insurance makes use of variables that are exogenous to the individual policyholder – such as area-level yields, or some objective weather event – but have a strong correlation to farm-level losses. For most insurance products, a precondition for insurability is that the losses across policyholders are uncorrelated (Rejda, 2001). A precondition for index-based insurance products is that the risk of policyholders within a defined geographical unit is spatially correlated. Weather patterns like drought or frost often affect yields of several farmers in a given region, therefore yield losses are spatially correlated, and index-based weather insurance represents an effective alternative to traditional farm-level crop insurance (Ibarra and Skees, 2007).

Problems associated with adverse selection and moral hazard are limited by index-based insurance since an exogenous, verifiable weather event is being insured, rather than the yield outcome (Skees et al., 1999). Administrative and transaction costs are also minimized since index-based insurance does not require costly inspections, monitoring and loss adjustment. Furthermore, index-based insurance comes without deductibles and co-payments, which are used by insurers providing farm-level yield (or revenue) insurance to mitigate adverse selection and moral hazard. The main disadvantage of index-based insurance products, however, is the existence of so-called basis risk. With insurance products that trigger payments based on some loss proxy, the insured faces the risk of not receiving any or only inappropriate indemnities that do not reflect the actual incurred losses. A trade-off thus exists between damage-based insurance products that induce moral hazard and adverse selection problems while providing a full-hedge, and index-based insurance products that eliminate problems associated with asymmetric information, but come at the potential cost of only partially hedging the weather exposure.

In the literature, two index-based insurance solutions are widely analyzed: area-yield insurance, and weather-based insurance. The work in index-based insurance dates back to Halcrow (1949), who first proposed area-yield insurance as a solution to asymmetric information problems. With area-yield insurance, coverage and indemnities are based on aggregate yields in a given geographical unit. The insured yield is established as a percentage of the average yield for the area. An indemnity is paid if the realized yield for the area is less than the insured yield – regardless of the actual yield (Miranda, 1991). Coverage of a weather-based insurance is based on realizations of a specific weather parameter measured over a pre-specified period of time at a particular weather station. Index-based weather contracts can be issued either in the form of an index-based weather insurance or a financial weather derivative. The two types of contracts differ from a regulatory and legal perspective, whereas from an economic perspective both instruments share the common feature of triggering indemnities based on an underlying weather index.[3]

Both the United States and Canada started to experiment with agricultural insurance products that trigger indemnities based on area-level (rather than farm-level) yield or revenue shortfalls to circumvent asymmetric information problems. While agricultural applications of index-based weather insurance are being widely discussed, their penetration is still very low. Index-based weather insurance is only available in 20% of high-income and 40% of middle-income countries (Mahul and Stutley, 2010). Except for India and Mexico, most of the index-based weather insurance schemes are still at the stage of implementing pilot projects (Hohl et al., 2007).[4] Nonetheless, index-based weather insurance has gained a lot of attention, and a number of empirical studies have investigated the potential of weather index insurance in the agricultural sector (Richards et al., 2004; Vedenov and Barnett, 2004; Deng et al., 2007; Martin et al., 2001; Miranda and Vedenov, 2001; Skees et al., 2001; Turvey, 2001; Chantarat et al., 2007; Breustedt et al. 2008; Zant, 2008; Berg et al., 2009; Musshoff et al., 2009; Turvey et al., 2010; Leblois et al., 2011).

[3]Throughout this dissertation, the term index-based insurance is used to describe existing products and structuring methods. The optimal index-based insurance contract, developed to structure a weather hedge with optimal hedging effectiveness, could also be issued as an "optimal" weather derivative. The term weather derivative is used to refer to the linear contracts traded at exchanges and in the OTC market.

[4]The most visible applications have been sponsored by the Commodity Risk Management Group at the World Bank, which has been piloting index-based weather insurance for developing country producers, agricultural businesses, and banks in India, Peru, Ukraine, Ethiopia, and Malawi.

1.2.3 Challenges in Designing Index-based Weather Insurance

The potential for index-based weather insurance in agriculture is large due to the sensitivity of the sector to the vagaries of weather. For index-based weather insurance to effectively transfer the risk, the contract has to be designed such that indemnities are triggered when losses occur, and the amount of indemnities compensates for actual yield losses. The degree to which weather risk exposure is reduced by hedging with a particular contract thus depends on the design of the product.

Acknowledging that there exists a relationship between the insurance design and the resulting risk reduction, the design process can be decomposed in two steps: 1) deriving an index that explains crop losses well (*index design*), and 2) designing the payoff structure (*contract design*). Each step critically affects the risk reduction that can be achieved.

With respect to the index design, the efficiency of a contract depends on the relationship between weather and yield (Goodwin and Mahul, 2004). Finding an index that explains crop losses well matters for reducing *meteorological basis risk*, i.e. the risk of the index not triggering any or insufficient payments despite the fact that crop losses occurred. Weather-based insurance contracts therefore have to be crop- and location-specific, since weather patterns, especially precipitation, are spatially variable, and the weather sensitivity varies across different crops. Basis risk can arise due to a number of reasons: 1) an imperfect correlation of the weather index with the weather-dependent output (yield loss, revenues, or costs), and 2) due to spatial and temporal discontinuities in weather.

For a given index, the hedging effectiveness of the contract can then be optimized through the design of the payoff structure. Vedenov and Barnett (2004) are the first to emphasize the importance of the insurance payoff structure with respect to achieving hedging effectiveness, i.e. the degree to which weather risk is being reduced by the insurance product. The design of the payoff structure matters for minimizing *structural basis risk*, i.e. the risk of receiving inadequate payments that do not fully cover the realized losses despite the fact that the index triggers payouts.

Studies investigating the potential of index-based weather products for the agricultural context have paid attention to the minimization of meteorological basis risk (Barnett et al, 2005; Ibarra and Skees, 2007; Barrett et al., 2007). The minimization of structural basis risk (for a given index) has so far received less attention in the literature. While different structuring methodologies have been proposed to determine the buyer's choice of the insurance parameters (Miranda, 1991; Mahul, 1999, 2001; Osgood et al., 2007; Berg et al., 2009; Musshoff et al., 2009; Leblois et al., 2011), these models share the assumption of a linear payoff function and they derive the payoff function by a priori imposing functional form assumptions on the contract. Until now, the traditional linear payoff structure that has originated in the energy sector, which stems from financial derivatives more general, has thus far been adopted in many agricultural studies and pilot projects (World Bank, 2011; IFAD, 2011).

1.3 Development of the Weather Risk Transfer Market

Recent years have witnessed rapid growth in the market for weather derivatives (WRMA, 2011; Roth et al., 2008). Weather derivatives originated first in the energy sector in 1997 and were used to hedge against temperature-related fluctuations in electricity demand. An exchange-traded weather derivative market soon developed thereafter. Since 1998, the Chicago Mercantile Exchange (CME) has offered standardized weather derivatives based on temperature, rainfall, frost, and snowfall for major cities in the U.S., Asia, and Europe. The available indices allow buyers to hedge against a range of straight-forward weather events, such as frost days, the lack or excess of snowfall, or temperature conditions exceeding certain thresholds. These standardized weather derivatives are available for a limited number of locations. For entrepreneurs with a weather exposure that is not explained by the conditions prevailing in major cities, or whose weather exposure is more complex, hedging with these exchange-traded products will not reduce their weather risk since these indices are uncorrelated with their company's weather exposure.

Location-specific weather derivatives for a wider range of weather phenomena are available in the Over-the-Counter (OTC) market. The OTC market offers the opportunity to buy weather derivatives that are custom-tailored to a particular business need, where only the number of weather phenomena measured by the meteorological stations restricts the index design. Nowadays, a growing number of entrepreneurs in weather-dependent industries, such as the energy sector, the retail sector, or the travel and leisure industry, are using exchange- and OTC-traded weather derivatives to manage weather risk in the same way as they manage their interest rate or exchange rate risk. Agribusiness stakeholders, in particular farmers, are however not making use of these risk transfer products (Brockett et al., 2005). A number of possible explanations exist explaining the low penetration of weather derivatives in the agricultural context.

1.4 Weather Derivatives and Agriculture

The buyer of an index-based risk transfer product is always left with basis risk, which is the risk of not receiving a payment, or an inadequate payment, in the event of a loss

(Woodard and Garcia, 2008). Meteorological basis risk is therefore cited as the main disadvantage of weather-based products, as it reduces the hedging benefits (Skees and Barnett, 1999; Osgood et al., 2007; World Bank, 2011).

In the agricultural sector, where bad weather is the major determinant of crop losses, the potential for basis risk is particularly high since the relationship between crop yields and the weather is rather complex (Dischel, 2001). A number of weather events throughout the growing season directly affect the physiological plant development, such as heat stress or frost, and the growing conditions by influencing the soil moisture conditions (Hanks, 1974; Nairizi et al., 1977; Meyer et al., 1993). Crop yields are not well explained (or predicted) when using only a single weather variable. The predictive power of an index for agriculture can be improved by using multivariate weather indices that jointly account for temperature, precipitation and soil moisture conditions (Karuaihe et al., 2006). The challenge thus lies in designing crop-specific weather indices that account for the multiple-weather impacts and the varying vulnerability across the phenology phases (Turvey, 2000).

A number of agriculture-specific weather indices have been proposed (Palmer, 1965; McKee et al., 1993; Tsakiris and Vangelis, 2005; Steinmann et al., 2005; Narasimhan et al., 2005; Tadesse, et al., 2005; Tsakiris et al., 2005, 2006). The OTC market however still focuses on providing hedging solutions for single-peril weather events. These named-peril weather derivatives are only useful to protect against the negative consequences of a particular weather event, for instance against frost during pollination or excess precipitation during harvest. Crop-specific, multi-peril indices that aggregate the influence of weather over the entire growing season are however needed to hedge weather-related causes of seasonal yield shortfall. Clearly, a tradeoff exists between choosing an index with a large number of weather variables that can improve the efficiency of a contract (compared to a single weather variable), and choosing a single-variable index that is easily understood by the growers.

Unfamiliarity with the weather market has been found to be another major factor determining the uptake of weather derivatives (CME Group, 2008). Potential buyers are generally overwhelmed by the number of factors that need to be considered when structuring a weather hedge. To obtain a weather derivative in the OTC market, a buyer has to select: a weather station reporting daily weather observations, an underlying weather index, the period over which the index accumulates (typically a season or month), and the parameters defining the payoff structure (Cao and Wei, 2004; Zeng, 1999).

The contract parameters defining the payoff function of a generic weather derivative are: strike, exit, cap, and tick size. Once the index realization passes the "strike" value, the derivative starts to pay off. The "tick size" is the monetary value attached to each move of the index value by one unit. Once the realized index value exceeds the "exit" value the maximum payout ("cap") is triggered. The payoff for a particular index realization is then defined as a specified monetary amount (tick size) multiplied by the difference between the strike level and the actual value of the index that occurred during the contract period. The payoff structure of weather derivatives is hence linear, and takes the following functional form in the case of a put option, where the concern is on the insufficiency of the weather event:

$$X = min\{cap, a \times max[0, strike - index]\},$$

where a is the tick size and X the stochastic indemnity.[5] The selection of the insurance parameters is of critical importance as it defines the payoff structure, which then determines not only the premium charged by the insurer for providing the protection, but more importantly the risk reduction that can be achieved. In practice, this implies that entrepreneurs intending to hedge their weather exposure with linear contracts first need to select a powerful index, i.e. they need to quantify the time period(s) during which their production (or revenues) suffer most from adverse weather conditions, as well as the meteorological phenomena responsible for their losses. Next, the relationship between the loss caused by a unit change of the underlying indices needs to be quantified to determine an appropriate payout (tick size). Furthermore, strike and exit values need to be determined such that the potential losses are adequately covered when bad weather strikes. While subjective knowledge about the relationship between weather and losses is informative, the contract design process should ideally be supported by data-driven analysis in order to analyze the non-trivial relationship between the costs of obtaining the weather hedge (the premium) and the benefits (the risk reduction). The lack of such a decision-support tool could further explain the under-investment in weather risk management products.

Moreover, for a weather-exposed entrepreneur to be hedged with linear weather derivatives, the damage caused by the weather event has to increase proportionally with the underlying weather index. Otherwise, part of the weather risk remains unhedged by the option. Many industries, such as the electricity sector, possess a linear weather risk exposure, i.e. electricity demand increases steadily with high temperatures (to satisfy cooling needs), and low temperatures (to satisfy heating demand). In agriculture, the relationship between crop losses and weather events is non-linear (Schlenker and Roberts, 2006),

[5] The payoff function of a call option, where the concern of the hedger is on the excessiveness of the weather phenomena, is analogously given by: $X = min\{cap, a \times max[0, index - strike]\}$.

which could further explain the low penetration of (linear) weather derivatives in the agricultural context. Barnett et al. (2005) note for the first time that typical derivatives that assume linear relationships for agricultural applications "simply may be the wrong models to use". The specific nature of agriculture requires designing crop-specific contracts that mirror the functional relationship between weather and crop growth.

1.5 Objectives and Research Questions

In light of climate change and the increased need to hedge weather risk, and after careful considering the current state of the weather risk transfer market, the purpose of this dissertation is to contribute to the development of weather risk transfer products by proposing a method that addresses the discussed problems related to the up-take of index-based weather products in the context of agriculture. The research questions addressed along this endeavor are outlined in the following.

1.5.1 Optimal Weather Insurance Design

In the second chapter, the focus is on designing weather insurance for agricultural risk management with optimal hedging effectiveness. I investigate the following questions:

- How can an optimal index-based weather insurance contract be characterized and empirically derived? Is the optimal index-based weather insurance contract sensitive to changes in estimation parameters? How does the optimal index-based weather insurance contract change its shape for different levels of risk aversion?
- How can an insurance contract that maximizes an insurer's profit such that the insured still considers it as a viable purchase be characterized and derived? How can the maximum loading factor for different levels of risk aversion be determined?

To address these questions, I consider the decision-making problem of a risk-averse economic agent faced with a stochastic, weather-dependent income. I assume that weather risk can be transferred to insurance markets. Insurers operating at insurance markets are risk-neutral economic agents willing to assume risk for adequate financial compensation – an insurance premium. In order to derive the indemnity structure that a risk-averse farmer requires to be optimally hedged against his weather-risk exposure from farming, an expected utility framework is used. Agents maximize their expected utility that depends on income from farming and the net-payments received from the insurer. The premium that a farmer has to pay to obtain coverage against weather risk is derived by using the so-called "burn-rate method." This pricing mechanism assumes that the premium is actuarially fair, i.e. the premium is equal to the expected payments made to the insured. The burn-rate method is used due to its simplicity and wide-spread application in similar work.[6]

By designing weather insurance products with optimal hedging effectiveness, I extend an approach recommended by Goodwin and Mahul (2004) for designing index-based weather products, build on work by Mahul (1999, 2000, 2001), and compute payments for an index-based weather insurance solution in a more general way than Osgood et al. (2007, 2009). To design an indemnity schedule, Goodwin and Mahul (2004) recommend defining a pseudo-production function where e.g. rainfall or temperature levels are the main inputs. Assuming a specific functional form, the individual yield function can be estimated. Musshoff et al. (2009) use this approach to construct the payments from a weather derivative (put) option by estimating a linear-limitational production function (for a specific weather index). Based on the estimated production function, Musshoff et al. (2009) calculate the revenue function, and define the payoffs from the weather derivative by taking the inverse of the revenue function.

Using a parametric approach to establish the relationship between weather and yield assumes that the conditional yield distributions at different levels of the weather index are homogenous - an assumption that I do not find to be satisfied with weather and yield data. Furthermore, the payoff function of the resulting weather derivative reflects the functional form assumption made about the production function. To derive the optimal indemnification schedule, I therefore abstain from specifying and testing different functional forms to define the weather-yield relationship. Instead, I derive conditional probabilities of yield for different levels of the weather index using a completely non-parametric approach. The estimated conditional yield densities are then used to solve the expected utility maximization problem of the insured subject to the actuarially fair pricing condition.

An alternative method used frequently in studies examining the potential of weather derivatives in agriculture is to select strikes by deriving the levels of indices at which the predicted yields were equal to the corresponding long-time average (Vedenov and

[6] The model can be extended by using any valid pricing mechanisms to compute the insurance premium. Alternative pricing methods are: indifference pricing, burn-rate method, Monte Carlo simulation (Jewson, 2003, 2004; Cao et al., 2004). However, one of the main areas of controversy in the weather derivative market is the choice of the pricing methodology in order to obtain the fair premium. To price financial derivatives with a traded underlying, such as derivatives on stocks or bonds, the preference-free Black-Scholes model can be used to price the contract. Weather derivatives are difficult to price since the underlying index, the weather, is not traded, hence the Black-Scholes cannot be applied (Dischel, 1998).

Barnett, 2004). In light of climate change, this approach is no longer adequate anymore (as will be shown in chapter 4). To select the remaining insurance parameters of the contract, namely the exit and the tick size, Vedenov and Barnett (2004) minimize an aggregate measure of downside loss or semi-variance (Markowitz, 1991).[7]

Similar to Vedenov and Barnett (2004), Osgood et al. (2007) optimize over piecewise linear contracts by minimizing the variance rather than maximizing expected utility. Osgood et al. (2007) optimize contracts only locally, thus making a linear contract more efficient, whereas I determine the global optimum by computing the optimal indemnification structure non-parametrically for a given index.

My model is most closely related to Mahul (1999, 2000, 2001, 2003) who uses expected utility models to investigate theoretically the optimal design of agricultural insurance for different sources of risk (i.e. price risk, yield risk). Mahul (2001) shows that the parameters of the optimal indemnity schedule (strike and cap) depend on the stochastic relation between weather and idiosyncratic risk, and on the risk aversion of the insured, and notes that "without further restrictions on the stochastic dependence (and the producer's behavior), the indemnity schedule can take basically any form." In contrast to Mahul (2000, 2001), I propose a more general method for deriving an optimal index-based weather insurance contract without imposing any functional form assumptions on the relationship between weather and yields, nor on the error term structure. In addition, I numerically compute the optimal indemnity schedule using actual weather and yield data.

As pointed out, designing index-based weather products necessitates an understanding of the complex relationship between weather and crop yields. Therefore, I define and quantify the sources of weather risk that cause crop losses in my case study region. A multivariate ordinary-least-squares regression model is used to explain crop losses accounting for changes in precipitation, potential evapotranspiration, and temperature conditions. Based on the findings from the weather-yield models, I construct multi-peril weather indices that are used to simulate the optimal and profit-maximizing insurance contracts. Deriving the shape of the optimal weather insurance contracts empirically by non-parametrically estimating yield distributions conditional on the weather index, I find that the optimal pay-off structure is non-linear for the entire range of the index realizations.

[7]Minimization of the semi-variance instead of full variance is chosen because only downside losses are of major concern to crop producers (Miranda, 1991; Miranda and Glauber, 1997). This approach has been developed in the literature as an alternative to the traditional mean-variance analysis for situations where reduction of losses or failure to achieve a certain target is of importance (Hogan and Warren, 1972). It has also been shown to be consistent with the expected utility maximization (Selley, 1984).

I also consider the more realistic scenario where insurers add transaction costs to cover administrative and operational expenses to the premium. Instead of adding a fixed markup to the fair premium, I determine the maximum loading factor that the insured (for a given level of risk aversion) still considers as attractive by deriving the payoff function that maximizes the insurer's profits subject to the condition that the insured is at least as well off (in expected utility terms) as in the unhedged situation.

For given contracts, I measure the risk reduction of optimal weather insurance contracts for different weather indices and levels of risk aversion. For moderate levels of risk aversion (coefficient of relative risk aversion around 2), I find that buying optimal index-based weather insurance is equivalent to increasing the insured's income (in all states of the world) by 1.25 to 1.95% depending on the contract. For higher levels of risk aversion (coefficient of relative risk aversion around 7), the insured's income would need to be increased by 10% to make the insured as well off (in expected utility terms) as in the unhedged situation. Considering profit-maximizing contracts, I find that at modest levels of risk aversion (coefficient of relative risk aversion around 2), a loading factor of 10% of the fair premium is possible such that the insurance contract remains attractive for the insured. With higher levels of risk aversion (coefficient of relative risk aversion around 7), insurers can add a loading factor of more than 40% to the actuarially fair contract with no effect on the purchase decision of the insured.

The structuring process that I propose to design optimal weather insurance contracts depends on a number of exogenous parameters. For instance, to derive optimal indemnification payments for different levels of the weather index, the kernel estimation procedure requires that weather and yield data is grouped into bins ("kernel bandwidth") in order to estimate conditional yield densities. I evaluate whether these modeling assumptions have a significant influence on the optimal indemnification schedule by conducting sensitivity checks with respect to all modeling parameters. For that purpose, the effect of model parameter changes on the hedging effectiveness of optimal contracts is evaluated. Since insurance has an income smoothing effect, I test the sensitivity of model parameters by quantifying the resulting changes of a risk measure. I find that the optimal and profit-maximizing contracts are robust to changes in the estimation parameter used to derive the conditional yield densities. Comparative static analysis is also performed with respect to the relative risk aversion coefficient.

This part of the dissertation makes use of a computer-based simulation program, which has been programmed in MATLAB, and that can be used for solving the constrained stochastic optimization problem in order to derive the optimal, as well as the profit-maximizing index-based weather insurance contract for a given weather index and level of risk aversion.

1.5.2 Weather Insurance Design and Climate Change

In chapter 3, I focus on assessing the potential for index-based weather insurance in light of climate change. The optimal index-based weather insurance model, outlined in chapter 2, is used to address the following research questions:

- To what extent do weather-exposed farmers benefit from hedging weather risk today and with climate change using adjusted optimal contracts that represent the prevailing weather and yield conditions? Are the results sensitive to the risk measure used to assess hedging benefits in both climatic conditions?
- To what degree can insurers expect to increase their profits from offering adjusted profit-maximizing contracts with climate change?
- How does the insurance industry practice of offering non-adjusted contracts that are priced and designed using historical weather and yield data affect the risk reduction of the insured and expected profits of the insurer?

In 1992, Warren Buffet already pointed out that "catastrophe insurers can't simply extrapolate past experience. If there is truly global warming, the odds would shift since tiny changes in atmospheric conditions can produce momentous changes in weather patterns" (Charpentier, 2008). The insurance industry, which has so far relied on backward-looking data to develop and price weather insurance contracts, is challenged by climate change since the assumption that weather and yield time series data is stationary ceases to hold true. In particular, the changing occurrence and frequency of extreme weather events implies that historical return periods underestimate the likelihood of agricultural losses in the future.

In light of climate change, I first examine the effects of using forward-looking data to price and design weather insurance products on the hedging effectiveness and profitability of insurance contracts. Simulated crop and weather data for today's and future climatic conditions is used to derive adjusted optimal weather insurance contracts, which account for the changing distribution of weather and yields due to climate change. I find that the payoff function of adjusted contracts changes its shape over time, and that adjusted contracts are defined over a wider range of so far unprecedented realizations of the weather index. Next, the hedging effectiveness and profits of adjusted contracts is assessed. For the case study region in Switzerland, I find that, with climate change, the benefits from hedging with adjusted contracts almost triple (for a coefficient of relative risk aversion equal to 2), and that these findings are robust to the choice of the risk measure. The increase in weather risk due to climate change generates also a huge potential for the weather insurance industry. With climate change, insurers can increase the loading factor, and hence increase their expected profits by about 240%, when the insured is moderately risk averse (coefficient of relative risk aversion equal to 2).

Furthermore, I investigate the effect on risk reduction (for the insured) and profits (for the insurer) from hedging future weather risks with non-adjusted contracts, which are based on historical weather and yield data. When offering non-adjusted insurance contracts, I find that insurers either face substantial losses, or generate profits that are significantly smaller than profits from offering adjusted insurance products. Non-adjusted insurance contracts that create profits in excess of the profits from adjusted contracts cause at the same time negative hedging benefits for the insured. I observe that non-adjusted contracts exist that create simultaneously positive profits and hedging benefits, however at a much larger uncertainty compared to the corresponding adjusted contracts. These findings suggest that insurance companies need to regularly update the design of index-based weather insurance products in light of climate change in order to guarantee that weather risk transfer products maintain their hedging effectiveness.

1.5.3 Linear Weather Derivatives and Optimal Contracts

In the Over-the-Counter (OTC) weather derivative market, customized weather derivative contracts can be obtained that possess a linear payoff structure. In agriculture, crop yields are affected by weather through a number of meteorological events. The relationship between weather and crop losses is hence non-linear. In chapter 4, I investigate the effect of hedging agricultural yield risk with linear weather derivatives in contrast to the non-linear optimal products developed in chapter 2. In particular, I focus on addressing the following research questions:

- How can the insurance parameters defining a linear weather derivative be derived from the optimal and profit-maximizing contracts?
- How does hedging agricultural yield risk with generic linear weather derivatives compared to non-linear optimal contracts affect the risk reduction of the insured? Does offering linear weather derivatives to agribusiness stakeholders compared to offering non-linear profit-maximizing contracts affect the insurers' profits?

- Are the findings robust to the methods proposed to approximate optimal and profit-maximizing contracts? Are the losses in risk reduction and profits sensitive to changes in climatic conditions?

In order to estimate the effect of hedging agricultural weather risk with linear weather derivatives on risk reduction (for the insured) and profitability (for the insurer), I propose two methods to approximate the optimal and profit-maximizing contracts. With the help of the approximation methods, the contract parameters (strike, exit, cap and ticksize), which define a generic linear weather derivative, are derived from the optimal and profit-maximizing contract.

The proposed methods are then used to simulate linear contracts with an actuarially fair premium that approximate the optimal contracts for today's and future climatic conditions. In addition, for both climate scenarios, approximated profit-maximizing contract are simulated which satisfy the constraint that the insured is indifferent (in expected utility terms) between hedging and remaining uninsured. A baseline approximation scenario is established for which the loss in risk reduction from hedging agricultural weather risk with linear contracts (in contrast to the non-linear optimal contracts) is derived.

For today's climatic conditions, I find that hedging with approximated optimal contracts reduces the risk reduction benefits of the insured by 20 to 23%, depending on the index. Expected profits for the insurer decrease by 20 to 24% from offering approximated profit-maximizing contracts. A sensitivity analysis is performed to evaluate the effect of altering the approximation parameters on the resulting risk reduction. The findings are robust to changes in the approximation parameters. For the climate change scenario, I find that the loss in risk reduction and profits decreases compared to the situation today. The increased weather variability improves the goodness of fit of the indices, and hence reduces the approximation losses.

The findings demonstrate that structural basis risk exists and that the hedging benefits, at a particular location and for a given crop, critically depend on the choice of the structuring method. By proposing a robust approximation method for deriving the contract parameters of a generic (linear) weather derivative from the optimal and profit-maximizing contract, the algorithm developed in chapter 2 is extended. In particular, a decision-support tool for entrepreneurs intending to hedge weather risk with linear contracts is proposed. Buyers no longer need to specify the critical contract parameters (strike, exit, and cap) based on subjective knowledge about their weather risk management needs. The optimal index-based insurance model, together with the proposed extension, can be used to facilitate the buyers' decision by identifying the contract parameters such that the best hedging effectiveness with a linear contract is achieved.

1.6 Data and Case Study Region

For the design of index-based weather products, data of historical yields measuring crop variability over time and the corresponding weather data is needed. The availability and credibility of data is central to the modeling of production risk and the structuring of weather risk transfer products.

In practice, the length of historical yield time series data is often insufficient for statistical analysis and rules out the use of non-parametric methods. Especially for deriving conditional yield probabilities a large enough yield data set is needed. For that reason, I work with simulated yield data that has been derived from a deterministic crop physiology growth model, named CropSyst (Stöckle et al., 2003). Process-based crop models are calibrated for specific crops and are adapted to local regions with the aim of re-producing historical crop yields (for historical weather conditions).[8] As inputs, biophysical crop simulation models require information about soil conditions, farm management practices, and daily observations of minimum and maximum temperatures, precipitation, and solar radiation. As the calibration of model parameters is subject to uncertainty, projections of biophysical models are also uncertain.

Biophysical crop growth models offer the possibility to generate large crop yield data sets by running several crop simulations for varying climatic conditions. Furthermore, process-based crop simulation models are widely used to study the effect of climate change on crop yields. To simulate the changes in crop production due to global warming, data accounting for the changes in the climatic conditions is needed. Climate change projections are derived from simulations with either General Circulation Models (GCMs) or Regional Circulation Models (RCMs). GCMs and RCMs are developed by climatologists in an effort to assess the impacts of human activity, as measured by the increase in atmospheric concentration of greenhouse gases, on the climate system. Climate models generally agree in predicting that global average temperatures are increasing, that the incidence of extreme climate events – such as droughts, hot spells and floods – is rising, and that sea-levels increase. With regard to the rate of change, the extent of overall change, and the effects in particular regions of the globe, predictions of some models differ from predictions of others, which gives rise to uncertainty.

Regional climate predictions for Schaffhausen (latitude: 47.69, longitude: 8.62), Switzerland, for an IPCC A2 emission scenario, were downscaled to local conditions using a

[8]The CropSyst calibrations for maize production representing the local conditions of the case study region, Schaffhausen, Switzerland, as well as the simulations of maize yields for the baseline and future scenario were carried out by Annelie Holzkämper and Tommy Klein at the research group of Jürg Fuhrer at Agroscope-Reckenholz-Taenikon (ART), Switzerland.

stochastic weather generator. LARS-WG, a weather generator developed by Semenov et al. (1998) was calibrated to local conditions using historical weather data representing today's conditions.[9] With the help of LARS-WG, daily precipitation, minimum and maximum temperature, as well as solar radiation were simulated for a climate change scenario representing climatic conditions at Schaffhausen around 2050. The daily weather projections were fed into CropSyst in order to derive maize yield projections for the baseline $(1981 - 2001)$, and for the future scenario $(2036 - 2065)$.

While the numerical results in this dissertation specifically refer to the growing conditions of maize in Schaffhausen, Switzerland, the methods developed in this dissertation can be applied to other crops and locations. In particular, the optimal index-based weather insurance model, together with the model to derive the contract parameters of a linear weather derivative, can be used to simulate optimal contracts (non-linear or linear) for any crop and at any location for which sufficient weather and yield data is available.

[9] The calibration of LARS-WG as well as the climate change projections for Schaffhausen, Switzerland, were carried out by Pierluigi Calanca, at the research group of Jürg Fuhrer at Agroscope-Reckenholz-Taenikon (ART), Switzerland.

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Chapter 2

Weather Insurance Design with Optimal Hedging Effectiveness

Journal of Agricultural Economics, revise and resubmit

2.1 Introduction

Agricultural production and agribusiness are exposed to many weather-related influences that cause fluctuations in crop yields – so-called yield or production risk. The management of weather risk is of fundamental importance for weather-dependent sectors, and will become even more important with increasing risk of extreme weather events. Insurance has been an integral part in dealing with weather risk, as it helps reduce the residual risk that cannot be prevented through cost-effective on-site (on-farm) risk management strategies. Traditional crop insurance schemes provide farmers with coverage to manage weather-related yield risks. Insurance schemes where the insurance pay-offs are based on an assessment of the crop yields – as is the case with individual, or multi-peril crop insurance – are plagued by moral hazard, adverse selection and costly enforcement (Smith and Goodwin, 1994; Skees et al., 1997; Goodwin, 2001). The use of index-based weather insurance has recently emerged as an alternative as it avoids many of the problems associated with traditional insurance (Hazell and Skees, 2005). With index-based insurance, an exogenous, verifiable weather event is being insured, rather than a yield outcome. Problems of moral hazard and adverse selection are minimized, and administrative costs are reduced substantially since published (weather) data is used to settle a claim (Ibarra and Skees, 2007).[1]

[1] The disadvantage of index-based weather insurance for the insured is that it comes at the cost of not being perfectly insured against weather related losses due to the imperfect correlation of yields and the

The focus of this paper is on designing weather insurance for agricultural risk management with optimal hedging effectiveness. An expected utility framework is used to model the decision-making behavior of a representative farmer. The design of weather insurance can be decomposed into two separate problems: finding a weather index that correlates well with crop losses, and the derivation of the insurance contract for that given index. I first derive weather indices taking the varying sensitivity of crops during the growing season into account. Given the weather indices, I simulate optimal insurance contracts for different levels of risk aversion. Compared to existing work, I aim at characterizing and deriving the optimal pay-off structure by allowing for a non-linear stochastic relationship between weather and yield. Previous approaches, such as Vedenov and Barnett (2004), Osgood et al. (2007), and Musshoff et al. (2009) relied on specifying functional forms to characterize the weather-yield relationship. By assuming a given (linear) relationship between the index and yields, functional form assumptions are imposed on the optimization problem, and the resulting pay-off structure reflects these assumptions. Instead, I estimate conditional probabilities of yield for different levels of the weather index using a fully non-parametric approach. The estimated conditional yield distributions are used to compute the expected utility maximizing insurance contract. Rather than restricting attention to piecewise linear contracts in the first place, I determine the classical parameters of a derivative contract (trigger[2] and limit) from the optimization problem and in addition derive the local slope of the pay-off function (tick size)[3] at each realization of the underlying index.

I implement the expected utility maximization problem numerically and apply the novel model to derive optimal weather insurance contracts for maize farmers in Schaffhausen (SHA), Switzerland. While the magnitude of the numerical results are crop- and location-specific, the insurance characteristics of the optimal weather insurance contract described in the following are crop- and location independent.[4] I propose a general method for deriving optimal weather insurance contracts that can be applied to any crop and to any location for which sufficient weather and yield data is available.

Examining the relationship between pay-offs and the frequency of payments, I find

weather index. The gap between the loss indicated by the index and the individual realized loss is known as basis risk. However, basis risk exists with farm-level multi-peril crop insurance as well. For a discussion, see Skees (2003).

[2]The trigger, or strike level, is the threshold level of the underlying meteorological index that triggers payments from the contract.

[3]The tick size is the incremental change in the payment for a change in the index.

[4]I also simulated optimal weather insurance contracts for wheat, potatoes, rape seed and sugar beet at two more locations in Switzerland, which confirmed the insurance characteristics of the optimal insurance contract described here. Results are available upon request.

that the optimal insurance contract offers high levels of protection for catastrophic weather events that occur with very low probabilities. At the same time, the optimal insurance contract offers moderate payments for small deviations from average weather conditions. For all contracts considered, I find that the insured breaks-even, i.e. receives an indemnification that compensates for the premium, in 48% of the cases. An insured with moderate risk aversion (coefficient of relative risk aversion of around 2) benefits from the contract as his income without insurance would need to be increased by 2% to offer him the same expected utility as in the situation with optimal insurance. Significantly higher benefits (equivalent to an income increase of up to 10%) from hedging with an optimal weather insurance contract arise at higher levels of risk aversion.

Insurers are first assumed to make zero profits, which allows using the "burn rate" method to price insurance contracts. Subsequently, I relax this assumption to determine the maximum loading factor on fair premiums so that the optimal insurance contract remains attractive to farmers in the sense that it yields the same expected utility as the no-insurance scenario. Comparing the optimal weather insurance contract with the profit-maximizing contract, I find that the profit-maximizing contract displays the same non-linear shape as the optimal contract but has lower pay-offs. In the case study, loading factors of 10% to 50% are possible depending on the level of risk aversion.

The remaining paper is organized as follows. I relate my approach to the literature on index-based insurance in the remainder of this section. In section 2.2, I propose a theoretical model that yields the optimal weather insurance contract as a solution. The numerical implementation is explained in section 2.3.1, and the data used for simulating the weather insurance contracts is described in section 2.3.2. In section 2.4, suitable weather indices are derived, and the simulated optimal weather insurance contracts are presented in section 5 together with an evaluation of their hedging effectiveness. Profit-maximizing contracts are derived in section 2.6, and the maximal amount of loading on fair premiums is determined. Section 2.7 concludes and provides an outlook on further research.

2.1.1 Relation to the Literature

Weather-based insurance contracts were firstly proposed by Turvey (2000, 2001) and Martin et al. (2001). The proposed pay-off structures are similar to the (linear) weather derivatives that have been traded at the Chicago Mercantile Exchange since 1996. In these initial works, the tick size is determined by estimating the relationship between weather and yield, and the strike and limit parameters, which are needed to define an indemnity function, have to be specified by the insured. Martin et al. (2001) develop precipitation derivatives, and Turvey (2001) proposes derivative contracts based on cumulative precipitation and heat units.[5] Both authors demonstrate that (for different contracts and values of risk-aversion) the certainty equivalent gains from using weather insurance exceed the no-purchase situation, and that the extent of the certainty equivalent gains from using weather insurance depends on the chosen contracts.

To reduce farmers' exposure to weather-related shocks, pay-offs from the weather insurance contract have to closely match incurred losses. In this context, Goodwin and Mahul (2004) point out that the design of an efficient insurance contract depends on the relationship between the individual yield and the underlying weather index, and Vedenov and Barnett (2004) specifically emphasize the importance of the weather insurance parameters (tick size, strike, and limit) with respect to achieving hedging effectiveness, i.e. the degree to which weather risk is being reduced by an insurance product. Since then, formal models to determine the buyer's optimal choice of the insurance parameters with respect to risk reduction have been developed, as outlined in the following.

Weather insurance pay-off functions have been designed by minimizing an aggregate measure of downside loss such as the semi-variance (Markowitz, 1991; Vedenov and Barnett, 2004).[6] Vedenov and Barnett (2004) derive the strike level by identifying the level of the index where predicted yields corresponded to the long time average. The remaining parameters are obtained by minimizing the semi-variance of loss assuming a linear relationship between index and insurance payments (between strike and maximum payout).

Another strand of literature maximizes the expected utility of the insured in order to derive the critical insurance parameters (tick size, strike, and limit), and then evaluates the insurance alternative based on their certainty equivalent gains[7] (Karuaihe et al., 2006; Berg et al, 2009; Leblois et al. 2011). These contributions share the assumption that the weather insurance contract is linear between the strike level and the maximum payout (limit). In contrast, I aim at deriving the entire pay-off structure optimally, without im-

[5]Martin et al. (2001) estimate the probability density function of the underlying precipitation index parametrically, and use a quadratic function for estimating the weather-yield relationship in order to determine the tick size. Turvey et al. (2001) use a Cobb-Douglas production function with cumulative rainfall and heat units as inputs for their design. Based on the chosen contract parameters, the insurance contracts are priced using the "burn rate" method in both contributions.

[6]Minimization of the semi-variance instead of full variance is chosen because only downside losses are of major concern to crop producers (Miranda, 1991; Miranda and Glauber, 1997). This approach has been developed in the literature as an alternative to the traditional mean-variance analysis for situations where reduction of losses or failure to achieve a certain target is of importance (Hogan and Warren, 1972). It has also been shown to be consistent with the expected utility maximization (Selley, 1984).

[7]The certainty equivalent is the amount of certain income that a risk-averse individual finds equally desirable to an alternative random income with a known probability distribution.

posing a priori functional form assumptions on the contract.

Osgood et al. (2007, 2009) design index-based weather insurance contracts for several African countries (Malawi, Tanzania, Kenya, and Ethiopia) that are implemented by the World Bank and Oxfam America under pilot projects. The contract design chosen by Osgood et al. allows the authors to optimize over piecewise linear contracts by minimizing the variance. Osgood et al. (2007, 2009) are able to locally optimize contract parameters of a linear pay-off structure, thus making the piecewise contract more efficient. I derive instead the globally optimal, non-linear insurance contract without making use of a piecewise linear structure, and the objective is to maximize the expected utility of the insured.

Another design method is proposed by Musshoff et al. (2009), who use the weather-yield relationship to construct the payments from a weather put option by estimating a linear-limitational production function (for a given weather index). Based on the production function, Musshoff et al. (2009) calculate the revenue function, and then define the payoffs from the weather derivative by taking the inverse of the revenue function. Using a parametric approach to establish the relationship between weather and yield assumes that conditional yield distributions at different levels of the weather index are homogenous - an assumption that I do not find to be satisfied in the data. Similar to the piecewise pay-off structure assumed by Osgood et al. (2007, 2009), Musshoff et al.'s assumption about the functional form of the production function has an effect on the insurance parameters, and thus affects the hedging effectiveness of the contracts. The objective is therefore to derive the insurance parameters without assuming a linear relationship between weather and yield, and without relying on a parametric production function or error term structure.

My work is most closely related to Mahul (1999, 2000, 2001, 2003) who uses expected utility models to investigate theoretically the optimal design of agricultural insurance for different sources of risk (i.e. price risk, yield risk). While the focus of Mahul (1999) is on the design of area-yield crop insurance, his framework and findings can be translated to the design of index-based weather insurance. To characterize the optimal area-yield insurance, Mahul (1999) follows earlier work by Miranda (1991) and assumes a linear relationship between weather and yield.[8] Mahul (1999) demonstrates more generally than Miranda (1991) that the optimal coverage with area-yield insurance depends on the sensitivity of the individual yield to the area yield and is independent from risk aversion and

[8] Individual yields are the sum of a weather (systemic risk) and an independent idiosyncratic component. Mahul's (1999) model would be more general if the beta-coefficient, which measures the sensitivity of farm-yields to movements in the weather index, were allowed to depend on weather, but instead he assumes that the covariance between weather and the error term is zero.

premiums. Mahul (2001) expands this model to examine the implications of a weather-yield production function that is decomposed into two separate components. Weather and idiosyncratic risk enter as two separate inputs into an additive production function.[9] Through the choice of the production function, yields depend on weather in a linear way conditional on inputs. Under these assumptions, Mahul (2001) shows that the parameters of the optimal indemnity schedule (strike and coverage) depend on the stochastic relation between weather and idiosyncratic risk, and on the risk aversion of the insured. Mahul (2001) compares the optimal coverage for the situation where weather and idiosyncratic risk are independent, and when they interact. When the two sources of risk are correlated, Mahul (2001) finds that "... without further restrictions on the stochastic dependence and the producer's behavior, the indemnity schedule can take basically any form." (Mahul, 2001, p: 596). Empirically deriving an optimal weather-based indemnity schedule within this framework would require distinguishing the different cases outlined by Mahul (2001). I therefore propose a more general method for deriving optimal weather insurance contracts which also allows us to drop the assumption of a linear relationship between weather and yields, and of a specific error term structure.

2.2 Theoretical Framework

2.2.1 The Insurance Problem

I consider ex ante identical farmers who face a stochastic yield $y \in \mathcal{Y} \equiv [\underline{y}, \overline{y}]$. The distribution of output depends on the weather variable z, which can be cumulative rainfall in the growing season, average temperature during particular phases, or an index combining multiple such variables. Let the cdf of $z \in \mathcal{Z} \equiv [\underline{z}, \overline{z}]$ be denoted by $G(z)$, and the corresponding density function by $g(z)$. Then the dependence of the distribution of yields y on the weather index z is captured by the conditional cdf $F(y|z)$ and the corresponding conditional density $f(y|z)$.

Farmers have preferences defined over consumption c given by $u(c)$. I assume farmers to be risk-averse with $u'(c) > 0$, $u''(c) < 0$. There are risk-neutral insurers who offer insurance to the farmers. The key restriction is that insurance contracts cannot directly insure yields y, but only condition on the realization of the weather index z. Suppose the net insurance payout to the farmer if weather index z is realized is given by $p(z)$.[10] Then I

[9] As before, weather impacts yields directly, and in addition through its effect on the idiosyncratic component.

[10] One could separate the net payout to the farmer into the indemnity $I(z)$ paid by the insurer in case of weather realization z, and a fixed premium P, so that $p(z) = I(z) - P$ for all $z \in \mathcal{Z}$. Only the net payout

require that the insurer does not make losses with the weather insurance contract $\{p(z)\}$ in expectation:

$$\int_{\mathcal{Z}} p(z)dG(z) \leq 0. \tag{2.1}$$

Constraint (2.1) requires the average net payout to the farmer to be non-positive, which is equivalent to the insurer's profits to be non-negative. The constraint can also be interpreted as a mechanism for pricing the insurance contract, and is known as "burn rate" method.[11] The "burn rate" method is widely used as the standard basis for calculating insurance premiums due to its simplicity (Skees and Barnett, 1999; Mahul, 1999; Turvey, 2001; Martin et al., 2001 ; Vedenov and Barnett, 2004). More complicated cost functions for the insurers could be adopted without effect for the following results.[12] Administrative and transactions costs born by the insurer can be considered in this framework by adding a mark-up to the premium (see section 2.6 on profit maximizing loading factors).

Then the farmers' expected utility maximizing contract $\{p^*(z)\}$ solves

$$\max_{\{p(z)\}} \int_{\mathcal{Z}} \int_{\mathcal{Y}} u(y + p(z))dF(y|z)dG(z) \tag{2.2}$$

subject to constraint (2.1).

2.2.2 Some Properties of Optimal Weather Insurance Contracts

Since Problem (2.2) is a strictly concave problem, it is immediate that there always exists a unique global optimum and first-order conditions are necessary and sufficient. In fact, setting up the Lagrangian

$$\mathcal{L} = \int_{\mathcal{Z}} \int_{\mathcal{Y}} u(y + p(z))dF(y|z)dG(z) - \lambda \int_{\mathcal{Z}} p(z)dG(z) \tag{2.3}$$

$p(z)$, however, matters to the farmer and the insurer.

[11]Insurance actuaries calculate an expectation on future losses based on historical payouts for a given insurance contract. Expected losses are then considered as an expected breakeven premium rate. This method assumes that the underlying index has a stationary distribution. With climate change this assumption may no longer be valid, and alternative pricing mechanisms need to be considered.

[12]Pricing based on standard option valuation models is not possible since these models require that one be able to construct (at least conceptually) a riskless portfolio of both the option and the asset which forms the underlying index (Hull, 2000; Dischel, 1998). Given that there is no actively traded forward market for the underlying index alternative pricing mechanisms have evolved, e.g. stochastic pricing for heat-degree contracts (Turvey, 2001a), indifference pricing (Xu et al., 2007), equilibrium pricing method (Richards et al., 2004).

yields the pointwise first-order conditions

$$\int_{\mathcal{Y}} u'(y + p(z))dF(y|z) = \lambda \ \ \forall z \in \mathcal{Z}, \tag{2.4}$$

where $\lambda > 0$ is the Lagrange multiplier on constraint (2.1). Optimality condition (2.4) requires the expected marginal utility of the farmer conditional on a realization of the weather index z to be equalized across all z at the optimal contract. This immediately leads to the following result:

Proposition 1. *Suppose $y \perp z$, i.e. yields y are independent from the weather variable z. Then $p(z) = 0$ for all $z \in \mathcal{Z}$.*

Proof. If y and z are independently distributed, then the conditional yield distribution $F(y|z)$ is in fact independent of z, so that the first order condition (2.4) becomes

$$\int_{\mathcal{Y}} u'(y + p(z))dF(y) = \lambda \ \ \forall z \in \mathcal{Z}.$$

Since $u''(.) < 0$, this can only be satisfied if $p(z)$ is independent of z and thus $p(z) = p$ where p is a constant. Then constraint (2.1) can only be satisfied if $p \leq 0$. Clearly the value of p that maximizes (2.2) subject to $p \leq 0$ is given by $p = 0$. □

Proposition (1) demonstrates that weather insurance is ineffective if the weather index does not contain predictive power for yields. In contrast, it crucially relies on weather and yield being correlated. I next consider the opposite special case, in which weather is perfectly predictive of yield:

Proposition 2. *Suppose that each weather-yield observation (y_i, z_i) occurs only once in the data set with $i = 1, ..., n$ observations, i.e. $Pr(y_i, z_i) = 1/n$. Then p is a full insurance contract independent of weather.*

Proof. Under the assumptions in the proposition, the first order condition (2.4) becomes

$$\int_{\mathcal{Y}} u'(y_i + p_i(z_i))\frac{1}{n} = \lambda \ \ \forall z \in \mathcal{Z}.$$

Since $u''(.) < 0$, this can only be satisfied if $y_i + p(z_i)$ is independent of z and thus $p(z_i) = -y_i + p$ where p is a constant. Given that the insurer can only make non-negative profits, the constant $p = \overline{y}$, such that $p(z) = -y_i + \overline{y}$ is a revenue insurance contract. □

Intuitively, if the relationship between weather and yield is perfectly known, and weather is the only input to crop production, then the insurance contract can be written such that any difference between the realized yield, y_i, and the expected yield, $\overline{y}$ is perfectly reimbursed. In that case, the basis risk for the farmer is zero. In the real world, crop yields are influenced by a number of factors, such as management practices, fertilizer usage, soil quality. In addition, crop data is also subject to measurement errors so that the conditions for Proposition (2) are not fulfilled. Forecasting crop yields with just weather as input will therefore not fully explain the variation in yields. A special case of such a stochastic dependence is considered in the following proposition:

Proposition 3. *Suppose the stochastic dependence of yields on weather is given by*

$$y = \psi(z) + \varepsilon,$$

where ε is a stochastic shock such that $\varepsilon \perp z$ and with cdf $H(\varepsilon)$. Then

$$p(z) = -\psi(z) + p,$$

where p is some constant.

Proof. Under the assumptions in the proposition, the first order condition (2.4) becomes

$$\int_{\varepsilon} u'(\psi(z) + p(z) + \varepsilon) dH(\varepsilon) = \lambda \ \forall z \in \mathcal{Z}.$$

Since $u''(.) < 0$, this can only be satisfied if $\psi(z) + p(z)$ is independent of z and thus $p(z) = -\psi(z) + p$ where p is a constant. □

An example that would seem particularly natural for the case where z captures a measure of cumulative rainfall, for instance, would be a function $\psi(z)$ that is hump-shaped: yields tend to be low both for very high values of z (excessive precipitation) and very low values (droughts), and highest for intermediate values. Then Proposition (3) shows that the optimal weather insurance contract features a U-shaped pattern of net payouts that is inversely related to $\psi(z)$. Or, yields tend to increase in a non-linear way with the underlying index, reflecting plant and phenology specific sensitivities to weather. In either way, the intuition is clear: the contract is supposed to insure the farmer against low yield realizations. Thus, net payouts to the farmer should be high whenever $\psi(z)$ is low and vice versa.

The assumptions in Proposition (3) are still quite restrictive, however. Not only may extreme weather events as captured by high and low realizations of z reduce *expected* yields. They may also change the *distribution* of yields in a more general way. Notably, one may think of extreme weather events increasing the *yield risk* as captured by the variance of yields conditional on z. The following two results show how such more general relationships between yields and weather affect the shape of the optimal weather insurance contract (see also Mahul, 2001).

Proposition 4. *At some given $z \in \mathcal{Z}$, $p'(z) \leq 0$ if $dF(y|z)/dz \leq 0$ for all $y \in \mathcal{Y}$ (first order stochastic dominance). Conversely, $p'(z) \geq 0$ if $dF(y|z)/dz \geq 0$ for all $y \in \mathcal{Y}$.*

Proof. Since the first order condition (2.4) has to hold for all $z \in \mathcal{Z}$, it can be differentiated w.r.t. z to obtain

$$p'(z) = -\frac{\int_{\mathcal{Y}} u'(y + p(z)) \frac{df(y|z)}{dz} dy}{\int_{\mathcal{Y}} u''(y + p(z)) dF(y|z)}. \tag{2.5}$$

Integrating the numerator by parts yields

$$\int_{\mathcal{Y}} u'(y + p(z)) \frac{df(y|z)}{dz} dy = u'(y + p(z)) \frac{dF(y|z)}{dz} \bigg|_{\underline{y}}^{\overline{y}} - \int_{\mathcal{Y}} u''(y + p(z)) \frac{dF(y|z)}{dz} dy. \tag{2.6}$$

Note that the first term on the RHS is zero because $dF(\overline{y}|z)/dz = dF(\underline{y}|z)/dz = 0$. Hence substituting (2.6) in (2.5) yields

$$p'(z) = -\frac{\int_{\mathcal{Y}} u''(y + p(z)) \frac{dF(y|z)}{dz} dy}{\int_{\mathcal{Y}} u''(y + p(z)) dF(y|z)}. \tag{2.7}$$

Recall that the denominator is always negative since $u''(.) < 0$. Hence the sign of $p'(z)$ is equal to the sign of $dF(y|z)/dz$, which is the result in the proposition. □

Proposition (4) is a generalization of Proposition (2). It shows that net insurance payouts to the farmer should be decreasing in the weather index if an increase in z induces higher yields in the first order stochastic dominance sense (FOSD), and vice versa. In the case of precipitation-based insurance, this again makes a non-linear shape of the optimal insurance contract plausible.

The following proposition captures the effect of changes in the *variability* of yields due to changes in the weather index on the shape of the optimal insurance scheme.

Proposition 5. *Suppose $u'''(c) > 0$ for all c. Then, at some given $z \in \mathcal{Z}$, $p'(z) \leq 0$ if $\int_{\underline{y}}^{y} \frac{dF(s|z)}{dz} ds \leq 0$ for all $y \in \mathcal{Y}$ (second order stochastic dominance). Conversely, $p'(z) \geq 0$ if $\int_{\underline{y}}^{y} \frac{dF(s|z)}{dz} ds \geq 0$ for all $y \in \mathcal{Y}$.*

Proof. Integrating the RHS of equation (2.6) by parts again yields

$$\begin{aligned} \int_{\mathcal{Y}} u''(y + p(z)) \frac{dF(y|z)}{dz} dy &= u''(y + p(z)) \int_{\underline{y}}^{y} \frac{dF(s|z)}{dz} ds \bigg|_{\underline{y}}^{\overline{y}} - \int_{\mathcal{Y}} u'''(y + p(z)) \int_{\underline{y}}^{y} \frac{dF(s|z)}{dz} ds dy \\ &= u''(\overline{y} + p(z)) \int_{\underline{y}}^{\overline{y}} \frac{dF(s|z)}{dz} ds - \int_{\mathcal{Y}} u'''(y + p(z)) \int_{\underline{y}}^{y} \frac{dF(s|z)}{dz} ds dy. \end{aligned} \tag{2.8}$$

Substituting the RHS of (2.8) in the numerator of (2.5) and the assumption $u'''(.) > 0$ yields the result. □

Proposition (5) captures the case where an increase in z increases the riskiness of yields in the second order stochastic dominance (SOSD) sense. It shows that the optimal insurance net payout increases with z if the additional condition is satisfied that the farmer is *prudent*, as characterized by $u'''(.) < 0$. Conversely, the net payout decreases with z if a decrease in z makes yields riskier. This again pushes towards a non-linear shape of $p(z)$ given the realistic case that extreme weather occurrences not only reduce expected yields, but also increase yield variability.

In summary, for a given crop and a given weather index the shape of the optimal weather contract, $p(z)$, depends on the shape of the conditional cdf $F(y|z)$, and can be determined empirically by solving the nonlinear, constrained optimization problem (2.2) subject to (2.1) numerically. I use a non-parametric estimation procedure to determine $F(y|z)$ in order to to avoid that $p(z)$ may reflect assumptions contained in the functional form of the relationship between y and z. I describe how I derive the solution to this problem in the following section.

2.3 Implementation and Data

2.3.1 Implementation of the Optimization Problem

The optimization problem is implemented in its discrete form. A discrete weather variable, z_i, such as rainfall can take $i = 1, ..., N_z$ possible realizations. Then the optimization problem has $N_z + 1$ first-order-conditions in $N_z + 1$ unknowns and can be solved numerically (using a mathematical programming tool such as Matlab). For the weather index, N_z defines the number of points for which to produce a density estimate. Similarly, N_y defines the number of density estimates to be produced for the yield data. The size of the conditional yield density matrix $f(y|z)$ is thus $N_y \times N_z$. N_z and N_y can be set to any finite number, restricted by the size of the data. Increasing N_z or N_y implies that fewer yield observations fall within one kernel grid cell, which explains why a sufficiently large data set is needed for estimation. It follows that N_z has an effect on the precision of $p(z)$ since the number of first order conditions increases, and thus the number of payments $p(z_i)$ that are determined for different realizations of the index z_i. The effect on the hedging effectiveness of the optimal contract due to changes in either N_z or N_y is demonstrated in section 2.5.4.

The optimization problem is solved by defining a specific functional form for the farmer's preferences. I assume that farmers have preferences of the following form: $u(c) = c^{1-\sigma}/(1-\sigma)$, i.e. the utility function is characterized by constant relative risk aversion (CRRA).[13] I use a coefficient of relative risk aversion of $\sigma = 2$ as a benchmark[14], but demonstrate how the results change for different levels of risk aversion (see section 2.5.3).

Both the conditional yield density matrix, $f(y|z)$, and the density of the weather index, $g(z)$, are estimated using a Gaussian kernel density estimation procedure. Given that yield and weather data follow different statistical distributions, and differ in their range, I allow the conditional yield density matrix $f(y|z)$ to be non-quadratic (Härdle, 1991). Moreover, I allow for kernel bandwidths for the weather index, $bw(z)$, and for yields, $bw(y)$. Once all input parameters are determined, the optimization problem is solved numerically.[15]

2.3.2 Description of Data

Historic yield time series data is often not sufficiently large for empirical applications as complex as the one I aim at. Following Torriani et al. (2007a, 2007b), I use a process-based crop simulation model to simulate $1,000$ yield observations.[16] For the purpose of this study, CropSyst, which is a multi-year, multi-crop, daily time step growth simulation model developed by Stöckle et al. (2003), is used to simulate crop development and total biomass accumulation of maize (*Zea mays L.*). The simulation of crop development is mainly based on the thermal time required to reach specific development stages. Thermal time is calculated as growing degree days (GDD) accumulated throughout the growing season (starting from sowing until harvest). With process-based crop models, the user can input management parameters such as the sowing date, cultivar genetic coefficients, soil profile properties (soil texture, depth), fertilizer and irrigation management, tillage and atmospheric CO_2 concentration, and the growing degrees needed to complete each

[13] CRRA preferences are supported in the literature by Pope and Just (1991), Chavas and Holt (1990), Martin et al. (2001), Zuniga et al. (2001), Wang et al. (2004), Karuaihe et al. (2006), Berg et al. (2009), Leblois and Quirion (2011).

[14] Arrow (1971) argues that the coefficient of relative risk aversion is near 1. Chetty (2006) shows that the coefficient of relative risk aversion is around 2 in his data. For agriculture, Pope and Just (1991) suggest that the relative risk aversion is constant.

[15] The nonlinear constrained optimization problem is solved by “shooting for lambda”, i.e. I assume a starting value for λ and solve the first order conditions given this λ. Next, I check whether the output of the optimization problem ($p(z)$,z) satisfies the constraint (1). If the constraint is not satisfied, the procedure is repeated until a λ-value is found for which the constraint is fulfilled. The optimal values, $p^*(z)$, satisfy the necessary and sufficient FOCs as well as the constraint (1), and thus constitute a global optimum.

[16] Process-based crop models are deterministic models that simulate crop physiological growth for given environmental and management conditions. In theory, their precision in estimating crop yields is greater compared to regression models, but they require detailed time series data in order to calibrate model parameters and for evaluating the model’s ability of predicting historic crop yields (Lobell et al., 2010).

phenological period.[17]

To simulate 1,000 yield observations, daily weather data was obtained from a stochastic weather generator.[18] LARS-WG, a weather generator developed by Semenov (1997, 2002), was first calibrated for the current weather conditions (from 1981 to 2001) prevailing in at the weather station Schaffhausen (SHA) (latitude: 47.69, longitude: 8.62) in Switzerland.[19] For the time period from 1981 to 2001, 1,000 years of daily weather observations were simulated and daily observations of minimum (T_{min}) and maximum temperatures (T_{max}) in Celsius, rainfall (R_i) in millimeters, and solar radiation (Sol_i), with $i = 1, ..., 365$ indicating the day of the year, were obtained.[20]

To derive the revenues from maize production per hectare, I use the average price for maize from 2006 to 2009, which was 41.00 CHF/100kg (SBV, 2010). This allows us to derive the insurance contract in monetary units.[21]

2.4 Constructing a Suitable Weather Index

Finding a suitable weather index involves identifying the source of weather risk that the insurance contract is intended to hedge. One way of identifying the risks that cause crop losses is by interviewing farmers. I use instead a quantitative approach to identify the weather events that explain deviations in yields. The objective is to create weather indices that possess a high correlation with yields as this affects the hedging effectiveness (Miranda, 1991; Vedenov and Barnett, 2004; Musshoff et al., 2009).

While it is well known that the susceptibility of crops to meteorological stress (such as heat stress or shortage of available water) varies during the growing season (Meyer et al., 1993), the use of fixed calendar time periods for the construction of weather indices is common in the literature (Turvey, 2001; Martin et al., 2001; Musshoff et al. 2009). Hanks (1974) notes that there is a strong relationship between total water consumption by a plant

[17] The calibrations of CropSyst for maize production in Switzerland have been carried out by Agroscope-Reckenholz-Taenikon Research Station (ART) in Switzerland. An overview of the calibration parameters for maize, winter wheat, and canola in Switzerland can be found in Torriani et al. (2007) together with a comparison of simulated yields with historical observations.

[18] Weather generators generate synthetic weather series which have statistical properties similar to the observed series. Means and variance of daily synthetic weather data are required to be not significantly different from those calculated from observed series, and the synthetic weather series should follow a probability distribution which is not statistically different from the observations.

[19] The weather data for SHA from 1981 to 2001 was obtained from MeteoSwiss.

[20] The calibration of LARS-WG for the weather measurement station SHA has been carried out by Agroscope-Reckenholz-Taenikon Research Station (ART) in Switzerland.

[21] A higher (lower) price for maize yields will shift the insurance contract up (down), but will not change the shape of the contract due to the assumption of CRRA preferences. Production costs are not considered here.

over the growing season and final yields. However, Hanks (1974) also points out that "... it is essential for any study dealing with the estimation of future yield to take into account the element of time when referring to the effects of stress." In the same vein, Jensen (1968) and Nairizi et al. (1977) show that the yield response of a crop to soil moisture stress depends on the crop being studied, and the phenology during which the stress occurs. In the context of index construction, Turvey (2000) is the first to mention that " ... (it) would be advantageous to correlate weather events to specific phenological events." Leblois et al. (2011) also note that using the actual sowing date together with information about the different growing stages improves the predictive power of the index. In their study examining the potential of rainfall insurance in Niger, Leblois et al. (2011) simulate growth phases (following a method developed by Sivakumar, 1988), and create indices that weigh the effect of rainfall depending on the growing phase. The authors find that indices that account for growing phases improve the gains from weather insurance.

In my study, I measure weather events at each phenology stage considering year to year shifts in phenology stages due to to inter-annual weather variability. For the index design, I estimate the individual effect of weather events on yields to account for the differences in the weather susceptibility of maize during the growing period. Based on this information, I construct indices using the estimated coefficients obtained from multivariate weather-yield regression models as weights.

2.4.1 Identifying the Phenology Phases

The concept of Growing Degree Days (GDDs) is used to identify the different phenological phases during plant development. Growing degrees (GD), also referred to as heat units, are defined as the number of temperature degrees above a certain threshold temperature, T_{base}, and below an upper level, T_{cut}, and are frequently used to describe the timing of biological processes (Neild, 1982; McMaster, 1997).[22] I use the following formula to calculate GDDs, starting at the sowing date, with $i = 1$, until the end of the growing season, with $i = n$ at the harvest time:

$$GDD = \begin{cases} \sum_{i=1}^{n}\left(\frac{T_{max,i}+T_{min,i}}{2} - T_{base}\right) & \text{if} \frac{T_{max,i}+T_{min,i}}{2} < T_{cut} \\ \sum_{i=1}^{n}(T_{cut} - T_{base}) & \text{if} \frac{T_{max,i}+T_{min,i}}{2} > T_{cut} \end{cases}$$

The day of the year (DOY) when sowing takes place is known from CropSyst, since a fixed planting mode is chosen. For maize in SHA, sowing takes place at $DOY = 130$. I use

[22] T_{base} is the temperature below which development stops, and T_{cut} is the upper threshold which still contributes to plant growth.

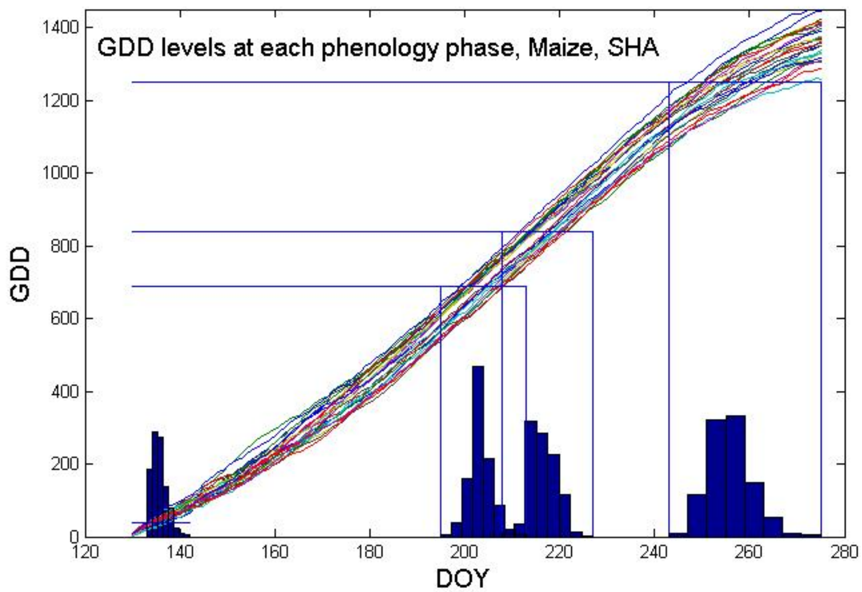

Figure 2.1: GDD during the growing phase.

the daily GDDs throughout the entire growing period to find the day of the year when a given phenology stage ends. The number of GDDs needed to complete each phenology stage are also known from the CropSyst calibration.[23] For maize production, 4 phenology phases are distinguished: the emergence, the vegetative growth period with flowering, the grain filling period, and maturity. Table 2.1 summarizes the GDD levels that correspond to each phenology phase for maize in Schaffhausen until maturity is reached, and reports the range of days, as well as the mean DOY, when the phenological stages end. For example, the grain filling phase ends on average on $DOY = 217$. Depending on the particular weather conditions in a given year, I observe that grain filling came to an end 9 days before, or 10 days after the average end date (i.e. between $DOY = 208$ to $DOY = 227$). For maturity, the range of possible end dates is even wider. When using fixed calender periods for index construction (based on average start and end dates), the weather index may not adequately capture the weather deviations in extreme years, thus creating additional basis risk.

Figure 2.1 shows the relationship between GDD values for each DOY starting at emergence ($DOY = 130$) to harvest ($DOY =$ 243-275) for maize in SHA for 30 different years. The histograms display the frequency of end dates for the 4 phenological stages and are

[23]For information about the CropSyst maize calibration used, see Torriani et al. (2007a). It should be noted that the approach recommended here for constructing phenology-specific weather indices can also be applied to historic yield data, since GDD requirements of plants at each phenology stage are often reported by breeding companies or agricultural extension services.

derived from the entire data.

Table 2.1: Timing of phenology phases and corresponding GDDs

Phases	Emergence	Vegetative Period	Grain Filling	Maturity
GDD	40	700	840	1250
DOY	133-142	195-213	208-227	243-275
Expected DOY	137	204	217	259

Crop: maize, location: SHA, sowing date: DOY=130.

2.4.2 Measuring Weather Risks

I measure different weather risks using weather indicators from the literature. The simplest quantifiers of the prevailing weather conditions in a given time period are the averages of daily precipitation, and minimum and maximum temperature values. Average, or respectively cumulative, precipitation and temperature measures are often found in weather-yield models (Martin et al. 2001; Turvey, 2001; Musshoff et al, 2009; Berg et al., 2009; Leblois et al., 2011). Their use is however criticized on the basis that sub-seasonal variations, such as long dry spells or short heat waves, which are critical to crop growth, are not captured (Lobell and Burke, 2010). Since I divide the growing period into 4 sub-periods, the use of average measures at each growing stage can be justified.

When using precipitation averages, the water consumption by the plant is however not adequately reflected by the index since low precipitation may evaporate – especially on hot days – or run off with excess precipitation. To construct an index that takes the actual water availability to the plant into account, I calculate the daily values of potential evapotranspiration (ETo) using the Priestley-Taylor radiation-based method recommended by the FAO (1998), and a temperature-based method by Hamon (1963). This allows us to construct the Reconnaissance Drought Index (RDI) proposed by Tsakiris and Vangelis (2005, 2006), which is the ratio between the cumulated quantities of precipitation and ETo (given a time period), using both ETo methods as inputs. In addition, I construct a Moisture Deficit Index (MDI), which is the difference between daily precipitation and ETo, to approximate for the moisture deficit.

2.4.3 Index Construction

I use a multivariate regression framework to evaluate the effect of the above-stated weather variables on crop yields. While three different weather related sources of yield risk exist –

drought, excess precipitation, and heat stress – I find that in Schaffhausen (SHA), weather events causing drought-like conditions explain the largest fraction of variation in maize yields. Some findings worth noting are that variations in maize yields are better explained by multivariate regression models which capture the effect of different weather events during the growing cycle, compared to bivariate models. Purely temperature based models were not further considered in the analysis since they can only explain a very small fraction of yield variation compared to precipitation-based models. Regression models that use measures of potential evapotranspiration in addition to precipitation perform the best, i.e. these models explain large fractions of yield variability. Including squared precipitation measures further increases the prediction accuracy of the model, and thus improves the quality of the weather index.

I select 4 multivariate regression models with different weather phenomena occurring at different phenology stages to construct weather indices. The 4 models vary in the time periods and weather events covered, and therefore in the complexity of communicating the index to the insured. For the contract design, working with 4 indices allows us to examine the effect of the goodness of fit of an index on risk reduction (see section 2.5.3 and 2.6.3). Table 2.2 provides an overview of which weather variables are used in each of the 4 models and shows the phenology phases at which these variables are measured.[24]

To construct Index 1, I only use mean precipitation during the vegetative period, which explains 37.1% of the variation in maize yields. Taking minimum temperatures during emergence and flowering, as well as the maximum temperatures during grain filling and maturity into account, Index 2 explains 49.3% of total maize yield variability.[25] Using the difference between mean precipitation and potential evapotranspiration to measure the water availability, I construct Index 3 with an adjusted R^2 of 47.1%. Considering the fact that precipitation has a nonlinear effect on crop growth, the squared mean precipitation is used in addition to the Reconnaissance Drought Index in Index 4. The rank correlation of Index 4 with yields is 78.9% and the adjusted R^2 is 62.5%. The goodness of fit of each of the 4 indices is described in Table 2.3, showing (Spearman) rank correlation, the adjusted R^2, and the Akaike Information Criterion (AIC).

[24] Table 2.11 in Appendix shows the estimated coefficients and the t-statistics for the 4 regression models. Only models with weather variables that are significant at 10% or less are considered for constructing weather indices.

[25] I report the adjusted R^2 to make the comparison with other studies possible. The adjusted R^2 is however not the optimal measure for evaluating the quality of an index for non-linear regression models. Therefore, I also report the Akaike Information Criterion (AIC) and the rank correlation coefficients.

Table 2.2: Description of weather indices

Index	Weather variable	No. of variables	Phenology Phase
Index 1	m.precip*	1	2
Index 2	m.precip, m.tmax**, m.tmin**	7	1-4
Index 3	P.ETo(Priest)***	3	2-4
Index 4	m.precip, m.precip^{2+}, RDI(Hamon)$^{++}$	9	2-4

Note: * m.precip is the mean of daily precipitation values. ** m.tmax and m.tmin are respectively the means of daily maximum and minimum temperatures. *** P.ETo(Priest) is the difference between daily precipitation and daily evapotranspiration (ETo), where ETo is measured using the Priestley-Taylor formula. $^{+}$ m.precip^2 are the squared daily mean precipitation values. $^{++}$ RDI(Hamon) is the Reconnaissance Drought Index derived using daily potential evapotranspiration, where ETo is measured using the Hamon formula.

Table 2.3: Goodness of fit of weather indices and yields

Index	Rank correlation	Adj.R^2	AIC
Index 1	64.7	37.1	16876
Index 2	74.1	49.3	16712
Index 3	71.3	47.1	16751
Index 4	78.9	62.5	16422

2.5 Results

2.5.1 Conditional Yield Distributions

In section 2.2, I showed that the optimal payoff structure has to reflect the information contained in the conditional yield distributions. Figure 2.2 shows the conditional yield densities for maize in SHA estimated with a two-dimensional kernel procedure for the four indices described in section 2.4. In particular, I observe that changes in the riskiness of yield production due to changes in the weather index have an effect on the local slope of the contract ($p'(z)$).

Maize yields in SHA range from 4,190 to 11,878 kilo per hectare (kg/ha), with an average of 9,241 kg/ha.[26] The weather index is measured in the same units (kg/ha) since the index has been constructed such that it possesses a high correlation with crop yields, and thus represents predicted yields for the given realizations of the weather index. Unless otherwise noted, the conditional yield densities are estimated using $ny = 25$ and $nz = 50$, and the Kernel bandwidth for the index, $bw(z)$, is set to 300, and for the yield data a

[26]Revenues from maize production thus range from 1,718 to 4,870 CHA per hectare.

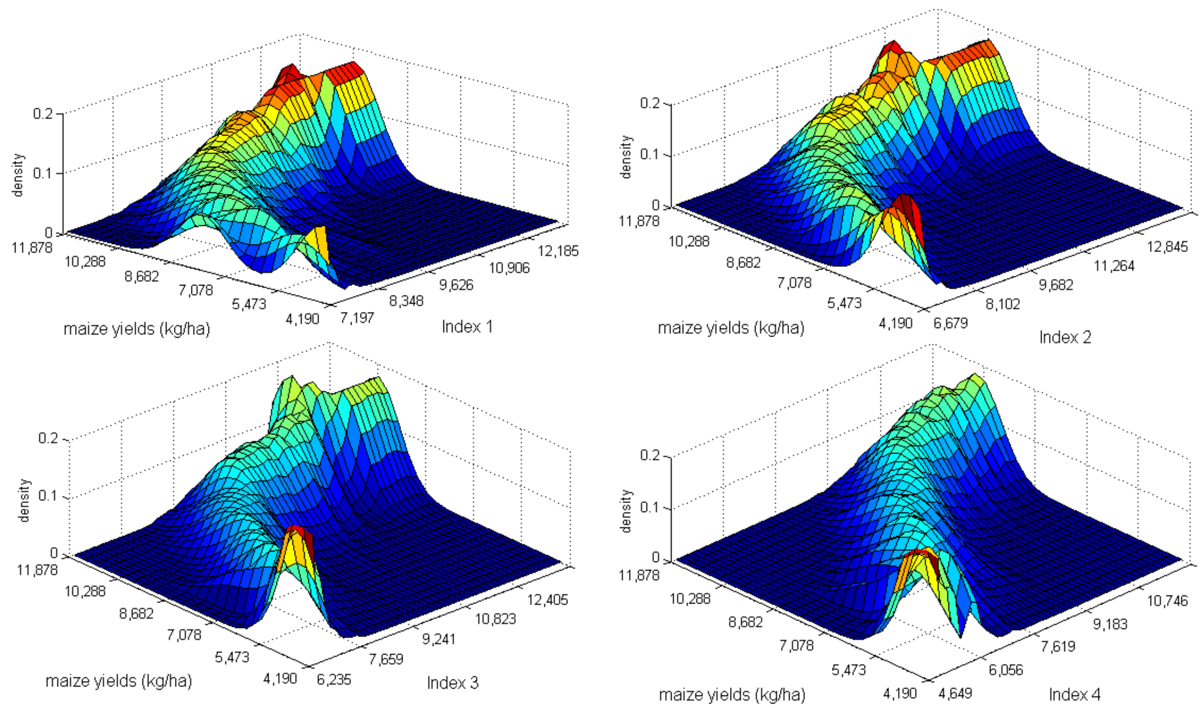

Figure 2.2: Conditional yield density for weather indices 1 to 4. Kernel estimates with $nz = 50, ny = 25, bw(z) = 300, bw(y) = 100$.

Kernel bandwidth, $bw(y)$, of 100 is used.

It can be seen that for all indices, low values of the index are associated with low expected yield levels. As the value of the index increases, maize yields tend to increase as well, albeit in a non-linear way. For Index 1 to 3, the conditional mean yield tends to increase rapidly for low values of the weather index. Once the weather index has reached its mean value, the increase in the conditional mean yield flattens out for a further increase in the underlying index. The conditional yield density for Index 4 behaves slightly different. For low values of Index 4, yields tend to increase only slowly, and almost linearly. The flattening of the conditional mean only occurs for very high values of the index (compared to Indices 1 to 3). Most notable is that the shape of the conditional yield distributions changes for different values of the weather index. This observations holds for all indices.[27]In particular, the riskiness of the conditional maize distributions may change in a non-continual way for small changes in the weather index. These changes in the riskiness explain why the optimal weather insurance contract is neither perfectly linear nor U-shaped, as will be demonstrated in the following.

[27]For further empirical research, it is worth noting that when estimating the relationship between weather and yields, one should account for the fact that the assumption of homogenously distributed error terms is not valid, as is obvious from Figure 2.2.

2.5.2 Optimal Insurance Contract

The optimal weather insurance contract for Index 2 (Index 4) is shown together with the conditional yield density in Figure 2.3 (Figure 2.4).[28] The shape of both contracts reflects closely the changes in the respective conditional yield distributions. Both contracts pay out for low values of the index, and have negative net-payments for high values of the index. Net-payments for contract 2 decrease faster than for contract 4 since for low values of the weather index 4 the probability of getting high yields is low. The maximum net-payment from contract 2 is 1,660.60 CHF per hectare of insured maize production. The minimum of the indemnification curve is at -828.36 CHF, which can be interpreted as the premium (P), or the amount of money a farmer would have to pay to obtain the weather insurance contract. Assuming that the insured pays a premium of 828.36 CHF to purchase the contract at the beginning of the growing season, the gross-payments for a given weather realization are determined by adding the premium to each net-payment.[29]

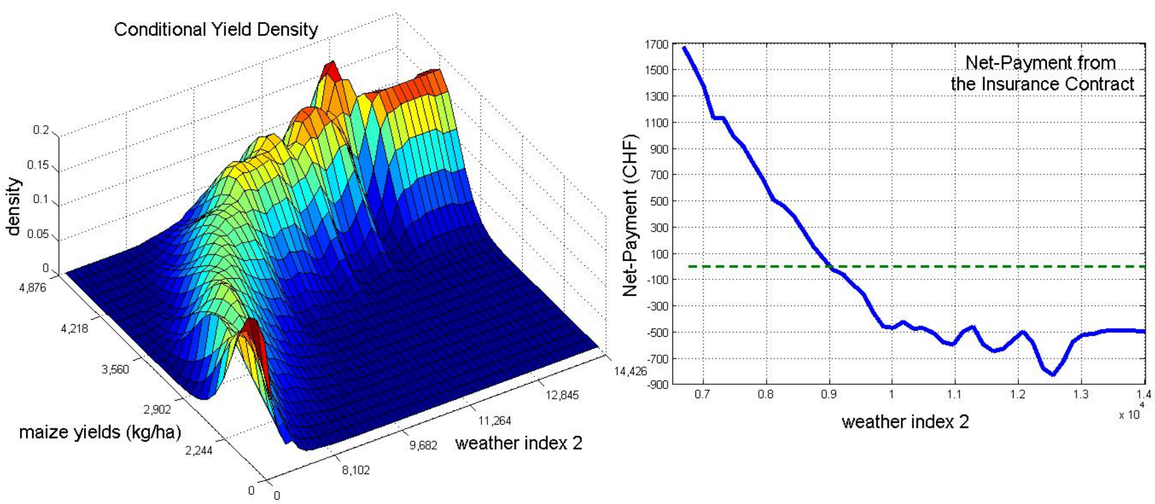

Figure 2.3: Conditional yield density and insurance contract for Index 2.

In Figure 2.5, all 4 optimal weather insurance contracts are shown together. The weather insurance contracts for Indices 1 to 3 possess similar contract shapes and contract parameters.

At the point where the net-payment is equal to zero, the purchaser of the contract recovers the premium. Once the weather index has reached values smaller than the "recovery point", the contract is "in the money" or has positive net-payments. The probability of this event ("recovery probability") can be derived from the probability density function

[28] For Index 1 and 3, the optimal contracts together with the conditional yield densities are shown in the Appendix (Figures 2.11 and 2.12).

[29] In the Appendix (see Figure 2.13), I show the gross-payments from the insurance contract for Index 4.

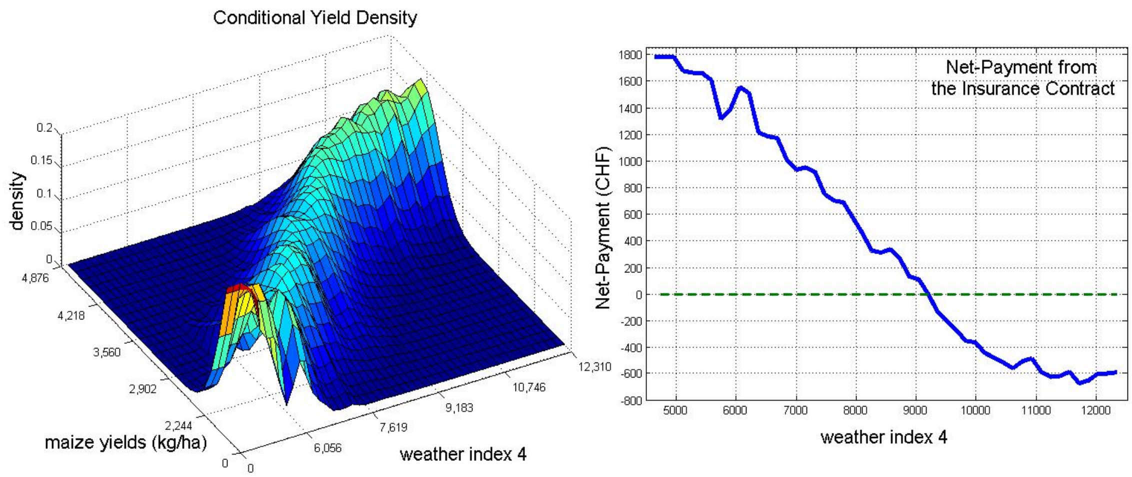

Figure 2.4: Conditional yield density and insurance contract for Index 4.

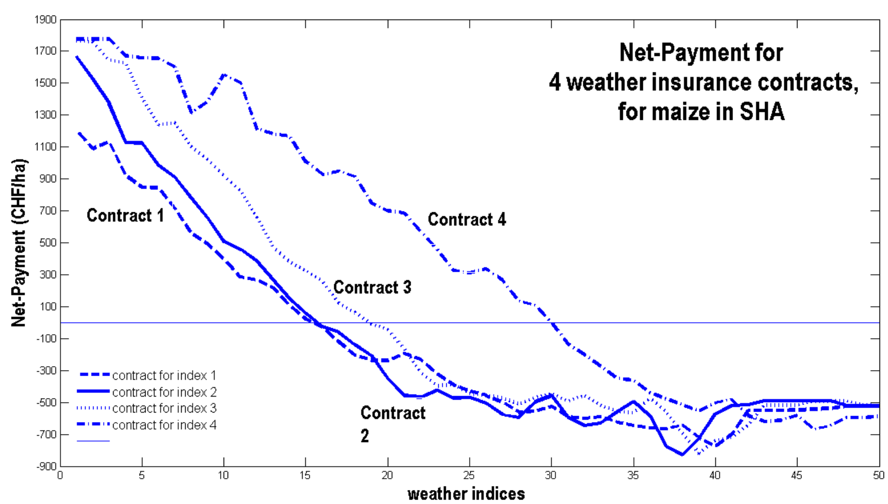

Figure 2.5: Weather insurance contracts for Index 1 to 4 and sigma=2.

of the underlying weather index. As shown in Table 2.4, the probability of the weather index being equal to or lower than the recovery point is between $46 - 49\%$ (depending on the index), i.e. the contract pays out (in net terms) almost every second year.[30] Furthermore, the premium and maximum payout, and the realization of the weather index at which the insured recovers the premium are shown in Table 2.4. Contract 4 has the smallest premium with 668.90 CHF, and at the same time the highest maximum net-payment with 1,775.60 CHF and in 49% of the cases the insured fully recovers the premium.

[30]The frequency of (historical) pay-outs has been found to be a critical factor influencing farmers' decision to purchase protection against adverse weather conditions (Patt et al., 2009). The optimal weather insurance

Table 2.4: Contract parameters

Index	Premium	max. Payout	Recovery Point	Recovery Probability
Index 1	776.30 CHF	1,207.20 CHF	9.081	0.48
Index 2	828.36 CHF	1,666.60 CHF	8.971	0.46
Index 3	821.10 CHF	1,762.50 CHF	8.003	0.47
Index 4	668.90 CHF	1,775.60 CHF	9.183	0.49

Note: Premium and maximum payout are measured in CHF. The recovery point is in the same units as the index. Recovery probability is the probability of realizing index values equal or smaller than the recovery point. Crop: Maize; Location: SHA; Contract parameters: $\sigma = 2$, $nz = 50, ny = 25, bw(z) = 300, bw(y) = 100$.

To describe the insurance properties of an optimal insurance contract, the information contained in the recovery point (trigger), maximum payout (cap) and premiums is insufficient. For a complete picture of the insurance coverage inherent in an optimal weather insurance contract, the relationship between the pay-out probabilities at different levels of the weather index and the respective net-payments has to be analyzed. For that purpose, I compare the net-payment curve with the probability distribution of the underlying weather index. In Figure 2.6, these two functions are shown for index 4. I find that very high net-payments only occur with low probabilities, and at the same time the probability of having to pay the full premium is also very low. The intuition for this observation is clear: the insured receives very high-payments for catastrophic weather events such as droughts that cause substantial losses. These events however only occur with a very low probability. Similarly, perfect growing conditions (as indicated by high values of the weather index) also occur only with a low probability, and therefore the insured faces a very low probability of paying the full premium. The optimal contract provides moderate payments between $0 - 500$ CHF for very likely deviations from the recovery point, and therefore comes in most years at moderate costs of 0 to -500 CHF for Index 1 and 2, which are even lower for Index 3 and 4.

To characterize the optimal insurance contract in terms of pay-out frequencies, I computed the probabilities of realizing net-payments that range between the maximum payout (limit) and 500 CHF, between 500 and 0 CHF, 0 and -500 CHF, and between -500 and the premium. Table 2.5 summarizes the pay-out probabilities for all 4 insurance contracts. In the case of contract 2, the probability of net-payments between 500 and 0 CHF is 39.60%, and together with the probability of 43.30% for net-payments between 0 and -500 CHF, this contract has net-payments between 500 CHF and -500 with a probability of

contract should thus be quite attractive to farmers given its high recovery probability.

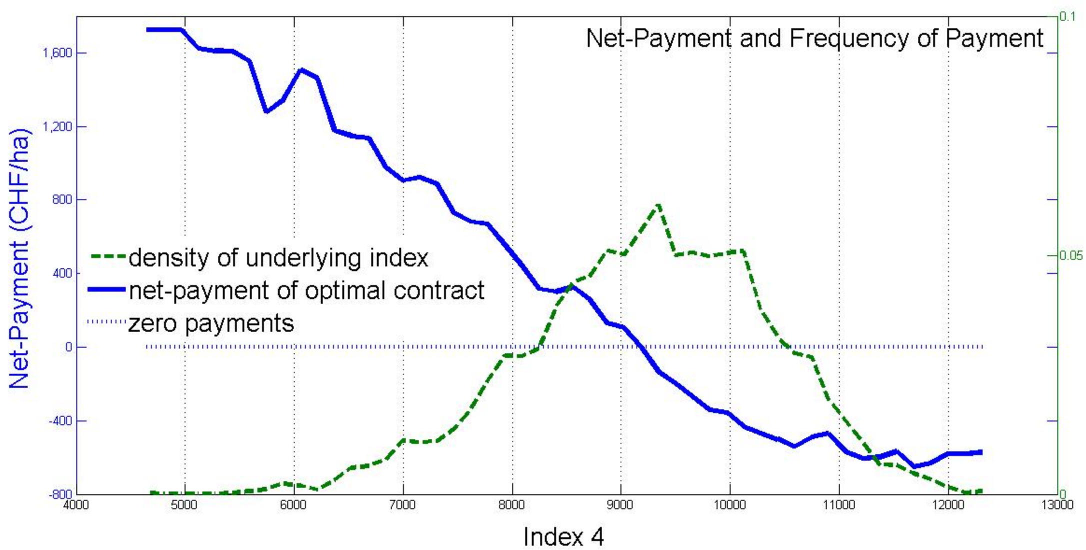

Figure 2.6: Probabilities of net-payments from insurance contract 4.

82.80%. At the same time, this contract offers high indemnities in times of severe weather events. The extended coverage comes at a cost of having to pay between −500 CHF and the premium when weather conditions are excellent, which occurs in 7.40% of the cases. Overall, all optimal insurance contracts are characterized by moderate net-payments of 500 to −500 CHF occurring with a probability of 78.60% (Index 4) to 86% (Index 1 and 3). Thus, optimal weather insurance offers protection for catastrophic, infrequent-high-loss events and compensates the insured on a regular basis for moderate fluctuations of yields.

Table 2.5: Pay-out probabilities of optimal insurance contracts

Net-Payment (in CHF)	500 to max.payout	0 to 500	-500 to 0	premium to -500
Index 1 probability	6.60%	39.20%	47.20%	7.10%
Index 2 probability	9.80%	39.60%	43.20%	7.40%
Index 3 probability	11.00%	39.60%	46.80%	2.60%
Index 4 probability	14.60%	34.50%	44.10%	6.80%

Note: Payments are measured in CHF. Crop: maize, location: SHA, contract parameters: $\sigma = 2$, $nz = 50$, $ny = 25$, $bw(z) = 300$, $bw(y) = 100$.

2.5.3 Evaluation of Hedging Effectiveness

The risk-reduction that can be achieved from using an optimal weather insurance contract can be evaluated by comparing the revenue distribution without insurance to the situation where the farmer hedges the weather exposure by buying insurance. In the situation without insurance, the income from maize production (per hectare) is equal to the revenues from maize production, i.e. maize yields y_i (kg/ha) in a given year i multiplied by the respective price p_m, which is 0.41 (CHF/kg). The income per hectare of maize production in SHA thus ranged from 1,718 to 4,870 CHF, with mean revenues of 3,696 CHF and standard deviation of 576.90 CHF. To derive the income of a maize farmer in SHA for the situation with insurance, the net-payments in each year are added to the revenues from selling maize. If the farmer hedges the weather risk, the lowest income realizations range from 2,162 to 2,376 CHF depending on the contract. By hedging, the farmer thus receives 25 to 38% more income in the worst possible year (depending on the contract) than without hedging. At the upper end of the income distribution, incomes of 4,821 to 4,959 CHF/ha are possible (depending on the contract).

Table 2.6 summarizes the statistical properties (mean, standard deviation, skewness, and the 10%, 25%, 50%, 75%, and 90% quantiles) of the income distributions with and without insurance. As expected, the mean income is the same in all scenarios since insurance reduces the risk of realizing low incomes, but does not cause a change in the mean income due to the zero profit condition (2.1).[31] Without insurance, the risk of realizing an income that is lower than 2,865 CHF is 10%. With insurance, in 10% of all cases the income falls below 3.109 to 3.268 CHF depending on the chosen contract, i.e. the risk of low incomes (in the 10% quantile) is substantially reduced.

All weather insurance contracts greatly reduce the standard deviation and skewness of the income distribution. Overall, farmers face less risk of obtaining low incomes.[32] The contract based on Index 4 almost halfs the standard deviation. While the incomes for the 10% and 25% quantiles increase with insurance, the incomes at the 75% and 90% quantiles decrease. As a result of facing less risk at the lower end of the income distribution, the insured faces now lower probabilities for realizing extremely high incomes (compared to the situation without insurance). The compression of the income distribution with insurance can also be seen in Figure 2.7, which shows the income distributions for the 4 insurance contracts, and for the scenario without hedging. Insurance contract 4 performs

[31] The fact that the reported mean incomes for the situations with insurance are by 5-7 CHF smaller than in the situation without insurance is due to numerical imprecision from solving the optimization problem.

[32] An Ansari-Bradley test has been performed, and for all weather insurance contracts we can reject at the 5% level the hypothesis that the income distribution with insurance has the same dispersion as the income distribution without insurance.

Table 2.6: Income with and without insurance for 4 weather insurance contracts

	Not Insured	Index 1	Index 2	Index 3	Index 4
mean	3696	3691	3691	3691	3689
std	576.9	436.0	369.0	379.3	338.2
skw	-0.73	-0.65	-0.54	-0.41	-0.50
10%	2865	3109	3211	3203	3268
25%	3337	3448	3478	3471	3501
50%	3815	3749	3725	3713	3708
75%	4147	4000	3946	3946	3908
90%	4349	4193	4138	4135	4094

Note: Units: CHF/ha, crop: maize, location: SHA, model parameters: $\sigma = 2$, $ny = 25$, $nz = 50$, $bw(1) = 100$, $bw(2) = 300$.

the best.

To measure the effect of hedging, I compute the percentage increase (of all income realizations) in the situation without insurance that makes the farmer equally well-off as in the situation with insurance. In equation (2.9), the farmers expected utility from insurance is set equal to the expected utility in the situation without insurance when all income realizations are multiplied by $(1+\delta)$. I solve the expression in the following equations (2.10-2.11) for δ.

$$\int_z g(z) \int_y f(y|z) \frac{(p(z)+y)^{1-\sigma}}{1-\sigma} dydz = \int_z g(z) \int_y f(y|z) \frac{((1+\delta)y)^{1-\sigma}}{1-\sigma} dydz \tag{2.9}$$

$$\Leftrightarrow \quad \int_z g(z) \int_y f(y|z)(p(z)+y)^{1-\sigma} dydz = (1+\delta)^{1-\sigma} \int_z g(z) \int_y f(y|z) y^{1-\sigma} dydz \tag{2.10}$$

$$\Leftrightarrow \quad \delta = \left(\frac{\int_z g(z) \int_y f(y|z)(p(z)+y)^{1-\sigma} dydz}{\int_z g(z) \int_y f(y|z) y^{1-\sigma} dydz} \right)^{\frac{1}{1-\sigma}} - 1 \tag{2.11}$$

The percentage increase (of all income realizations) in the situation without insurance that would lead to the same level of expected utility as in the situation with insurance, δ, is a measure of the value of weather insurance. I compute δ for the 4 contracts described in section 2.5.2 with risk aversion of $\sigma = 2$. Buying optimal weather insurance is equivalent to increasing the insured's income (in all states of the world) by 1.25 to 1.95 % depending on the contract. The benefit from hedging with weather insurance can reach considerable

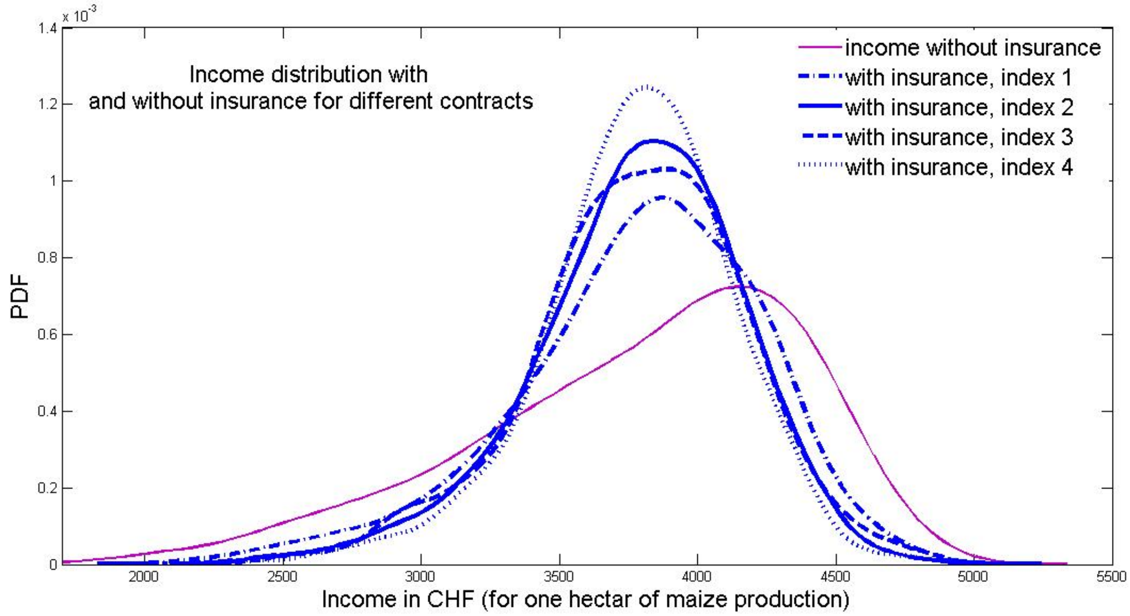

Figure 2.7: Income distribution without insurance and for 4 weather insurance contracts.

values ($\delta > 10\%$) for higher levels of risk aversion ($\sigma > 5$).[33] Table 2.7 shows δ (in percent) for the 4 indices and different levels of risk aversion. I also observe that δ tends to be higher for contracts for which the quality of the weather index is high (see Table 2.3). For Index 1, which has a (Spearman) rank correlation coefficient of 64.7%, a δ of 0.57% to 10.2% can be achieved. For Index 4, which possesses the highest rank correlation of 78.9%, I find δ's in the range of 0.89% to 16.92% depending on the level of risk aversion.

The contracts shown in Figure 2.3 to 2.5 are derived for a risk aversion of $\sigma = 2$. For Figure 2.8, I computed the optimal contract for Index 4 for different levels of risk aversion ($\sigma = 1, 2, 5, 7, 10$). The more risk averse the insured, the more protection is being sought in the optimum, which can be seen in a shift in the recovery point, and higher compensation (in the form of positive net-payments) for medium deviations of the weather index from its mean. To compensate for the increased protection, a higher premium has to be charged since moderate deviations tend to occur quite frequently. The hedging effectiveness as expressed by δ increases by factor 8 when sigma increases by factor 5 (from $\sigma = 2$ to $\sigma = 10$). For low levels of risk-aversion ($\sigma = 1, 2$), the optimal contract focuses on providing high payments in times of catastrophic weather events, as soon as yields tend to increase,

[33]The observation that benefits from risk reduction increase with risk aversion is in line with related findings in the literature. For instance, in an empirical analysis of the incentives to participate in the U.S. multi-peril crop insurance scheme Just et al. (1979) find that risk-avers farmers generally have larger risk premiums (compared to risk-neutral farmers).

Table 2.7: δ (in %) for different levels of risk aversion

	Index 1	Index 2	Index 3	Index 4
$\sigma = 1$	0.57	0.80	0.79	0.89
$\sigma = 2$	1.25	1.76	1.72	1.95
$\sigma = 4$	3.06	4.29	4.23	4.75
$\sigma = 5$	4.22	5.94	5.88	6.56
$\sigma = 7$	6.78	9.69	9.68	10.7
$\sigma = 10$	10.2	15.31	15.47	16.92

Note: δ is the percentage increase of all income realizations without insurance compared to the situation with insurance. Crop: maize, location: SHA, model parameters: $ny = 25$, $nz = 50$, $bw(1) = 100$, $bw(2) = 300$.

net-payments tend to decrease sharply. The reduced protection for moderate deviations from the mean, which a farmer with low risk aversion seeks, is at the same time available at a lower premium.

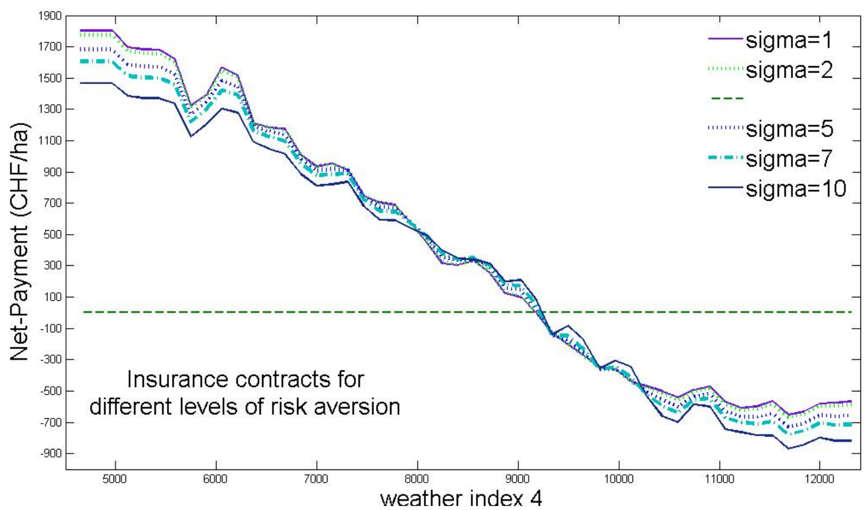

Figure 2.8: Optimal weather insurance contract for different levels of risk aversion.

2.5.4 Effect of Kernel Density Estimation Parameters

The robustness of the optimal insurance contract, $p(z)$, is finally evaluated for changes in the parameter choice of the nonparametric kernel density estimation. It turns out that the choice of the kernel function does not have an effect on the results, so I use a standard bivariate normal kernel for all my analysis. The choice of the bandwidth in both dimensions ($bw(z)$ and $bw(y)$) is however an important factor affecting the estimates since it controls the amount (and orientation) of smoothing induced (Wand and Jones, 1995). It can be shown that increasing the kernel bandwidth for both the weather index ($bw(z)$) and yields ($bw(y)$) has an effect on the smoothness of the contract, and consequently on the measure of risk reduction δ. The smoother the contract $p(z)$ is, due to high values for $bw(z)$ and $bw(y)$, the lower the risk reduction as measured by δ. With less smoothing, the net-payment curve responds more to small changes in the weather index, i.e. the noise in the data receives more attention. At the same time, the income distribution with insurance becomes smoother. When over-smoothing the contract, less weather-related variability in the income is hedged. Consequently, the income distribution becomes less smooth.

Table 2.8: δ (in %) for different kernel estimation parameters

	Index 1	Index 2	Index 3	Index 4
specification 1	1.25	1.76	1.72	1.95
specification 2	1.57	2.19	1.84	2.31
specification 3	1.31	1.83	1.75	2.01
specification 4	1.40	1.92	2.03	2.03

Note: All results are for a risk aversion of $\sigma = 2$.
specification 1: $nz = 50, ny = 25, bw(z) = 300, bw(y) = 100$
specification 2: $nz = 50, ny = 25, bw(z) = 100, bw(y) = 40$
specification 3: $nz = 20, ny = 15, bw(z) = 300, bw(y) = 100$
specification 4: $nz = 20, ny = 15, bw(z) = 100, bw(y) = 40$

Increasing ny increases the number of yield density estimates that are derived for a given value of z. It can be shown that changes in ny have only small effects on risk reduction. In contrast, the choice of nz has a bigger effect on δ.[34] I find that increasing nz decreases the risk reduction as measured by δ. Overall, changes in either of the estimation parameters have a small impact on risk reduction as can be seen in Table 2.8. I derived δ for different specifications of the estimation parameters for all contracts considered. In particular, when comparing specification 1 with 2 (and 3 with 4), the effect of over-smoothing can be seen.[35] Increasing the kernel bandwidth from $bw(z) = 100$ and $bw(y) = 40$ to $bw(z) = 300$ and $bw(y) = 100$ decreases δ by about 10% on average. Comparing the specification 1 with 3 (and 2 with 4), the effect of increasing nz on δ can be seen.

[34] In general, when estimating the conditional yield densities at more points (higher nz) – while holding ny constant – fewer weather-yield observations are available at the various evaluation points. To derive the density estimates, the kernel procedure has to interpolate more.

[35] Specification 1 constitutes the baseline scenario which is used throughout the paper.

2.6 Optimal Insurance Contract for the Insurer

2.6.1 The Profit-Maximization Problem

Contrary to the assumption stated in the theoretical model (see section 2.2), expected profits from offering weather insurance are in reality not found to be zero. The insurer requires a positive expected-return to cover his administrative and transaction costs. Depending on the nature of the transaction and the degree of systemic risk in the insured pool, the insurer must factor costs for re-insurance in the premium. Therefore, weather insurance contracts must sell at a price above the expected pay-outs so that location-specific weather insurance coverage can be provided in the long-run. For the insured, the difference between the fair premium, which reflects his expected losses, and the additional costs represent the price for transferring weather-related risks. For the insured to be willing to buy insurance, this cost must not be excessive compared to bearing the weather risk himself.

One mechanism to examine whether a profit-making (loaded) weather insurance contract is attractive for the insured is by comparing the risk reduction achieved from a fair insurance contract with the risk reduction from a contract that includes a mark-up, i.e. factors additional costs into the premium. Berg et al. (2009) add a mark-up of around 10% to the premium to address this question. Vedenov and Barnett (2004) evaluate the effect of transaction costs on risk reduction by adding different loading factors on the premium and comparing the changes in the insured's income under these loaded contracts.

I derive instead the optimal weather insurance contract, $p_m(z)$, that maximizes profits of the insurer subject to the constraint that the insured is indifferent between buying the contract and remaining uninsured. This allows us to numerically determine the maximum loading factor on fair premiums that the insured is still willing to bear. Hence, the insurer is faced with the following constraint:

$$\int_{\mathcal{Z}} \int_{\mathcal{Y}} u(y + p_m(z)) dF(y|z) dG(z) \geq \int_{\mathcal{Z}} \int_{\mathcal{Y}} u(y) dF(y|z) dG(z). \tag{2.12}$$

The insured's expected utility in the situation with the profit-maximizing contract has to be equal to or greater than his expected utility without insurance. Otherwise, the insured would not be willing to buy the insurance contract. The net-payments $p_m(z)$ constitute liabilities for the insurer. Thus, the insurer maximizes his expected profits by selecting a contract, $\{p_m^*(z)\}$, for which the expected net-payments are as small as possible given the constraint (2.12). The insurer's profit-maximizing contract $\{p_m^*(z)\}$ solves

$$\max_{\{p_m(z)\}} -\int_{\mathcal{Z}} p_m(z)dG(z) \tag{2.13}$$

subject to constraint (2.12). The Lagrangian can be written as follows:

$$\mathcal{L} = -\int_{\mathcal{Z}} p_m(z)dG(z) + \lambda_m \left\{ \int_{\mathcal{Z}} \int_{\mathcal{Y}} u(y + p_m(z))dF(y|z)dG(z) - \int_{\mathcal{Z}} \int_{\mathcal{Y}} u(y)dF(y|z)dG(z) \right\} \tag{2.14}$$

which yields the pointwise first-order conditions

$$\int_{\mathcal{Y}} u'(y + p_m(z))f(y|z)dy = \frac{1}{\lambda_m} \ \ \forall z \in \mathcal{Z}, \tag{2.15}$$

where $\lambda_m > 0$ is the Lagrange multiplier of constraint (2.12). Optimality condition (2.15) requires that the expected marginal profit of the insured conditional on a realization of the weather index z is equalized across all z by the optimal contract. I implement the profit-maximization problem by assuming CRRA preferences for the insured with σ=2. The implementation is analogous to the one described in section 2.3.

2.6.2 The Profit-Maximizing Insurance Contract

Comparing the profit-maximizing insurance contract with the optimal (zero-profit) insurance contract in Figure 2.9 (top panel), we find that the profit-maximizing contract $p_m(z)$ displays the same shape as the optimal insurance contract $p(z)$. As pointed out in section 2.5.1, the shape of $p(z)$ is influenced by the changes in the riskiness of the conditional yield distributions. With respect to the shape of $p_m(z)$, Propositions 1 to 5 apply analogously. While both contracts possess the same shape, they differ in their absolute amount of net-payments. For the entire range of the weather index, net-payments are lower for the profit-maximizing contract. In Figure 2.9 (bottom panel), the difference between the net-payments from the optimal contract and the profit-maximizing contract are shown (for Index 4). The optimal insurance contract pays between 69 to 71.50 CHF more depending on the realized value of the index. The insurer can capture the absolute difference in net-payments because the profit-maximizing contract makes the insured as well-off (in expected utility terms) as in the situation without insurance.

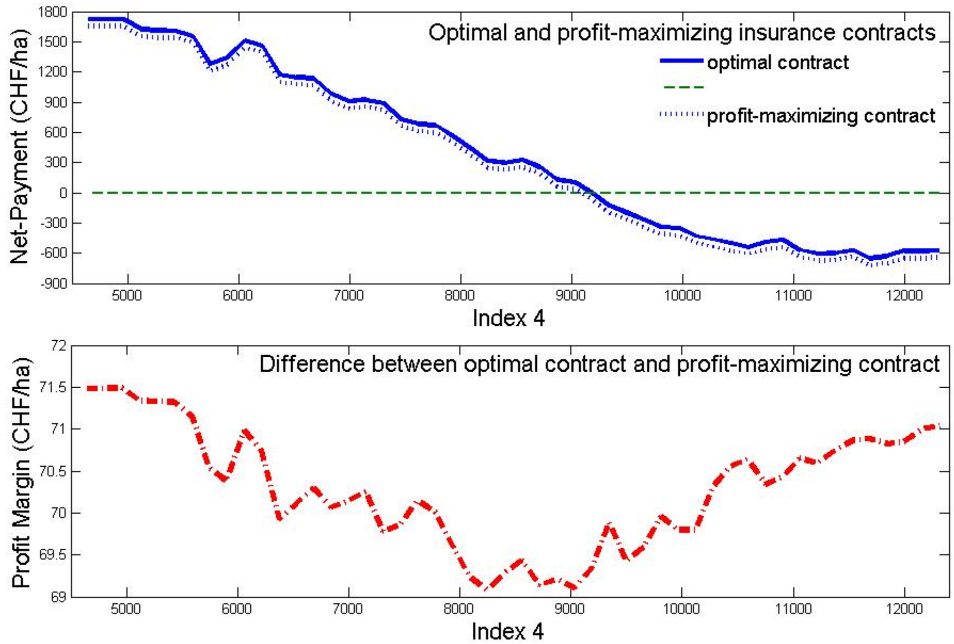

Figure 2.9: Optimal and profit-maximizing insurance contract *(top panel)* and profit margin *(bottom panel)* for Index 4 and $\sigma = 2$.

2.6.3 Evaluation of the Profit-Maximizing Insurance Contract

The profits that an insurer can expect to earn by offering the profit-maximizing insurance contract are calculated by

$$\prod = -\int_{\mathcal{Z}} p_m^*(z) dG(z). \tag{2.16}$$

Expected profits for the 4 insurance contracts are derived for different levels of risk aversion and are summarized in Table 2.9. For low levels of risk aversion, such as $\sigma = 2$, the insurer can expect to earn between 43.30 to 69.70 CHF per hectare of insured maize production (depending on the contract offered). Expected profits increase to substantial values (123 to 207 CHF) the higher the coefficient of relative risk aversion ($\sigma = 5$).

Profits are found to be positively correlated with the goodness of fit of the underlying weather index. The higher the correlation coefficient of an index (see Table 2.3), the better the hedging effectiveness as measured by δ (see section 2.5.3). With rational insurers, I expect an insurance contract similar to contract 4 to be offered since it possesses the highest expected profits. At the same time, insurance contract 4 delivers the highest risk reduction, as measured by δ, and is therefore also the most attractive risk management tool for the insured.

As I set out to determine the maximum amount of loading on fair premiums, I com-

Table 2.9: Expected profits for different levels of risk aversion

	Index 1	Index 2	Index 3	Index 4
$\sigma = 1$	20.10	30.60	29.10	34.90
$\sigma = 2$	43.30	57.80	59.90	69.70
$\sigma = 4$	100.20	141.80	139.78	154.33
$\sigma = 5$	123.00	182.80	181.20	207.90
$\sigma = 7$	179.30	267.60	267.30	298.10
$\sigma = 10$	221.90	349.60	355.70	389.40

Note: Profits are measured in CHF/ha. Crop: maize, location: SHA, model parameters: $ny = 25$, $nz = 50$, $bw(1) = 100$, $bw(2) = 300$.

pare the premium of the profit-maximizing contract to the premium of the fair (optimal) contract. The loading factors (in percent) of fair premiums are presented in Table 2.10 for different levels of risk aversion. I find that at moderate risk aversion, it is possible to add a 10% mark-up on the fair premium (for Index 4). As before, with a higher levels of risk aversion, loading factors of 30 to 50% become possible (for Index 4).

Table 2.10: Loading of fair premium for different levels of risk aversion

	Index 1	Index 2	Index 3	Index 4
$\sigma = 1$	2.89	4.02	3.89	5.63
$\sigma = 2$	5.93	7.72	7.75	10.88
$\sigma = 4$	12.90	17.32	17.18	23.24
$\sigma = 5$	15.41	21.90	21.88	30.72
$\sigma = 7$	(32.63)	31.03	31.16	41.77
$\sigma = 10$	23.88	36.65	39.32	53.38

Note: The loading factor is expressed in % of the optimal premium. Crop: maize, location: SHA, model parameters: $ny = 25$, $nz = 50$, $bw(1) = 100$, $bw(2) = 300$.

Finally, I evaluate the benefits for the insured from hedging with a profit-maximizing insurance contract. The income distribution of the situation without insurance is compared to the income situation where the insured bought a profit-maximizing contract, and to the situation with a fair contract.[36] Figure 2.10 shows the different income distributions for Index 4. As can be seen, the income distribution from a profit-maximizing contract is less risky (compared to the un-hedged situation), but has a lower mean income. With profit-maximizing insurers, the income distribution from the optimal contract is shifted to the left and the difference between the two mean incomes is captured by the insurer.

[36] The changes in the statistical properties (mean, standard deviation, skewness and the 10%, 25%, 50%, 75%, and 90% quantiles) are reported in the Table 2.12 in the Appendix.

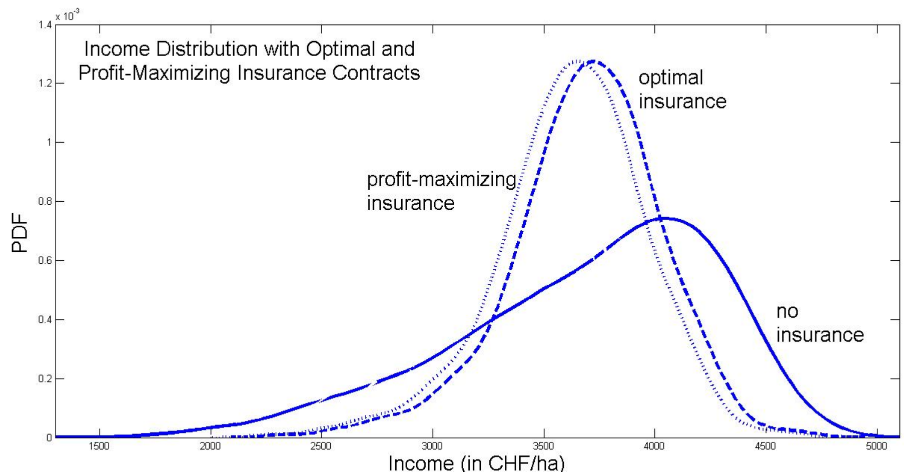

Figure 2.10: Income distributions for optimal and profit-maximizing weather insurance contracts for Index 4.

2.7 Conclusion

2.7.1 Summary and Outlook

I propose a new method to derive an index-based weather insurance contract with optimal hedging effectiveness. To illustrate it, I apply it to simulated crop and weather data of maize production in Switzerland, and derive nonparametrically the shape of the optimal contract, and demonstrate that the slope of an optimal weather insurance contract is characterized by changes in the estimated conditional yield distributions.

I show how to quantify the risk reduction from hedging weather-related production risk with my novel approach. By comparing the income distribution without insurance to a hedged situation, I find that income without insurance can be increased (depending on the underlying index) by 1.8 to 2.2% for the benchmark level of risk aversion ($\sigma = 2$), and that benefits can become quite substantial (equivalent to a more than 10% increase in incomes) for higher levels of risk aversion ($\sigma = 5$). Furthermore, I demonstrate the robustness of the optimal contract to changes in the parameters used to derive the conditional yield densities.

In an extension of the model, I show how to derive a profit-maximizing insurance contract in order to determine the maximum amount of loading on fair premiums so that the contract remains attractive to the insured. I find that loading factors can become quite substantial (120 to 200 CHF/ha, and, respectively, 15 to 30%) depending on the weather index and the level of risk aversion ($\sigma = 5$). The question of how the efficiency gains from hedging farmers' weather exposure are shared between the insurer and the insured is a matter of market power in the weather insurance sector, and depends on the cost of obtaining re-insurance. The analysis provides the bonds between which insurance contracts will be located for any distribution of bargaining power.

Due to the spatial correlation of weather, small (localized) insurers are faced with systemic risk, i.e. they face high pay-outs in the situation of extreme weather events, which requires them to obtain re-insurance. The presence of systemic risk can therefore be an obstacle of insurability (Quiggin, 1991). While we cannot answer the question whether the optimal loading factors are large enough to cover re-insurance (and administrative costs), the approach characterizes the entire set of mutually-feasible insurance contacts (by deriving both the optimal and the profit-maximizing contract).

By construction, the proposed optimal weather insurance contract implies that no other insurance contract can achieve more risk reduction. In future work, this advantage remains to be quantified. In particular, using the same weather and yield data – ideally for different crops – weather insurance contracts can be derived using the classical derivative structure proposed by Turvey (2000, 2001) and Martin et al. (2001), the semi-optimization approaches described by Berg et al. (2009) and Leblois et al. (2011), and the parametric method proposed by Musshoff et al. (2009). Differences in the hedging effectiveness from these contracts are then solely attributable to the new methodology used for the pay-off structure design.

I realize that optimizing an insurance contract and evaluating its hedging effectiveness on the same data exposes the results to the risk of over-fitting. One way of dealing with over-fitting is by conducting a cross-validation analysis (Vedenov and Barnett, 2004). Given the size of the data, I rate this risk as rather small. In contrast, the risk of over-fitting from using simulated crop yield data should be analyzed. I therefore propose to compare the hedging effectiveness from an insurance contract, which has been derived using simulated yield data, to the risk reduction of contracts which were designed using historical yield and weather data (for the same region and crop). I leave this to be demonstrated in future applications.

It is well known that the wealth level of the insured has an effect on the risk reduction sought. In my study, I implicitly assume that the wealth of the insured is entirely earned from the production of the insured crop. I leave the question of how initial wealth affects the optimal contract to future research.

To my knowledge, I am the first to propose a method for implementing weather insurance contracts based on phenology-driven weather indices. While I found that these more complex indices outperform indices based on fixed time windows, a more thorough investigation of this observation with data from different crops may be insightful.

Weather insurance is by construction a specific-peril insurance. I account for the influence of different weather events (occurring throughout the growing season) by constructing indices that weight these events and their respective impacts on crops. I then use the statistical distribution of the index to design and price the insurance contracts. This procedure may not adequately account for the fact that the probability of a given weather phenomena occurring at the beginning of the season impacts the likelihood of other weather events occurring later in the season. Future research could explore the design of multi-peril index-based weather insurance where the conditional probabilities of sequential weather events are explicitly modeled.

2.7.2 Practical Considerations for Implementing Optimal Weather Insurance

I conclude with some remarks on how the proposed optimal insurance contracts could be implemented. Weather insurance is intended to hedge against production risk rather than price risk, therefore choosing the crop price for converting net-payments in monetary units is a critical aspect. I recommend to use the crop price at the end of the growing season to determine the insurance payments. Using the end-of-season crop price helps reduce price uncertainty, and farmers' decisions to obtain weather insurance are independent from price variability and thus speculation. Farmers' individual yields will usually not be correlated with the crop price if the commodity sector is engaged in international trade and the total production supplied is small relative to world production, i.e. the country is a price taker.[37] Farm revenues are therefore subject to price volatilities. Using a crop price different from the end-of-season price exposes the farmer unnecessarily to price risk. In practice, the insured and the insurer sign a contract before the growing season, which stipulates the index and pay-off structure in yield units, and agree that yield units are converted into monetary units using the end-of-season crop price. Alternatively, if future-markets exist for the crop to be insured, the future price can be used.

I argued that the use of weather indices that consider the phenological timing improves the goodness of fit between index and yields. As shown, the insurer and the insured benefit from using more accurate weather indices since both profits and risk reduction are enhanced. To derive phenology-sensitive weather indices, the farmer has to correctly report the sowing date of the insured crop to the insurer. The insured has a self-interest in correctly reporting the sowing date as this information affects the correct

[37]Otherwise, a "natural hedge" exists, which compensates negative yield variations through higher prices.

measurement of the index, and thus insurance payments. Based on the sowing date, the insurer can determine the start and end dates of the phenology phases with the help of a process-based crop simulation model – as demonstrated in this paper – or by using the GDD levels corresponding to the crop's phenology phases.

2.8 Appendix

Table 2.11: Weather-yield regression outputs

Weather variable	Index 1	Index 2	Index 3	Index 4	Phenology Phase
m.precip.2	969.8***	13.6***		4446.2***	2
m.precip.3		224.5***		430.2**	3
m.precip.4		304.2**		975.5**	4
m.tmin.1		−13.3*			1
m.tmin.2		214.2**			2
m.tmax.3		34.6*			3
m.tmax.4		108.6**			4
P.ETo.2			12.8***		2
P.ETo.3			15.5***		3
P.ETo.4			6.9**		4
RDI.2				−111810.6***	2
RDI.3				−3949.2*	3
RDI.4				−2447.5**	4
m.precip.2^2				−282.7***	2
m.precip.3^2				−16.2***	3
m.precip.4^2				−51.8**	4
Adj.R^2	37.1	49.3	47.1	62.5	

Note: $***$ significant at the 1% level. $**$ significant at the 5% level. $*$ significant at the 10% level.
m.precip is the mean of daily precipitation values.
m.tmax and m.tmin are, respectively, the means of daily maximum and minimum temperatures.
P.ETo(Priest) is the difference between daily precipitation and daily evapotranspiration (ETo), where ETo is measured using the Priestley-Taylor formula. m.precip^2 are the squared daily mean precipitation values.
RDI(Hamon) is the Reconnaissance Drought Index derived using daily potential evapotranspiration, where ETo is measured using the Hamon formula.

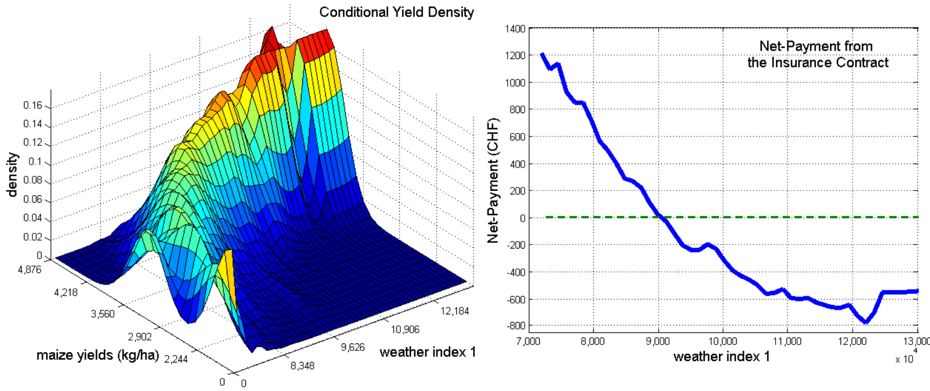

Figure 2.11: Conditional yield density and insurance contract for index 1.

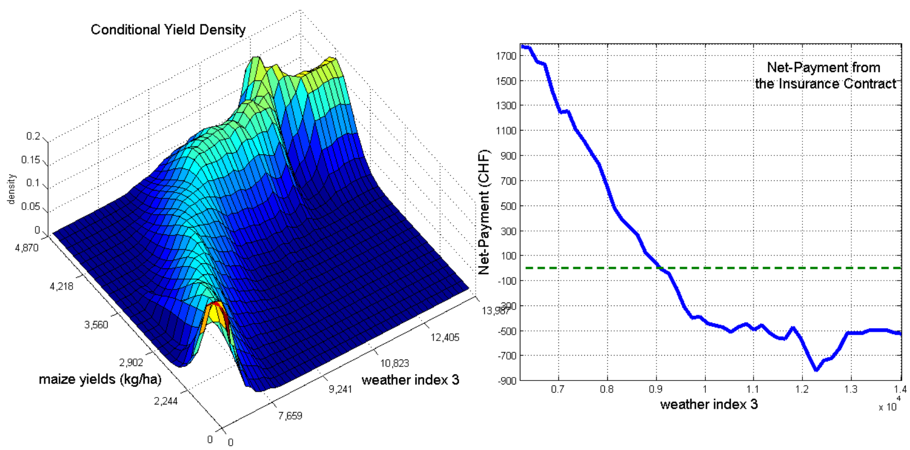

Figure 2.12: Conditional yield density and insurance contract for index 3.

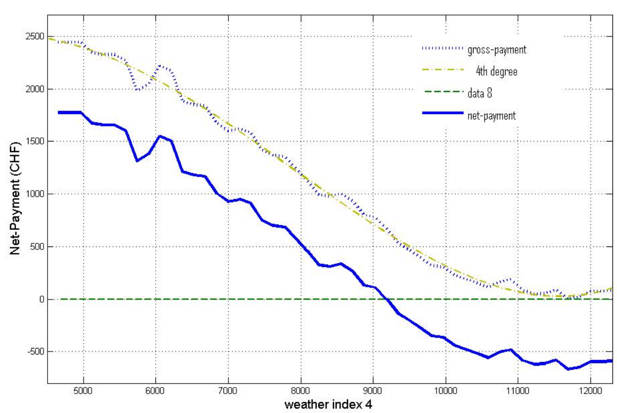

Figure 2.13: Gross and net-payments for insurance contract 4.

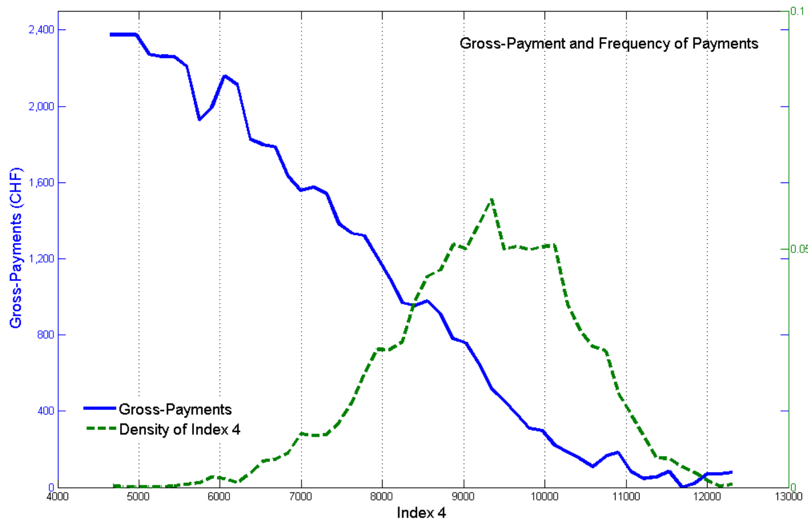

Figure 2.14: Gross-payments with payment probabilities for insurance contract 4.

Table 2.12: Comparison of income distributions for the optimal and profit-maximizing insurance contracts

	Not Insured	Index 1	Index 2	Index 3	Index 4
mean	3696	3691	3691	3691	3689
	-	*(3648)*	*(3630)*	*(3630)*	*(3619)*
std	576.9	436.0	369.0	379.3	338.2
	-	*(436.2)*	*(369.0)*	*(379.4)*	*(338.2)*
skw	-0.73	-0.65	-0.54	-0.41	-0.50
	-	*(-0.65)*	*(-0.54)*	*(-0.41)*	*(-0.50)*
10%	2865	3109	3211	3203	3268
	-	*(3066)*	*(3151)*	*(3143)*	*(3199)*
25%	3337	3448	3478	3471	3501
	-	*(3404)*	*(3417)*	*(3411)*	*(3431)*
50%	3815	3749	3725	3713	3708
	-	*(3706)*	*(3665)*	*(3653)*	*(3638)*
75%	4147	4000	3946	3946	3908
	-	*(3956)*	*(3885)*	*(3886)*	*(3839)*
90%	4349	4193	4138	4135	4094
	-	*(4150)*	*(4078)*	*(4075)*	*(4024)*

Note: In brackets are the results for the profit-maximizing contract. Units: CHF/ha, crop: maize, location: SHA, model parameters: $\sigma = 2$, $ny = 25, nz = 50, bw(1) = 100, bw(2) = 300$.

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Chapter 3

Climate Change, Weather Insurance Design, and Hedging Effectiveness

with P. Calanca and A. Holzkämper
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3.1 Introduction

Climate change causes shifts in average weather conditions and an increase in the weather variability due to changes in the frequency and occurrence of extreme events.[1] Some of the extreme weather events that occurred between 2001 and 2010 exceeded already in intensity, duration, and geographical extent the most significant historical events on record (WMO, 2011). Evidence is mounting that with climate change, the frequency of heatwaves is increasing, for instance, Stott et al. (2004), Beniston (2004), Meehl and Tebaldi (2004), Schär et al. (2004), Fischer and Schär (2010).[2] As a consequence, the return period of events like the pan-European heatwave of 2003 are becoming shorter.

Agricultural production, as well as many other industrial sectors, are sensitive to changes in climatic conditions. An increase of prolonged drought-like conditions, caused by higher temperatures or more frequent heatwaves, has implications for the productivity of the agricultural sector. Scientific evidence, showing that climate change shifts the

[1] According to IPCC (2007), is is very likely ($90-99\%$ probability) that there will be higher maximum temperatures, more hot days, higher minimum temperatures, fewer cold days, and more intense precipitation events over many land areas. It is likely ($67-90\%$ probability) that there will be increased summer drying over most mid-latitude continental interiors and associated risk of drought.

[2] Stott et al. (2004) find an increased probability of hot summers like the 2003 heatwave. Stott et al. (2004) state that it is very likely that human influence on climate has doubled the current risk of a heatwave such as the one that occurred in 2003, compared to preindustrial times.

mean and variance of crop yields, is accumulating. The effect of changes in climatic variables on mean crop yields has been studied widely (Reilly et al., 2002; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009). The year-to-year change in climatic conditions is found to be a major determinant of crop yield fluctuations (Mearns et al., 1992; Olesen and Bindi, 2002; Chen et al., 2004; Isik and Devadoss, 2006; McCarl et al., 2008).[3] Climate change thus makes agricultural production more risky (IPCC, 2001; IPCC, 2007), and without risk management less profitable.[4] Consequently, agricultural insurance solutions become more important to protect against a climate change induced increase in weather-related losses.

The changing occurrence and frequency of extreme weather events implies, however, that historical return periods underestimate the likelihood of agricultural losses in the future. In the context of water-resource risk management, Milly et al. (2008) were the first to note that "climate change undermines a basic assumption that historically has facilitated management of [...] risks." Risk analysis and management relied on the assumption that distributions are stationary over time in order to estimate return periods of weather-related events.[5] In the context of agriculture, McCarl et al. (2008) examine historical crop yield data and find that the stationarity assumption is no longer valid. McCarl et al. (2008) conclude that risk analysis in light of climate change requires to use distributions with non-stationary means and variances along with possibly shifting higher order moments. In conclusion, future agricultural losses cannot be predicted any longer by extrapolating historical trends of weather and yield data.

Insurers have historically provided insurance solutions for weather-related losses, and are going to play an integral role for society to cope with the consequences of climate change. Weather-related insurance losses have increased in recent years, according to Mills (2005), much faster than non-weather related events.[6]

The insurance industry started to pay attention to the implications of climate change for their business (Lloyds of London, 2006; Hawker, 2007; Clemo, 2008; Maynard, 2008; Dlugolecki 2008; Mills, 2009). Traditionally, insurers have used historical data to design

[3]Mearns et al. (1992) investigate how climate variability affects agricultural production. The authors find that increases in variability of temperature and precipitation result in significant increases in yield variability and that precipitation changes have an even more pronounced effect.

[4]The pan-European heatwave of 2003 caused, for example, uninsured crop losses of around USD 12.3 billion (Schär and Jendritzky, 2004).

[5]Milly et al. (2008) defines stationarity as follows: "Stationarity is the idea that natural systems fluctuate within an unchanging envelope of variability. Stationarity implies that any variable has a time-invariant (or a one year periodic) probability density function, whose properties can be estimated from the instrument record."

[6]According to Munich Re (2005), weather-related insurance costs have risen continuously (from 1950 to 2005).

and price insurance products.[7] However, as noted by Hawker (2007) "a changing climate has the potential to reduce the insurance industry's capacity to calculate, price, and spread weather-related risk." Therefore, according to Mills (2009) "insurers' traditional modeling techniques are ill-suited for understanding the implications of climate change ...". Only within natural catastrophe modeling, insurers started to couple climate models with catastrophe models to examine the financial implications of climate change on insured risk (Bresch et al., 2000; ABI, 2009; Wuest et al., 2011). The impact of climate change on other insurance lines, such as index-based weather insurance, however remains to be demonstrated. The aim of this paper is to fill in this gap.

The literature examining the link between climate change and insurance focuses on damage-based forms of weather insurance, such as property and liability insurance (Clemo, 2008; Ward et al., 2008). For damage-based insurance products, climate change implies that new extreme events may occur that cause damages which exceed the extent of previously known damages, and in addition the frequency of weather-related losses is increasing.[8] These studies share the view that if weather related insurance losses continue to rise, insurers will need to respond by increasing premiums, possibly restricting coverage and increasing deductibles for their damage-based weather insurance products. Less attention has been devoted to climate change and *parametric* weather insurance, which is the focus of this work.[9]

Index-based weather insurance is attractive from the perspective of insurers since no uncertainty regarding the extent of payments (i.e. the losses for the insurer) exists. The payoff structure defines the range of all possible payments. Climate change only affects the uncertainty of incorrectly estimating the underlying weather (index) distribution, and thus charging an inadequate premium. For the insured, however, this implies that losses beyond the maximum payment are not insured. In contrast to damage-based insurance, the risk reduction of parametric weather insurance depends on the weather distribution (by affecting the premium) and on the pay-off structure, which determines the indemnity for given realizations of the underlying weather index. With this in mind, we also aim at shedding light on the consequences of using historical data for designing and pricing parametric weather insurance products with respect to risk reduction.

[7] According to Mills (2005), insurers' weather related loss models focus on catastrophic events, and loss-frequency curves are predicted on extrapolating historical trends.

[8] Damage-based insurance products indemnify the insured for weather-related losses based on an inspection of the loss. The insured is thus guaranteed an indemnification according to the terms of the contract, and the insurance product thus delivers the desired risk reduction. Uncertainty about the extent and frequency of losses is born by the insurer.

[9] Parametric insurance, such as index-based weather insurance, indemnify the insured based on the realization of an exogenous, verifiable weather event.

The objective of this paper is twofold. First, we determine the potential for weather insurance in light of climate change. To do so, we evaluate the benefits from hedging weather risk given today's climatic condition, and compare them to the benefits from hedging weather risks with adjusted insurance contracts in a warming and more variable future climate. An adjusted insurance contract explicitly takes the expected changes in the mean and variability of both weather and crop yields into account. To design an adjusted weather insurance contract, we use simulated (forward-looking) weather and yield data representing a possible climate change scenario.

Second, we assess the effect on risk reduction from hedging weather risk in a changing climate with non-adjusted weather insurance contracts. Non-adjusted insurance contracts are designed using historical (backward-looking) data.

We use a process-based crop simulation model to derive maize yields for today's and future climatic conditions. In particular, we use simulated maize yields for Schaffhausen (SHA, latitude: 47.69, longitude: 8.62), Switzerland, that are derived with a process-based crop simulation model, for the current climatic conditions (1981-2001), and for an IPCC A2 emission scenario reflecting climatic conditions around 2050.

To derive weather insurance contracts, we simulate the pay-off structure using the method developed by Kapphan (2011). Other methodologies for deriving weather insurance contracts exist, and could be used in general to address the research questions outlined here. We use the model by Kapphan (2011) since the resulting contracts are designed to yield optimal hedging effectiveness for the insured, or maximal profits for the insurer. The optimal contracts are derived by non-parametrically estimating yield distributions conditional on weather, and maximizing the expected utility of the insured, or by maximizing expected profits for the insurer. Optimal weather insurance contracts are characterized by a non-linear payoff structure (for the entire range of weather realizations).

Given the insurance contracts, we evaluate the benefits from hedging weather risk for today's climate by using an insurance contract that has been simulated for today's conditions, and then compare the findings with the benefits from hedging weather risk in a future climate. To account for the increase in the weather and yield variability due to climate change, we apply the insurance contract that has been derived using future (projected) yield and weather data to future weather conditions. This comparison sheds light on the potential of using weather insurance to hedge weather risks in a changing climate under the assumption that insurers account for the non-stationarity of the underlying weather and yield distributions. We find that, with climate change, the benefits from hedging with adjusted contracts almost triple, and that expected profits increase by about 240% (depending on the contract).

To address our second research question, we use insurance contracts that are designed for today's climate and evaluate the risk reduction that can be achieved with them in a future climate, i.e. we determine the risk reduction of non-adjusted insurance contracts. By comparing the risk reduction of non-adjusted contracts with the benefits from adjusted insurance contracts, we quantify for the first time the effect of not adapting insurance contracts on risk reduction (expected profits) for the insured (the insurer). Our results indicate that insurers may either face substantial losses or generate profits that are significantly smaller than profits from offering adjusted insurance contracts. While our numerical results are crop- and location-specific, our approach for evaluating the potential of parametric weather insurance in a changing climate and for assessing the consequences of offering non-adjusted contracts can be applied to any crop or location for which sufficient data (for calibrating a process-based crop model) exists.

A large strand of literature exists that examines the potential of index-based weather insurance to hedge agricultural yield risk using historical weather and yield data (Vedeneov and Barnett, 2004; Breustedt et al, 2008; Musshoff et al., 2009; Berg et al., 2009; Leblois and Quirion, 2011). By using simulated weather and yield data, we follow Torriani et al. (2007b), who first used climate change data to analyze the benefits from hedging drought risk in today's and future climatic conditions. The idea to use "forward-looking risk models that take climate change into account" is supported, for instance, by Mills (2009). We extend the work by Torrini et al. (2007b) in two aspects. First, we use an optimal weather insurance model to simulate the payoff structure and to determine the hedging benefits for the insured, as well as the expected profits for the insurer, under both climates. Second, and more importantly, we compare for the first time the benefits from hedging future weather risk with an adjusted contract to the risk reduction from a non-adjusted contract.

The remaining paper is structured as follows. In section 3,2, the theoretical approach together with the insurance model and its numerical implementation is explained. The data and climate change scenario used in this study are discussed in section 3.3. The design of the underlying weather indices is outlined in section 3.4. In section 3.5, the results for adjusted insurance contracts are presented, and section 3.6 shows the effect of using non-adjusted contracts to hedge future weather risk. Section 3.7 concludes and provides an outlook on further research.

3.2 Theoretical Approach

We use the model developed by Kapphan (2011) to numerically derive the pay-off structure of an index-based weather insurance with optimal hedging effectiveness for today's and future climatic conditions. For the numerical analysis, we consider five time periods with different climatic conditions, indexed by c. In each climatic period, the insured is faced with a stochastic revenue $y \in \mathcal{Y}_c \equiv [\underline{y}_c, \overline{y}_c]$.[10] We assume for the moment that c only represents either today's, t, or future climatic conditions, f, i.e. $c = \{t, f\}$.[11] Then, for a given climatic scenario c, yields in a given year i are represented by $y_{c,i}$ and $z_{c,i}$ represents the corresponding realization of a weather index. The influence of weather on yields under given climatic conditions is captured through the conditional distribution of yields with cdf $F_c(y|z)$ with density $f_c(y|z)$. The distribution of the weather index, $z \in \mathcal{Z}_c \equiv [\underline{z}_c, \overline{z}_c]$ is characterized by the cdf $G_c(z)$ and density $g_c(z)$. Following Kapphan (2011), the conditional distribution of yields $F_c(y|z)$ and the cdf of the weather index $G_c(z)$ are estimated non-parametrically using a Gaussian kernel function.

The insured is risk-averse and has preferences over consumption, θ, with $\theta = y + p_c(z)$, which are characterized by constant relative risk aversion (CRRA), i.e. $u(\theta) = \frac{\theta^{1-\sigma}}{1-\sigma}$ with $\sigma > 0$.[12] To derive the optimal weather insurance pay-off structure $p_c(z)$ the insured's expected utility is maximized subject to the constraint that risk-neutral insurers charge an actuarially fair premium for the contract.[13] Formally, $p_c^*(z)$ solves the expected utility of the insured

$$\max_{p_c(z)} \int_{\mathcal{Z}_c} \int_{\mathcal{Y}_c} u(y + p_c(z)) dF_c(y|z) dG_c(z) \tag{3.1}$$

subject to the constraint

$$\int_{\mathcal{Z}_c} p_c(z) dG_c(z) = 0. \tag{3.2}$$

Constraint (3.2) implies that insurers make on average zero profits, which is a widely used method, known as the "burn rate" method, to price insurance contracts. The premium P is then determined by the minimum of the net-payment function $p_c^*(z)$.

[10]The insured generates revenue solely from selling the production output. An average price is used to compute the revenue, and production costs are not considered in this framework.

[11]In the numerical section 3.6.2, we add 3 more climatic scenarios that represent the transition period, so that in total 5 periods are analyzed.

[12]To numerically derive the optimal insurance contract, we use a moderate coefficient of relative risk aversion, i.e. $\sigma = 2$. For explorations of how σ affects the shape of the optimal weather insurance contract, see Kapphan (2011).

[13]$p(z)$ represent the net-insurance payments, i.e. the difference between the premium, P, and the insurance indemnity.

Solving (3.1) subject to (3.2) with today's conditional yield cdf, $F_t(y|z)$, and the cdf of today's weather index, $G_t(z)$, yields $p_t^*(z)$. To obtain the optimal weather insurance contract for future climatic conditions $p_f^*(z)$, the optimization problem is solved analogously with $F_f(y|z)$, and $G_f(z)$, which are obtained from simulated weather and yield data that takes climate change into account. In reality, the insurer may add a mark-up on fair premiums to cover additional costs associated with offering weather insurance. In order to determine to which extent fair contracts can be loaded such that the insured still finds the contract attractive, we also derive insurance contracts that maximize the insurer's profit. Formally, for given climatic conditions, c, the profit-maximizing insurance contract $\tilde{p}_c^*(z)$ is derived by solving

$$\max_{\tilde{p}_c(z)} \Pi_c \equiv -\int_{\mathcal{Z}_c} \tilde{p}_c(z) dG_c(z) \tag{3.3}$$

subject to the constraint that the insured's expected utility is equal to or greater than his expected utility in an uninsured situation, i.e.

$$\int_{\mathcal{Z}_c} \int_{\mathcal{Y}_c} u(y + \tilde{p}_c(z)) dF_c(y|z) dG_c(z) \geq \int_{\mathcal{Z}_c} \int_{\mathcal{Y}_c} u(y) dF_c(y|z) dG_c(z). \tag{3.4}$$

Maximum loading factors (in percent) are then determined by comparing the premium of the optimal (zero-profit) contract P with the premium of the profit-maximizing contract $\tilde{P}$ (see Kapphan, 2011). By deriving both the optimal (zero-profit) insurance contract and the profit-maximizing contract, the range of insurance contracts that could feasibly be traded is fully characterized.

To quantify the risk reduction potential of an optimal insurance contract, we compute the percentage increase of all income realizations in the situation without insurance that makes farmers equally well-off (in expected utility terms) as in the situation with insurance (see Kapphan, 2011). Formally, this percentage increase $\delta_c(p_c)$ solves

$$\int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Y}_c} f_c(y|z) \frac{(p_c(z) + y)^{1-\sigma}}{1-\sigma} dy dz = \int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Y}_c} f_c(y|z) \frac{((1 + \delta_c(p_c))y)^{1-\sigma}}{1-\sigma} dy dz, \tag{3.5}$$

with solution:

$$\delta_c(p_c) = \left(\frac{\int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Y}_c} f_c(y|z)(p_c(z) + y)^{1-\sigma} dy dz}{\int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Z}_c} f_c(y|z) y^{1-\sigma} dy dz} \right)^{\frac{1}{1-\sigma}} - 1. \tag{3.6}$$

Thus, $\delta_c(p_c)$ measures the insured's value of weather insurance for a given optimal insurance contract p_c and given climatic conditions c. Furthermore, the statistical moments of the income distribution with insurance are compared to the situation without insurance to evaluate the benefits from hedging. In addition, we compute the relative Value at Risk (VaR) for the situation with insurance, which is the 5% Value at Risk (denoted $VaR^{I}_{c,5\%}$) of the income distribution relative to the mean income, and compare it to the relative $VaR^{NI}_{c,5\%}$ of the situation without insurance. To obtain a complete assessment of the hedging effectiveness of weather insurance, we eventually derive the conditional VaR, which is also referred to as the Expected Shortfall, for the hedged ($ES^{I}_{c,5\%}$) and unhedged situation ($ES^{NI}_{c,5\%}$).

For the insurer, we determine the expected profit from offering a profit-maximizing insurance contract for given climatic conditions as follows:

$$\Pi_c(\tilde{p}_c) = -\int_{\mathcal{Z}_c} \tilde{p}_c(z) dG_c(z). \tag{3.7}$$

By construction, the benefits from hedging with a profit-maximizing contract for the insured, $\delta_c(\tilde{p}_c)$, and the expected profits for an optimal insurance contract, $\Pi_c(p_c)$, are zero. The benefits from hedging with an optimal (zero-profit) insurance contract for today's climatic conditions, $\delta_t(p_t)$, are derived by evaluating the risk reduction in today's climate, δ_t, using an optimal contract $p_t(z)$. The benefit from hedging weather risk in the future with an optimal contract, $p_f(z)$, is then given by $\delta_f(p_f)$.

Comparing the future hedging effectiveness of an optimal contract, $\delta_f(p_f)$, with today's hedging effectiveness of an optimal contract, $\delta_t(p_t)$, allows us to quantify the benefits from using adjusted weather insurance contracts to cope with future weather risk (for the insured). Similarly, by comparing today's expected profits, $\Pi_t(\tilde{p}_t)$ with the expected profits from offering a profit-maximizing contract in the future, $\Pi_f(\tilde{p}_f)$, we quantify the profitability of offering weather insurance in light of climate change.

The risk reduction of a non-adjusted, optimal insurance contract is then given by $\delta_f(p_t)$, and $\Pi_f(p_t)$ measures the expected profits from offering non-adjusted, optimal insurance contract with climate change.[14] We also derive the expected profits for the insurer if he continues to offer today's profit-maximizing contract with climate change, $\Pi_f(\tilde{p}_t)$, i.e. if the today's profit-maximizing contract is not adjusted over time. Similarly, we evaluate the hedging effectiveness of today's profit-maximizing contract with climate change, $\delta_f(p_t)$.

By comparing future expected profits from adjusted, profit-maximizing contracts, $\Pi_f(\tilde{p}_f)$, with the expected profits from offering non-adjusted, profit-maximizing con-

[14] If an optimal insurance contract is offered in climatic conditions that are different from the ones used to design and price the contract, $\Pi_f(p_t)$, is not necessarily equal to zero.

tracts, $\Pi_f(\tilde{p}_t)$, we evaluate the effect of offering non-adjusted insurance contracts on expected profits. Similarly, by comparing the risk reduction of an adjusted, optimal insurance contract, $\delta_f(p_f)$, with the risk reduction from a non-adjusted, optimal contract, $\delta_f(p_t)$, the effect of hedging with non-adjusted weather insurance contracts for the insured is quantified. Table 3.1 provides an overview of the notation and the different comparisons outlined.

Table 3.1: Notation for profits and deltas from adjusted and non-adjusted contracts

Climate		Contract		Profits	Delta
today	**adjusted**	optimal	p_t	0	$\delta_t(p_t)$
		profit-maximizing	$\tilde{p}_t$	$\Pi_c(\tilde{p}_t)$	0
future	**adjusted**	optimal	p_f	0	$\delta_f(p_f)$
		profit-maximizing	$\tilde{p}_f$	$\Pi_c(\tilde{p}_f)$	0
	non-adjusted	optimal	p_t	$\Pi_f(p_t)$	$\delta_f(p_t)$
		profit-maximizing	$\tilde{p}_t$	$\Pi_f(\tilde{p}_t)$	$\delta_f(\tilde{p}_t)$

Note: Insurer's profit (Π_c) and insured's benefit (δ_c) in a given climate scenario ($c = t, f$) depend on the contract type (p_c, or $\tilde{p}_c$), and the climatic condition for which the contract was designed (for c, or $c-1$). If contract p_c or, respectively $\tilde{p}_c$, is used for risk reduction in the climate scenario c, then $\delta_c(p_c)$ represents the risk reduction of an adjusted, optimal contract. $\delta_c(\tilde{p}_c)$ represents the risk reduction from an adjusted, profit-maximizing contract. $\delta_c(p_{c-1})$ represents the risk reduction of an optimal, non-adjusted contract. $\delta_c(\tilde{p}_{c-1})$ represents the risk reduction of a profit-maximizing, non-adjusted contract.

3.3 Data and Climate Change Simulations

To derive maize (*Zea mays L.*) yield data for today's climatic conditions and a climate scenario, we follow Torriani et al. (2007a, 2007b) and use a process-based crop simulation model in connection with a weather generator to simulate $1,000$ yield realizations for each climate scenario. Synthetic weather data needed as input are generated with the stochastic weather generator LARS-WG (Semenov et al., 1998). Observed daily weather data collected between 1981 and 2010 at Schaffhausen (latitude: 47.69, longitude: 8.62) were used to condition LARS-WG, and baseline statistics were modified according to a climate change scenario to yield daily weather series representing future climatic conditions.

As for the climate change scenario (2036-2065), we refer to the same data as used by Lazzarotto et al. (2010) and Finger et al. (2011), that is regional projections for Europe developed by Vidale et al. (2003) with the CHRM regional model in the framework of the PRUDENCE project (Christensen et al., 2007) on the basis of a A2 emission scenario

(Nakicenovic et al., 2000). In practice, differences in monthly averages for the length of wet and dry spells, total rainfall, daily minimum and maximum temperature, and daily totals of solar radiation were first inferred for the time span between 1961-1990 and 2071-2100 originally addressed by PRUDENCE. The differences were then re-scaled in time to yield a corresponding climate change signal for our baseline (1981-2010) and selected future time window (2036-2065).

The synthetic daily weather data feeds into the process-based crop model CropSyst (Stöckle et al., 2003) for maize. CropSyst is a deterministic crop physiological growth model that simulates crop yields for given environmental and management conditions. The calibration for maize is based on Torriani et al. (2007a, 2007b) and was adapted for the newer CropSyst version 4.13.09.[15] Process-based crop simulation models are widely used to study the response of plants to climate change, and to evaluate possible adaption options (Bindi et al., 2010; Finger et al., 2011). Except for the sowing date, all input parameters in CropSyst are kept constant. In today's climate, sowing takes place on calender day 130 (*DOY*). With climate change, the sowing data was shifted by 7 days following Schmid (2006), and takes place on $DOY = 123$.

Table 3.2: Climatic interim scenarios

Climatic scenarios	Today *1981-2001*	Scenario 1 *moderate*	Scenario 2 *medium*	Scenario 3 *strong*	Future *2036-2065*
Weights (t%/f%)	100/0	75/25	50/50	25/75	0/100
Contracts	$p_t(z_t)$	$p_{75/25}(z)$	$p_{50/50}(z)$	$p_{25/75}(z)$	$p_f(z_f)$

Note: Interim scenarios for both weather and yields are created by interpolation of today's and future data. t% is the percent of data used from today's yield and weather distribution, and f% is the percent of data drawn from the simulated weather and yield distribution for the 2036-2065 climate scenario.

For the purpose of this study, three additional weather and yield scenarios were created using weighted random drawings from today's and 2050's weather series. Weights of 75% and 25% (today and future), 50% and 50%, and 25% and 75% were assumed to create interim scenarios.[16] Table 3.2 summarizes the notation for the interim scenarios, and the interpolation weights used for their creation. These interim scenarios cannot be related to particular years between today and 2050, since the climate system may not change linearly from today's conditions to the projected climate around 2050.

Table 3.3 summarizes the statistical moments of the simulated maize data for the baseline and the four climate scenarios. Average maize yields decrease from $9,266$ kilo per

[15]Further details on the parametrization of CropSyst and of LARS-WG can be found in Torriani et al. (2007a, 2007b), together with a comparison of simulated yields with historical yield observations.

[16]Thus, c reflects 5 possible climate scenarios with $c = \{t, 75/25, 50/50, 25/75, f\}$.

hectare (kg/ha) under today's climatic conditions to 8,190 kg/ha for the full 2036-2065 climate change scenario. At the same time, the standard deviation (std) increases from 1,456.5 to 2,105.7 kg/ha, with a corresponding increase in the coefficient of variation (CV) from 0.157 to 0.257. Overall, we observe that mean yields decrease and maize production is becoming more risky. This tendencies can also be inferred from Figure 3.1. This can also be inferred from Figure 3.1 (left), which shows the boxplots for the 5 yield distributions, and the change in the revenues from maize production (right).[17] Hence, without adaptation, maize production is not only becoming less profitable, but also more risky over time.

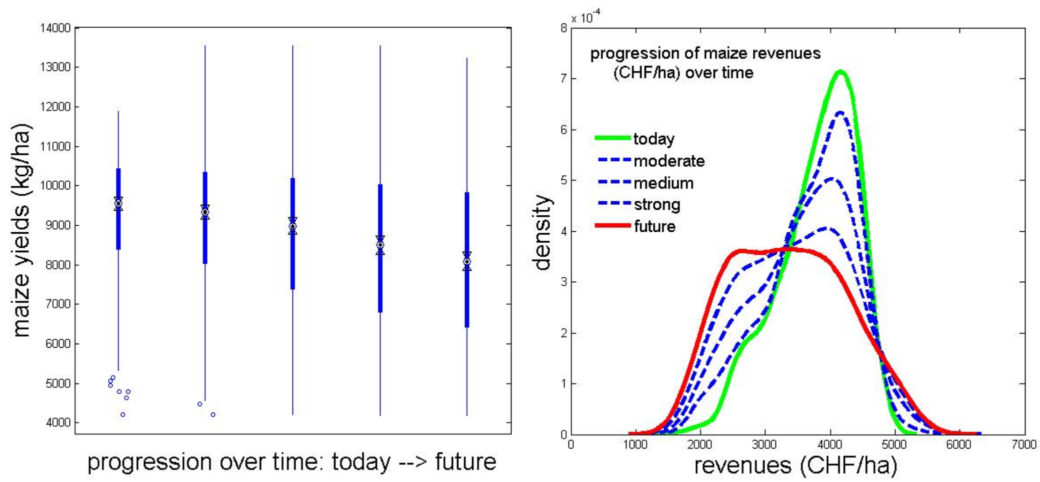

Figure 3.1: Evolution of the maize yield and revenue distribution over time.

Table 3.3: Descriptive analysis of simulated maize yields

Climatic scenario	Today *1981-2001*	Scenario 1 *moderate*	Scenario 2 *medium*	Scenario 3 *strong*	Future *2036-2065*
mean (kg/ha)	9266	9038	8762	8449	8190
std (kg/ha)	1456.5	1681.7	1885.7	2022.2	2105.7
CV	0.157	0.186	0.215	0.239	0.257
skewness	-0.6881	-0.5992	-0.2615	-0.0042	0.1840

Note: Evolution of maize yield statistics for SHA over time.

[17] Revenues from maize production are derived by multiplying crop yields with the average price for maize from 2006 to 2009, which was 41.00 CHF/100kg (SBV, 2010). Production costs are not considered.

3.4 Weather Index Design

The core assumption underlying weather insurance is that there exists a co-variate relationship between crop yields and the underlying weather index. The design of an index-based weather insurance product thus involves identifying a weather index that predicts crop yields well. By creating weather indices that possess a high correlation with crop yields, basis risk is minimized.[18] Since plant development is affected throughout the growing phase by various weather events, multi-peril weather indices tend to predict crop yields better than single weather events (such as cumulated precipitation or mean temperature). We therefore use a phenology driven approach developed by Kapphan (2011) to create weather indices that provide risk protection for a number of weather events occurring throughout the growing period.

To account for the fact that with climate change phenology phases occur earlier in the season, weather variables are derived at each phenology phase for both climatic scenarios (c, f). Phenology stages are estimated based on growing degree days ($GDDs$), the sowing date, and the number of GDDs needed to complete each phenology phase. For maize, 4 phenology phases are distinguished: emergence, vegetative period, grain filling, and maturity. Table 3.4 shows the GDD levels that correspond to each phenology phase and the corresponding calender dates for today's and future climatic conditions. In particular, we use the following variables: averages of maximum and minimum temperatures ($m.tmin$, and $m.tmax$), mean precipitation ($m.precip$), the moisture availability to the plant ($P.ETo$), and the potential evapotranspiration (RDI), which were set in accordance with GDD thresholds used in CropSyst.[19] Next, multivariate regressions are performed to identify weather events that explain a large fraction of the maize yield variability in both climates. The estimated coefficients are then used to construct weather indices. The resulting weather indices thus represent predicted yields, and are measured in kg/ha.

We use this approach to construct multi-peril weather indices for today's and future climatic conditions using the respective weights, as shown in Table 3.15 in the Appendix. For the purpose of this study, we select 4 weather indices – single as well as multi-peril indices – that offer risk protection for different weather phenomena and vary in their goodness of fit. Since precipitation is found to be a major driver of maize growth in Schaffhausen, all indices use precipitation as an input.[20] Figure 3.2 shows the densities of

[18]Basis risk is defined as the risk that the payoffs for a given insurance contract do not correspond to the yield shortfall.

[19]For more information about the weather variables, see Kapphan (2011).

[20]Precipitation enters either directly as an average (as in Index 2), or indirectly via the computation of potential evapotranspiration (as in Index 3), or for deriving the moisture deficit measure (as in Index 4).

Table 3.4: Timing of phenology phases and corresponding GDDs

Phenology Phases	Emergence	Vegetative Period	Grain Filling	Maturity
GDD level	40	700	840	1250
Today (*DOY*)	133-142	195-213	208-227	243-275
avg. DOY	*136*	*204*	*217*	*257*
Future (*DOY*)	126-133	186-200	199-212	230-244
avg. DOY	*128*	*192*	*204*	*236*

Note: Crop: maize, location: SHA, Sowing date for today's climatic conditions: DOY=130, Sowing data for future conditions: DOY=123.

Index 2 and 4 for today's and future climatic conditions. We observe a leftward shift of all index densities, which is caused by a decrease in precipitation in our climate scenario. Further, we find that with climate change the effect of weather on maize yields increases. For example, for today's weather condition, Index 2 explains 50.3% of maize yield variations, while with climate change 68.3% are explained. For Index 3, the Spearman rank correlation coefficient increases from 46.3% to 67.8% with climate change. Overall, a larger fraction of maize yields is explained by weather, which implies that the potential for hedging yield risk with weather-based insurance products improves. Table 3.5 summarizes the Spearman correlation coefficients and adjusted R-Square for the 4 weather indices for both climate scenarios.

We derive interim scenarios for the weather indices (predicted yields) by interpolating the distributions $g_t(z)$ and $g_f(z)$ in the same manner as for crop yields (see section 3.3). As with crop yields, we observe over time a decrease in mean index values, and a widening of the standard deviation over time for all indices.[21]

3.5 Results: Adjusted Weather Insurance Contracts

3.5.1 Comparison of Optimal Contracts Today and with Climate Change

We start by comparing the optimal adjusted weather insurance contract for today's conditions, p_t, with the optimal adjusted contract for future conditions, p_f. The shape of the optimal contracts, p_t and p_f, reflects the changes in the riskiness of the respective conditional yield distributions, as explained in Kapphan (2011), and is non-linear for the entire

[21] In the Appendix, Table 3.16 reports the statistical moments over time for all indices. Thus, we find that neither the maize yield data, nor the data of the underlying (predicted) weather indices is stationary over time.

Table 3.5: Descriptive statistics of weather indices

	in %	Index 1	Index 2	Index 3	Index 4
Today	Corr	60.8	70.9	68.1	78.9
	adj.R^2	37.0	50.3	46.3	62.2
Future	Corr	62.6	82.6	82.3	86.3
	adj.R^2	39.2	68.3	67.8	74.5

Note: Today's weather indices are selected based on the Spearman rank correlation coefficient (Corr) and the adjusted R-Square (adj.R^2) from the weather-yield regression for today's conditions. Future weather indices are constructed using the same weather variables, measured during future phenology phases, and using the coefficients from future weather-yield regressions as weights.

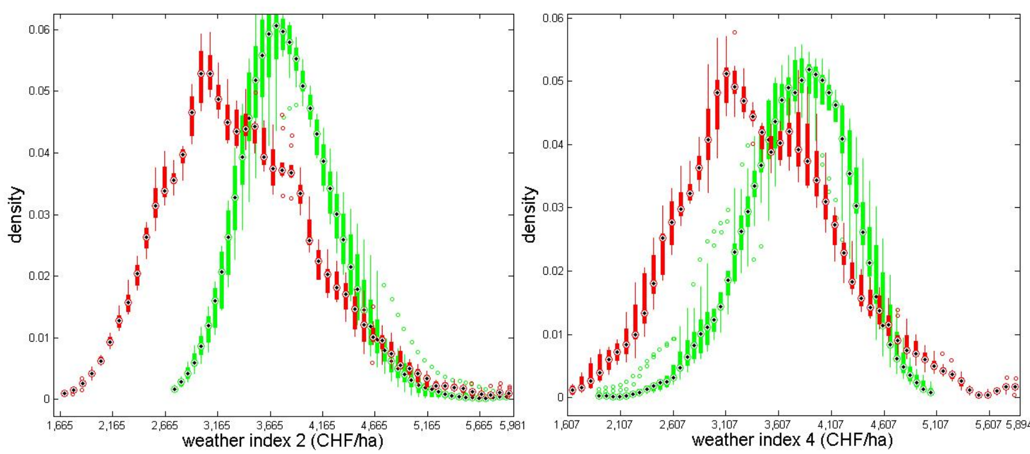

Figure 3.2: Densities of weather Index 2 and 4 for today's (*green*) and future (*red*) climatic conditions. Estimates of the mean and standard deviation at each realization of the weather index are shown as boxplots.

range of weather realizations. All optimal contracts pay out for low values of the weather index, and have negative net-payments (corresponding to a premium payment) for very high values of the index. At the point where the net-payment is equal to zero, the insured fully recovers the premium. The minimum of the pay-off function defines the premium.[22]

Figure 3.3 shows the optimal weather insurance contract for Index 2 for today's and future climatic conditions.[23] We obtain estimates of the standard deviation for $p_c(z)$ (at each realization of z) by 10 times randomly drawing 900 observations with replacement

[22]The gross-payoff function can be obtained by adding the premium to each net-payment. The recovery point of the net payoff function thus represents the trigger level of a stylized (linear) weather derivative. Analogously, the maximum payment of the optimal gross-payoff function can be interpreted as the cap of a stylized weather derivative contract.

[23]In the Appendix, Figure 3.10 shows the optimal weather insurance contracts for all indices for today's and future climatic conditions. The results described here for Index 2 are similar for the other indices.

from the data, and solving (3.1) subject to (3.2) as described in section 3.2.[24] The standard deviation of p_t for moderate z is on average equal to 68.7 CHF/ha, and with climate change, $std(p_f)$ is on average equal to 67.9 CHF/ha. The standard deviation of p_t and p_f increases only for very extreme realizations of the weather index, i.e. $std(p_t) = 119.2$ CHF/ha, and respectively, $std(p_f) = 150.3$ CHF/ha, i.e. for very high, and rare weather events. Our method for simulating optimal weather insurance contracts thus produces robust results.

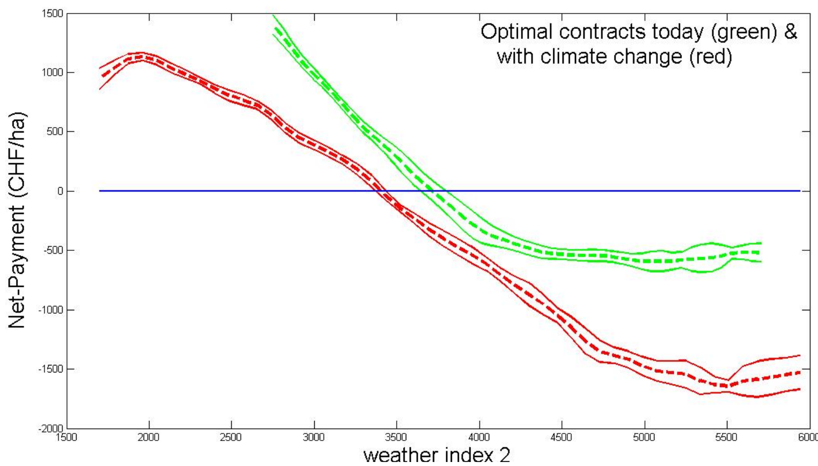

Figure 3.3: Optimal contracts (*dashed line*) for Index 2 with standard deviation (*solid lines*) given today's (*green*) and future (*red*) climatic conditions.

As pointed out in section 3.4, the density of the weather index, $g_c(z)$, shifts to the left with climate change (see Figure 3.2), which is due to a decrease in precipitation during the growing season. In addition, the weather density widens with climate change (i.e. from $c = t$ to $c = f$), which is due to an increase in the number of drought-like weather events. The optimal future contract accounts for these new weather conditions in two ways: i) the payoff function covers these additional weather extremes, and ii) the shape of the payoff function changes (for each realizations of the index). In particular, we find that the future optimal payoff function, p_f, is defined over a wider range of index realizations that covers these additional drought-like conditions. Under today's climatic conditions, p_t for Index 2 is defined for values of z between $2,749$ CHF/ha and $5,707$ CHF/ha. With climate change, the smallest value of z is $1,791$ CHF/ha and the maximum is $5,941$ CHF/ha.

While the range of weather events covered increases, the magnitude of each net-payoff decreases with climate change for the entire range of the weather index. The maximum net-payment decreases from $1,399$ CHF for today's contract to 1.133 CHF for an adjusted

[24]This procedure is also used to obtain estimates for the standard deviation of the risk reduction, as measured by δ_c, and the expected profits, as measured by Π_c, discussed in sections 3.5.2 to 3.5.3.

optimal contract (given Index 2). Note that the probability of having to pay the full premium is in both climate scenarios very small, as can be seen from Figure 3.4, which shows today's optimal contract and the future optimal contract together with the densities of the respective weather indices.[25] At the same time, the premiums for optimal adjusted contracts more than double (depending on the index). For instance, in today's conditions an optimal insurance contract costs 593.0 CHF, and with climate change, an adjusted optimal contract costs 1,645 CHF (based on Index 2).

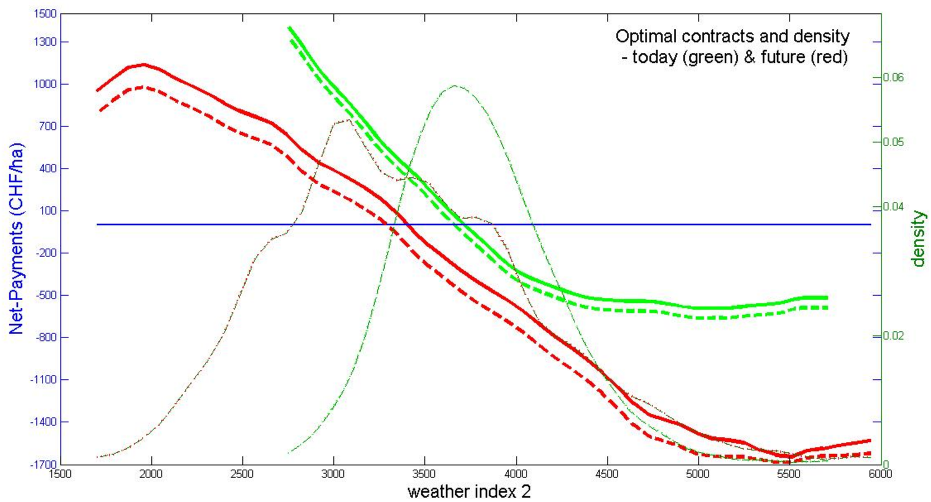

Figure 3.4: Optimal (*solid line*) and profit-maximizing (*dashed line*) insurance contracts for Index 2 with density, for today's (*green*) and future (*red*) climatic conditions.

We also find that while the recovery point of adjusted future contracts shifts to the left, the recovery probability increases.[26] Given today's climate, the insured recovers the premium almost every second year ($49.5-51.5\%$), and with climate change the recovery probability increases to $51.9-57.7\%$ (depending on the index). Table 3.6 provides an overview of the premiums, maximum payments, and the recovery probabilities for today's and future climatic conditions. For today's climate, high net-payments ($p_t \geq 500$ CHF) only occur with low probabilities ($11.5-16.7\%$), and the likelihood of weather events that cause net-payments less than -500 CHF ($p_t \leq -500$) is between 2.6% and 10.2% (depending on the index). With climate change, the probability of the contract paying more than 500 CHF almost doubles (for Index 2 and 3), and ranges from $15.6-27.2\%$ (depending on the index). This explains why we observe an increase in the premiums and

[25]In the Appendix, Figure 3.11 to 3.13 show the optimal and profit-maximizing insurance contracts for Index 1, 3, and 4 together with the density of their underlying weather indices for today's and future climatic conditions.

[26]The recovery probability is the probability of realizing index values equal or smaller than the the recovery point.

in their likelihoods. For all indices, the probability of moderate net-payments between 500 CHF and 0 CHF decreases, together with the probability of having to pay between 0 and -500 CHF. Figure 3.4 shows in addition the adjusted, profit-maximizing insurance contracts. While the profit-maximizing contracts, $\tilde{p}_t$ and $\tilde{p}_f$, possess the same shape as their actuarially fair counterparts, p_t and p_f, they pay out less at each realization of z. The difference in net-payments ($\tilde{p}_c - p_c$) is captured by the insurer. With climate change, the difference in net-payments increases, and hence profits increase (see section 3.5.2).

Future optimal contracts thus offer an increased protection against extreme events (i.e. higher probability of high net-payments with $p_f \geq 500$), while they provide slightly reduced moderate payments (between 500 and -500 CHF) for moderate deviations from the mean of the weather index. The increased coverage against the more frequent occurrence of extreme events is partially financed by decreasing net-payments over the entire range of all weather realizations and by substantially increasing the premiums in those rare years with excellent weather conditions.

Table 3.6: Contract parameters of optimal, adjusted contracts

Net-Payment	Premium	max. payout	recovery probab.	500 to max.payout	0 to 500	-500 to 0	premium to -500
Index 1 today	640.3	971.8	51.2%	11.5%	39.2%	42.1%	7.2%
future	1.634	776.2	51.9%	15.6%	36.6%	37.4%	10.7%
Index 2 today	593.0	1.399	49.6%	12.8%	36.7%	40.3%	10.2%
future	1.645	1.133	57.7%	24.2%	33.6%	23.1%	19.1%
Index 3 today	624.7	1.579	51.5%	13.4%	38.1%	45.9%	2.6%
future	1.640	1.149	55.6%	26.6%	29.1%	23.8%	20.5%
Index 4 today	602.9	1.650	49.5%	16.7%	32.9%	41.8%	8.6%
future	1.675	1.141	55.2%	27.2%	28.1%	23.6%	21.1%

Note: Payments and maximum payout are measured in CHF/ha.

3.5.2 Hedging Effectiveness of Optimal Adjusted Contracts

We evaluate the risk reduction from hedging weather risk by deriving δ_c for all climatic scenarios as described in section 3.2, for a moderate risk aversion level ($\sigma = 2$). Buying optimal weather insurance today is equivalent to increasing the income of the insured in all states of the world by $1.37 - 2.09\%$ (depending on the index). We observe that with climate change, δ_c from hedging with adjusted optimal contracts increases continually over time, and more than doubles up to the year 2050. When buying an adjusted optimal contract in the future, the insured's income in the situation without insurance would need to be increased by $3.00 - 5.42\%$ (depending on the index) to make the insured as well off (in expected utility terms) as in the situation with insurance.

Thus, with climate change, the insured attributes a higher value of hedging weather risk with an optimal adjusted contract. The standard deviation for these estimates does not increase significantly over time. We have restricted the analysis to a moderate level of risk aversion. The hedging benefits for a more risk-averse individual ($\sigma > 2$) under both today's and future climate conditions are even more substantial.[27] Table 3.7 shows the estimates of δ_c with the corresponding standard deviation for all indices and climatic scenarios, and in Figure 3.5, we show boxplots of δ_c over time for all indices.

Table 3.7: δ (in %) for optimal adjusted contracts over time

	Index 1	Index 2	Index 3	Index 4
today	1.37	1.83	1.82	2.09
(std)	*(0.15)*	*(0.18)*	*(0.23)*	*(0.24)*
moderate	2.23	3.04	2.98	3.31
(std)	*(0.19)*	*(0.18)*	*(0.18)*	*(0.16)*
medium	2.78	3.90	3.86	4.20
(std)	*(0.00)*	*(0.12)*	*(0.11)*	*(0.15)*
strong	3.01	4.57	4.54	4.92
(std)	*(0.17)*	*(0.10)*	*(0.11)*	*(0.11)*
future	3.00	4.99	4.98	5.42
(std)	*(0.20)*	*(0.25)*	*(0.28)*	*(0.26)*

We also compare the income distribution without insurance to the situation where the farmer uses an optimal adjusted contract, p_c, and, respectively, a profit-maximizing contract, $\tilde{p}_c$, to hedge his weather risk in today's and future climatic conditions. Given today's weather conditions, the mean income without insurance is $3,696$ CHF/ha with a standard deviation of 186.3 CHF/ha. The optimal insurance contract, p_t, preserves the mean income, but greatly reduces the standard deviation to $106.6 - 139.9$ CHF/ha (depending on the index). The income distribution with a profit-maximizing contract, $\tilde{p}_t$, possess the same standard deviations as with p_t, but the average income is reduced by $49 - 75$ CHF/ha (depending on the index). With climate change, the mean income without insurance decreases by more than 10% (to $3,294$ CHF/ha), while the standard deviation increases by 49.9% (to 279.4 CHF/ha). An adjusted optimal insurance contract, p_f, such as the one based on Index 4, can reduce the future standard deviation by factor 2 (to $130,6$ CHF/ha). The profit-maximizing adjusted contract, $\tilde{p}_f$, achieves the same risk

[27] Kapphan (2011) shows for today's climatic conditions using the same weather indices and optimal contracts that with a coefficient of relative risk aversion of $\sigma \in [5,7]$, δ_t is between 4.2% and 10.7%.

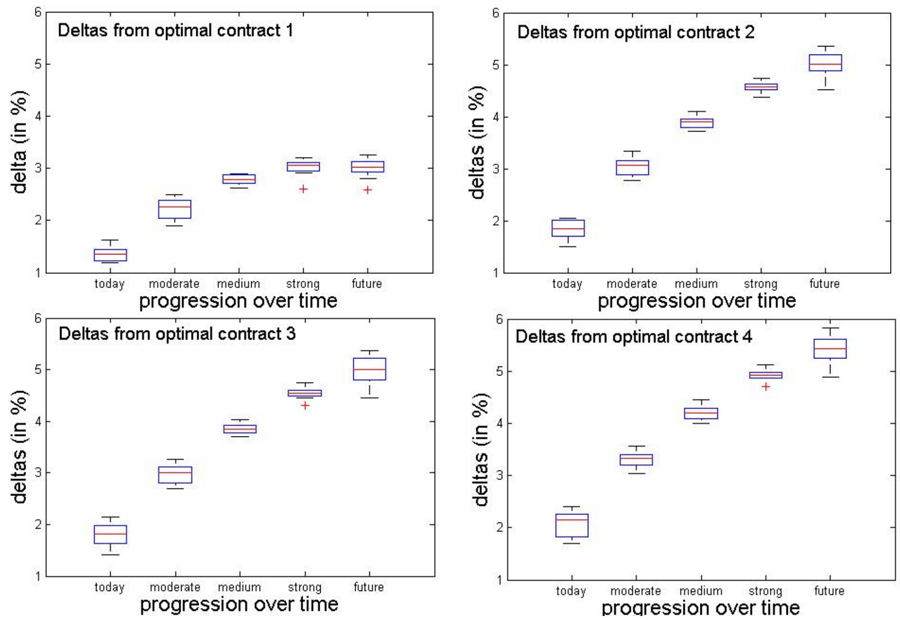

Figure 3.5: Evolution of δ (in %) over time for all optimal adjusted contracts.

reduction, but lowers the average future income (by $88-163$ CHF/ha, depending on the index) compared to the future un-hedged situation. Table 3.8 summarizes the statistical properties (mean, standard deviation, skewness) of the income distributions with and without insurance for today's and future climatic conditions.[28] Figure 3.6 shows the income distributions with insurance, for both the optimal and profit-maximizing contract, and for the scenario without hedging for both climate scenarios.[29]

When hedging weather risk today and in the future with climate change, the insured faces less risk of realizing very low incomes, and lower probabilities of realizing very high incomes, i.e. the insurance contracts compresses the income distribution. An optimal weather insurance contract thus redistributes incomes over time from good harvest years to bad years.

The relative Value at Risk (VaR_α) is another preference-free risk measure, and is defined as follows:

$$rel.VaR_{\alpha\%} = \frac{(\bar{y} - y_{\alpha\%})}{\bar{y}}, \tag{3.8}$$

where $\bar{y}$ represents the mean income and $y_{\alpha\%}$ the income at the $\alpha\%$ quantile. We evaluate the effect of weather insurance by comparing the relative VaR of the income distribution

[28]In Table 3.17 in the Appendix, we report changes in the statistical moments of the income distributions with and without insurance over time for Index 3 and Figure 3.14 shows the boxplots of the income distribution with and without insurance for Index 3.

[29]A comparison of the income distributions with and without insurance for both climate scenarios and all indices can be found in Figure 3.15 in the Appendix.

Table 3.8: Income without and with insurance

optimal		no insurance	Index 1	Index 2	Index 3	Index 4
today	mean	3.696	3.696	3.696	3.696	3.696
	std	186.3	139.9	116.0	120.0	106.6
	skw	-0.222	-0.192	-0.075	-0.030	-0.042
future	mean	3.294	3.294	3.294	3.294	3.294
	std	279.4	208.2	147.2	146.3	130.6
	skw	0.061	0.149	-0.024	-0.008	0.025
profit		no insurance	Index 2	Index 2	Index 3	Index 4
today	mean	3.696	3.647	3.627	3.630	3.621
	std	186.3	139.9	116.0	120.1	106.6
	skw	-0.222	-0.191	-0.074	-0.030	-0.042
future	mean	3.294	3.206	3.145	3.145	3.131
	std	279.4	208.4	147.4	146.5	131.3
	skw	0.061	0.149	-0.027	-0.010	0.021

Note: Descriptive statistics of income without and with optimal and profit-maximizing insurance contracts for all indices and today's and future climatic conditions. Units: CHF/ha.

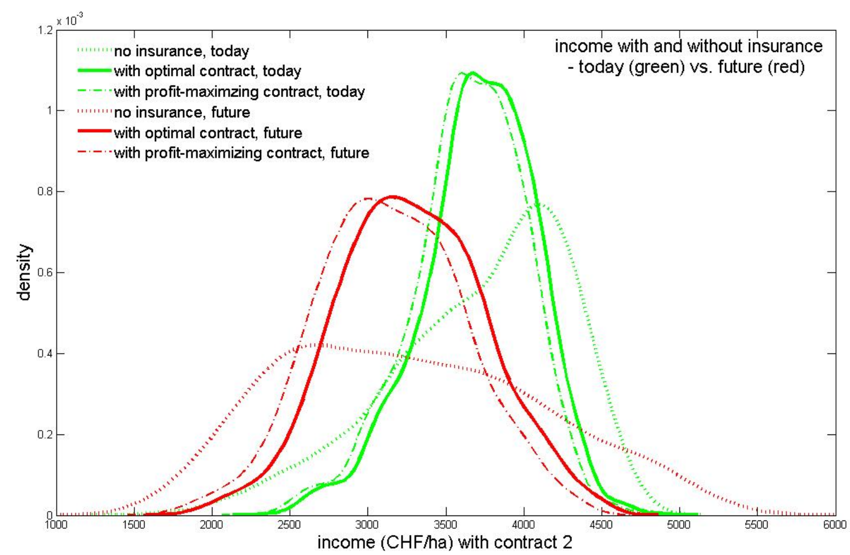

Figure 3.6: Income distributions with optimal (*solid line*) and profit-maximizing (*dashed line*) insurance based on Index 2 and without insurance (*pointed line*) for today's (*green*) and future (*red*) climatic conditions.

without insurance ($VaR^{NI}_{\alpha\%}$) with the relative VaR of the income distribution with insurance ($VaR^{I}_{\alpha\%}$) and thus measure the reduction in the likelihood of income loss for the extreme weather events that occur with a probability α%. In Table 3.9, we report $VaR^{NI}_{\alpha\%}$ and $VaR^{I}_{\alpha\%}$ for all climatic scenarios and indices, for $\alpha = 5\%$.

For today's climatic conditions, there is a 5% probability that the insured realizes an income (loss) that is 31.1% lower than the average income without insurance, i.e. $VaR^{NI}_{t,5\%} = 31.1\%$. With climate change, the income loss increases gradually to 38.7% (with respect to $\bar{y}$) with a 5% likelihood. An optimal insurance contracts reduce the income loss today to $16.7 - 22.8\%$ (depending on the index). With a profit-maximizing contract, today's income loss is also reduced, but $VaR^{I}_{t,5\%}(\tilde{p}_t)$ is on average 2 percentage points higher, compared to $VaR^{I}_{t,5\%}(p_t)$. Under future climatic conditions, hedging with an optimal adjusted contract reduces the income loss to $29.1 - 21.1\%$ compared to the future average income ($\bar{y}_f$).

Table 3.9: Relative 5%-Value at Risk for adjusted contracts

	$VaR^{NI}_{5\%}$	$VaR^{I}_{5\%}$	Index 1	Index 2	Index 3	Index 4
today	31.1	optimal	22.8	18.8	18.5	16.7
	0.65	*std*	*0.93*	*1.09*	*1.05*	*1.03*
	-	profit	24.2	20.6	20.3	18.7
	-	*std*	*0.95*	*1.10*	*1.12*	*0.96*
moderate	35.5	optimal	24.5	20.1	19.9	18.0
	1.04	*std*	*0.44*	*0.43*	*0.38*	*0.41*
	-	profit	27.3	25.3	25.1	19.2
	-	*std*	*0.65*	*1.02*	*0.86*	*0.65*
medium	38.1	optimal	25.9	20.8	20.4	18.7
	0.62	*std*	*0.70*	*0.77*	*0.65*	*0.63*
	-	profit	26.6	21.4	21.0	19.3
	-	*std*	*0.61*	*0.87*	*0.77*	*0.67*
strong	39.1	optimal	27.7	22.2	21.7	20.0
	0.67	*std*	*0.84*	*0.75*	*0.53*	*0.62*
	-	profit	27.6	22.3	22.0	20.2
	-	*std*	*0.75*	*0.72*	*0.51*	*0.59*
future	38.7	optimal	29.1	22.9	22.7	21.2
	1.13	*std*	*0.60*	*0.77*	*0.73*	*0.53*
	-	profit	29.0	23.5	23.3	21.4
	-	*std*	*0.78*	*0.62*	*1.02*	*0.68*

Note: $VaR^{I}_{5\%}$ (in %) of the income distribution for adjusted optimal and profit-maximizing insurance contracts, and $VaR^{NI}_{5\%}$ (in 5%) for the income situation without insurance are derived for all climatic scenarios.

We finally derive the average magnitude of income loss given that an extreme weather event occurs (for the $\alpha = 5\%$-level). The expected shortfall (ES) is the probability weighted average of the worst $\alpha = 5\%$ incomes and thus represents the expectation of income in the case that a tail event occurs.[30] We derive the ES for the income scenarios with ad-

[30] The ES is a measure of tail-risk and is also referred to as the conditional tail expectation, expected tail loss, worst conditional expectation, or tail conditional VaR.

justed insurance contracts ($ES^{I}_{c,5\%}$) and for the situation without insurance ($ES^{NI}_{c,5\%}$) for today's and future climatic conditions.[31] Table 3.10 shows the 5%-VaR and the expected shortfall for today's and future climatic conditions. Without insurance, the $ES^{NI}_{t,5\%}$ is equal to $3,292$ CHF/ha for today's conditions. With optimal adjusted insurance, the expected income $ES^{I}_{t,5\%}$ given that the lower 5%-extreme weather events happen is between $3,390$ and $3,475$ CHF/ha, i.e. optimal adjusted insurance increases the expected income given an extreme event by 100 to 180 CHF/ha. With climate change, the expected unhedged income is $2,727$ CHF/ha for the situation with the 5%-extreme event. With an adjusted contract, the expected income in that 5%-event is $2,886$ to $3,023$ CHF/ha.

Table 3.10: 5%-VaR and expected shortfall (ES) for adjusted contracts

	no. ins.	contract		Index 1	Index 2	Index 3	Index 4
today	3,377	optimal	$\mathbf{VaR}^{I}_{t,5\%}$	3,415	3,502	3,503	3,518
	-	profit		3,402	3,434	3,437	3,443
	3,292	optimal	$\mathbf{EX}^{I}_{t,5\%}$	3,390	3,453	3,447	3,475
	-	profit		3,341	3,385	3,381	3,399
future	2,839	optimal	$\mathbf{VaR}^{I}_{f,5\%}$	2,954	3,052	3,052	3,081
	-	profit		2,865	2,903	2,905	2,915
	2,727	optimal	$\mathbf{EX}^{I}_{f,5\%}$	2,886	2,981	2,990	3,023
	-	profit		2,797	2,832	2,840	2,858

Note: 5%-VaR and Expected Shortfall (ES) at the 5% level of the income distribution with ($ES^{I}_{c,5\%}$) and without insurance ($ES^{NI}_{c,5\%}$) are shown for today's and future climatic conditions and for all indices. Unit: CHF/ha.

In conclusion, both types of adjusted insurance contracts reduce the risk of realizing low incomes. When comparing the hedging effectiveness of our contracts over time, we find that the benefits from using weather insurance increases significantly with climate change, which is due to the fact that with climate change weather exerts a stronger influence on crop yields. That is, with climate change, the preconditions for hedging yield risk with an index-based weather insurance product improves. We have shown that these findings are robust across indices and independent from the risk measure used. If a mark-up is added to the fair premium, the insured gets the same risk reduction benefits (as with a zero-profit contract) but at the cost of a reduced (average) income. By evaluating the hedging benefits of a profit-maximizing contract, we have considered the extreme case where the insurer captures the entire gain from hedging, so that the insured is (in ex-

[31] In contrast to the literature (Dowd and Blake, 2006), where the ES is derived for the loss distribution, we derive the ES for the income distributions with and without insurance, and compare the expected shortfall from hedging, $ES^{I}_{c,5\%}$, to the situation without hedging, $ES^{NI}_{c,5\%}$.

pected utility terms) indifferent to the un-hedged situation. In practice, these gains can be shared between the insurer and the insured. For all risk measures, we observe that there is a variation of hedging benefits across contracts. In general, the better the goodness-of-fit of the underlying index with crop yields, the better the risk reduction.

3.5.3 Expected Profits from Profit-Maximizing Adjusted Contracts

We derive the expected profits, Π_c, that an insurer can expect to earn from offering a profit-maximizing insurance contract by solving (4.8) for all climatic conditions given $\tilde{p}_c$ and $g_c(z)$.[32] Table 3.11 shows the expected profits for all indices over time together with the estimated standard deviation, for $\sigma = 2$. For today's climatic conditions, the insurer can expect to earn between 41.6 to 67.2 CHF/ha of insured maize. We find that with climate change, expected profits increase gradually over time and reach substantial values. For instance, expected profits for Index 1 double, and they increase by 240% for the other three indices by the year 2050. In Figure 3.7, we present boxplots of expected profits over time for all indices.

Table 3.11: Profits (Π) from profit-maximizing adjusted contracts over time

	Index 1	Index 2	Index 3	Index 4
today	41.61	61.29	58.78	67.29
(std)	*(4.24)*	*(5.84)*	*(4.96)*	*(6.42)*
moderate	74.80	103.08	100.94	112.56
(std)	*(6.10)*	*(5.99)*	*(6.01)*	*(5.30)*
medium	89.51	126.93	125.62	137.32
(std)	*(2.94)*	*(3.85)*	*(3.58)*	*(4.64)*
strong	92.20	142.2	141.48	153.84
(std)	*(5.32)*	*(3.23)*	*(3.51)*	*(3.43)*
future	88.28	149.56	149.20	163.30
(std)	*(5.92)*	*(7.42)*	*(8.30)*	*(8.00)*

Note: Profits are measured in CHF/ha.

We observe that the variation in expected profits across indices as well as the variation of δ_c across indices (as seen in section 3.5.2), is related to the goodness-of-fit of the underlying weather indices with maize yields (see section 3.4, Table 3.5). The higher the correlation of the weather index with yields, the better the hedging effectiveness (as measured by δ) and the higher are expected profits (as measured by Π).

[32]Note that the expected profits from an optimal adjusted insurance contract are zero by construction.

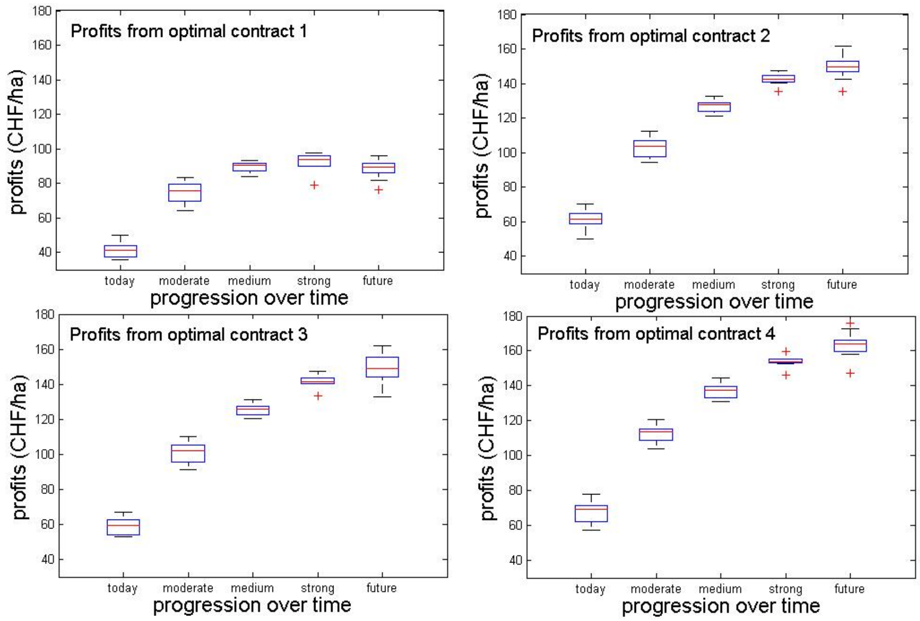

Figure 3.7: Evolution of profits (in CHF/ha) over time for all profit-maximizing adjusted contracts.

3.6 Results: Non-Adjusted Weather Insurance Contracts

3.6.1 Comparison of Adjusted and Non-Adjusted Contracts

We now examine the risk reduction from hedging future weather risk with non-adjusted insurance contracts. For that purpose, we first analyze the payout probabilities of non-adjusted contracts, which were initially priced and designed for today's weather conditions, but are used under future climatic conditions. We then compare the payout-probabilities of non-adjusted contracts to the payout characteristics of adjusted contracts in future climatic conditions (see Table 3.12).

We find that the non-adjusted contracts based on Index 1 and 4 have higher recovery probabilities than the corresponding adjusted contracts. For instance, the insured recovers the premium of an adjusted contract (based on Index 4) with a probability of 55.2%, while the premium is recovered with a probability of 84.6% with the non-adjusted contract. The increase in the recovery probability of non-adjusted contracts 1 and 4 is a result of an increase in the occurrence of weather events that trigger very high net-payments. For Index 4, the probability of net-payments above 500 CHF increases from 27.2% (given an adjusted contract) to 55.2% with the non-adjusted contract.

For Indices 2 and 3, we find that the likelihood of fully recovering the premium decreases. The adjusted contract based on Index 2 triggers very high net-payments ($p_f(z) >$

500 CHF) with 24.2%, while the non-adjusted contract delivers high net-payments only with a probability of 10.0%. This implies that the non-adjusted contracts based on Index 2 and 3 do not provide sufficiently high net-payments when needed.

The non-adjusted contracts based on Index 1 and 4, provide however very high net-payments even in situations where smaller payments would have been sufficient to cover the losses. For Index 1 and 4, the non-adjusted contracts trigger net-payments of less than -500 CHF ($p_f(z) \leq -500$) less often than the corresponding adjusted contracts. For instance, the probability of net-payments that are less than -500 CHF is 2.2% with the non-adjusted contract, compared to 21.1% with the adjusted contract. With future weather conditions, an actuarial fair contract implies that the insured can expect to pay the full premium approximately every 5th year (given that excellent weather conditions have a return period of 21.1%).

With non-adjusted contracts (based on Index 4), this event happens only every 50th years. This already suggests that the non-adjusted contract will no longer be profitable to the insurer (see section 3.6.2).

Comparing the payout probabilities of non-adjusted contracts with those from adjusted contracts provides a first impression of the weather events that are being hedged by non-adjusted contracts. Non-adjusted contracts 1 and 4 provide positive net-payments with a higher probability, while the probabilities of negative net-payments decreases (compared to the corresponding adjusted contract). For contracts 2 and 3, it is less clear if the insured is better or worse off with the non-adjusted contracts. For that purpose, we turn to the evaluation of the hedging effectiveness of non-adjusted contracts. Risk measures are better suited to discriminate between different insurance contracts. For the remaining analysis, δ_c is our preferred measure for comparing the risk reduction of adjusted with non-adjusted insurance contracts.[33]

[33] In section 3.5.2, we showed that it produces the same qualitative results as the other preference-free risk measures, and that it is better suited for comparing the hedging effectiveness across climatic scenarios as it considerers the effect of insurance on the entire income distribution.

Table 3.12: Pay-out probabilities of optimal adjusted and non-adjusted insurance contracts

Contract	Type	Climate	Premium	max. payout	rec. probab.	500 to max.payout	0 to 500	-500 to 0	premium to -500
Index 1	**adjusted**	today	640.3	971.8	51.2%	11.5%	39.2%	42.1%	7.2%
		future	1.634	776.2	51.9%	15.6%	36.6%	37.4%	10.7%
	non-adjusted	future	-	-	**61.1**%	**19.1**%	**42.0**%	**33.1**%	**5.8**%
Index 2	**adjusted**	today	593.0	1.399	49.6%	12.8%	36.7%	40.3%	10.2%
		future	1.645	1.133	57.7%	24.2%	33.6%	23.1%	19.1%
	non-adjusted	future	-	-	**39.5**%	**10.0**%	**29.5**%	**41.5**%	**19.0**%
Index 3	**adjusted**	today	624.7	1.579	51.5%	13.4%	38.1%	45.9%	2.6%
		future	1.640	1.149	55.6%	26.6%	29.1%	23.8%	20.5%
	non-adjusted	future	-	-	**46.3**%	**15.2**%	**31.1**%	**46.8**%	**6.9**%
Index 4	**adjusted**	today	602.9	1.650	49.5%	16.7%	32.9%	41.8%	8.6%
		future	1.675	1.141	55.2%	27.2%	28.1%	23.6%	21.1%
	non-adjusted	future	-	-	**84.6**%	**55.2**%	**29.4**%	**13.2**%	**2.2**%

Note: Payments and maximum payout are measured in CHF/ha. The insurance characteristics of the non-adjusted contract are derived from analyzing today's optimal insurance contract under future climatic conditions. Note that the premium and maximum payout of the non-adjusted contracts in future conditions are the same as for the adjusted contract in today's conditions.

3.6.2 Hedging Effectiveness and Expected Profits of Non-Adjusted Contracts

To determine the hedging effectiveness of non-adjusted contracts, we derive δ_c from hedging with the optimal and profit-maximizing non-adjusted contracts, and compare it with the hedging effectiveness of the adjusted contract. For a more realistic comparison, we take into account that insurers are updating the design (and pricing) of their insurance products over long time periods, such as the one considered here, i.e. between 1990 and 2050. In particular, we assume that insurers adapt their weather insurance products at the end of each climatic scenario, i.e. they use the new weather and yield data that is becoming available to update their contracts for the coming scenario. For that purpose, we use the interim scenarios and simulate first the adjusted insurance contracts (p_c and $\tilde{p}_c$) for all scenarios $c \in \{t, 75/25, 50/50, 25/75, f\}$. We derive the income distributions in each climatic scenario c from hedging with the non-adjusted (optimal and profit-maximizing) contracts from the previous period $c-1$. We then determine δ_c for hedging weather risk in c with non-adjusted optimal insurance products, i.e $\delta_c(p_{c-1}(z))$, and for hedging with a non-adjusted profit-maximizing contract, i.e. $\delta_c(\tilde{p}_{c-1}(z))$.[34] Table 3.13 summarizes the results, and Figure 3.8 shows the evolution of δ_c for adjusted and non-adjusted contracts over time for all indices. We find that $\delta_c(p_{c-1}(z))$ can be bigger or smaller than $\delta_c(p_c(z))$. In contrast to hedging with adjusted contracts, we observe that $\delta_c(p_{c-1}(z))$ takes on negative values, i.e. the expected utility of the insured is reduced through insurance. As a result, such non-adjusted contracts would not be purchased.

Furthermore, we determine the expected profits for insurers from offering non-adjusted weather insurance contracts. For that purpose, we derive the expected profits, Π_c, in each climatic scenario from offering the non-adjusted, optimal ($p_{c-1}(z)$) and non-adjusted, profit-maximizing contract ($\tilde{p}_{c-1}(z)$). We then compare $\Pi_c(p_{c-1}(z))$ and, respectively, $\Pi_c(\tilde{p}_{c-1}(z))$ with the expected profits from the adjusted profit-maximizing contract, $\Pi_c(\tilde{p}_c(z))$. Table 3.14 reports the profits from non-adjusted contracts together with the profits from adjusted contracts (from section 3.5.3, Table 3.11), and Figure 3.9 shows the evolution of profits from adjusted and non-adjusted contracts over time for all indices. We find that some non-adjusted contracts create losses for the insurer, and as a result would not be offered. By evaluating the risk reduction (for the insured) from non-adjusted contracts, and simultaneously assessing the profitability (for the insurer), we capture over time the effect of using backward looking data to design and price weather insurance products in light of climate change.

[34] Note that $\delta_c(\tilde{p}_{c-1})$ is in contrast to $\delta_c(\tilde{p}_c)$ not necessarily equal to zero.

Table 3.13: δ (in%) for adjusted and non-adjusted insurance contracts

			Index 1	Index 2	Index 3	Index 4
today	**adjusted**	optimal	**1.37**	**1.83**	**1.82**	**2.09**
		(std)	*(0.15)*	*(0.18)*	*(0.23)*	*(0.24)*
moderate	**adjusted**	optimal	**2.23**	**3.04**	**2.98**	**3.31**
		(std)	*(0.19)*	*(0.18)*	*(0.18)*	*(0.16)*
	non-adjusted	optimal	-2.42	-6.98	-5.34	12.93
		(std)	*1.10*	*1.37*	*1.38*	*2.67*
		profit	-3.82	-8.95	-7.23	10.81
		(std)	*1.10*	*1.38*	*1.38*	*2.67*
medium	**adjusted**	optimal	**2.78**	**3.90**	**3.86**	**4.20**
		(std)	*0.00*	*0.12*	*0.11*	*0.15*
	non-adjusted	optimal	9.28	6.23	6.56	5.88
		(std)	*1.60*	*1.39*	*1.67*	*2.04*
		profit	7.23	3.40	3.76	2.76
		(std)	*1.60*	*1.38*	*1.67*	*2.04*
strong	**adjusted**	optimal	**3.01**	**4.57**	**4.54**	**4.92**
		(std)	*0.17*	*0.10*	*0.11*	*0.11*
	non-adjusted	optimal	6.31	8.87	8.74	9.39
		(std)	*1.16*	*0.53*	*1.19*	*1.60*
		profit	3.37	6.07	4.87	5.21
		(std)	*1.17*	*0.52*	*1.19*	*1.58*
future	**adjusted**	optimal	**3.00**	**4.99**	**4.98**	**5.42**
		(std)	*0.20*	*0.25*	*0.28*	*0.26*
	non-adjusted	optimal	5.36	8.12	8.14	10.04
		(std)	*1.82*	*0.97*	*3.04*	*1.93*
		profit	2.24	3.39	3.43	4.92
		(std)	*1.82*	*0.95*	*3.02*	*1.92*

Note: δ is the percentage increase of all income realizations without insurance compared to the situation with insurance. Deltas ($\delta_c(z)$) from non-adjusted contracts in a given climate scenario (c) are derived by applying the optimal ($p_{c-1}(z)$) or the profit-maximizing ($\tilde{p}_{c-1}(z)$) insurance contract from the previous climatic scenario ($c-1$) to the current climate scenario. Deltas from adjusted contracts are derived by applying the optimal insurance contract ($p_c(z)$) to the conditions for which it is derived, namely to c.

In the moderate scenario, we observe that non-adjusted optimal and profit-maximizing contracts, based on index 1, 2 and 3 generate positive profits. These profits, $\Pi_{75/25}(p_t(z))$ $= 145.8 - 310.1$ CHF/ha and, respectively, $\Pi_i(\tilde{p}_t(z)) = 192.9 - 375.9$ CHF/ha, are substantially higher than the profits from the adjusted profit-maximizing contracts.
$\Pi_{75/25}(\tilde{p}_{75/25}(z))$ ranges between $=$ 74.8 to 112.5 CHF/ha depending on the index. In contrast, the non-adjusted contracts based on Index 4 generate negative profits (-260.6 to -332.8 CHF/ha, depending on the type of contract) for the insurer. At the same time,

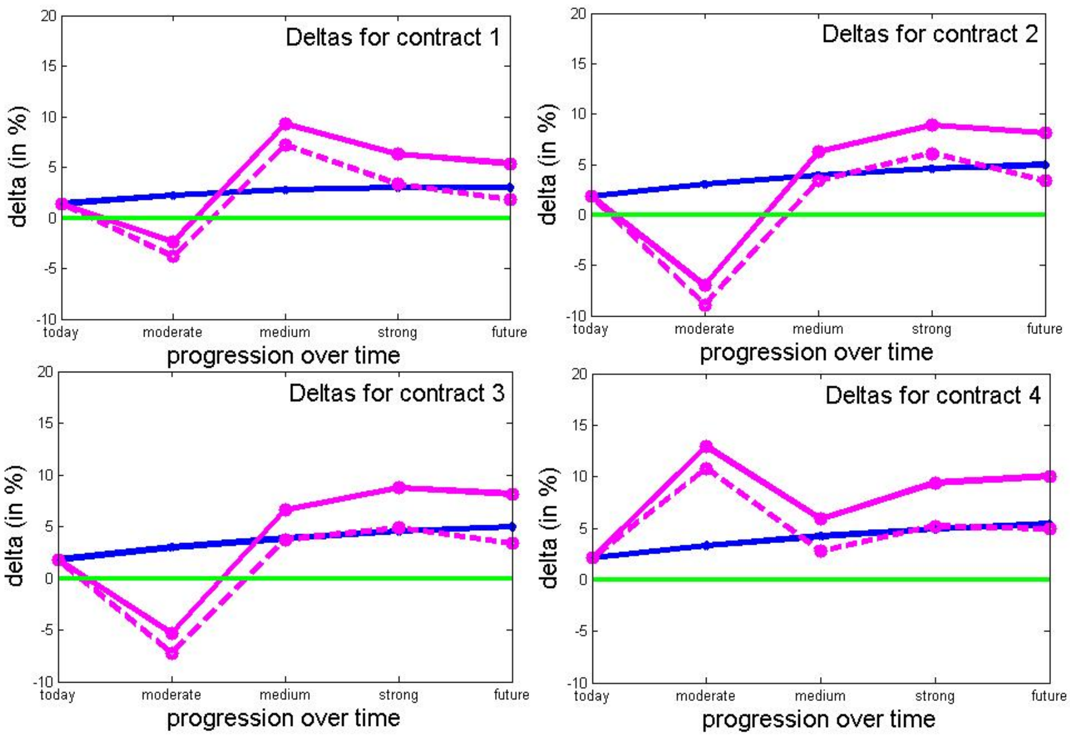

Figure 3.8: Delta (in %) for adjusted (*blue*) and non-adjusted optimal (*pink, solid line*) and non-adjusted profit-maximizing contracts (*pink, dashed line*) are shown over time for all indices. The non-adjusted δ_c from hedging with an optimal contract $\delta_c(p_{c-1}(z))$ is derived by determining the risk reduction in climatic scneario c from hedging with an optimal contract $(p_{c-1}(z))$ from the previous period $c-1$. Hedging in c with a non-adjusted profit-maximizing contract from the previous period yields $\delta_c(\tilde{p}_{c-1}(z))$.

$\delta_{75/25}(p_t(z))$ is between -2.42% and -6.98%, for Index 1, 2 and 3. The non-adjusted profit-maximizing contract makes the insured in the moderate scenario even worse off, i.e. $\delta_{75/25}(\tilde{p}_t(z))$ is between -3.82% and -8.95% for contracts based on Index 1, 2, and 3. Therefore, contracts 1, 2, and 3 would not be bought by the insured.

Hedging with an adjusted contract, $\delta_{75/25}(p_{75/25}(z))$, in contrast generates positive hedging benefits of $2.23 - 3.31\%$ (depending on the index). With the non-adjusted contracts based on Index 4, which generate a 4-times higher δ_c than the corresponding adjusted contract, the insured's crop losses would be overcompensated. Since this contract generates losses of -260.6 to -332.8 CHF/ha (depending on the type of contract), it will however not be offered by the insurer.

The situation changes in the medium scenario. For all indices, $\delta_{50/50}(p_{75/25}(z))$ takes on values that are higher than $\delta_{50/50}(p_{50/50}(z))$ from the adjusted contracts. The hedging effectiveness of the non-adjusted contract 3 (6.55%) is almost twice as high as for the

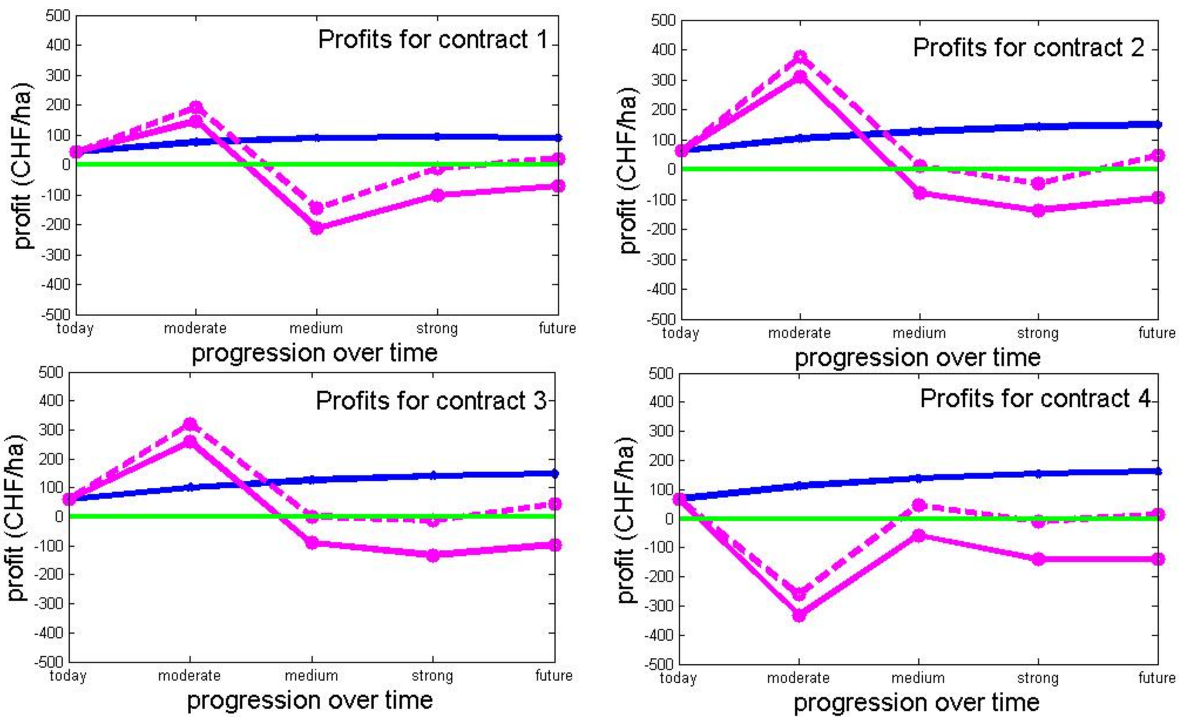

Figure 3.9: Profits (in CHF/ha) for adjusted (*blue*) and non-adjusted, optimal contracts (*pink, solid line*) and non-adjusted, profit-maximizing (*pink, dashed line*) are shown over time for all indices. The Π_c from hedging with an optimal non-adjusted contract $\Pi_c(p_{c-1}(z))$ is derived by determining the expected profits in climatic scenario c from offering an optimal contract ($p_{c-1}(z)$) from the previous period $c-1$. The Π_c from offering a non-adjusted profit-maximizing contract from the previous period yields $\Pi_c(\tilde{p}_{c-1}(z))$.

corresponding adjusted contracts (3.86%), and the non-adjusted profit-maximizing contract yields almost the same hedging benefits (3.76%) as the adjusted contract (3.85%). All non-adjusted optimal contrasts generate losses for the insurer.

While the non-adjusted optimal contracts generate losses for the insured, some non-adjusted profit-maximizing contracts (based on Index 2 and 4) generate positive profits. Expected profits for non-adjusted profit-maximizing contracts, $\Pi_f(\tilde{p}_{75/25}(z))$, range between 13.8 and 46.4 CHF/ha (depending on the index). In addition, we observe that the insured is (almost) indifferent between the non-adjusted profit-maximizing contract and the adjusted optimal contract.[35] Since $\delta_{50/50}(\tilde{p}_{75/25}(z))$ and $\Pi_{50/50}(\tilde{p}_{75/25}(z))$ are both positive, these non-adjusted contracts would be traded. We observe this pattern also in the future scenario.

[35]When taking the standard deviation of δ_c into account, which is 1.6% for the non-adjusted contract, compared to 0.11% for the adjusted contract, it turns out that the hedging performance of the non-adjusted contract is more variable, making the non-adjusted contracts less attractive.

In the future scenario, both non-adjusted contracts generate a higher δ_c than the adjusted contract. The non-adjusted optimal contract produces a higher δ_c than the non-adjusted profit-maximizing contract. Given that expected profits for the non-adjusted optimal contracts, $\prod_f(p_{25/75}(z))$, is negative, these contracts will not be offered. The insurer could generate positive profits by offering the non-adjusted profit-maximizing contracts, as they yield a positive risk reduction. In the future scenario, $\delta_f(\tilde{p}_f(z))$ is 5.42%, while $\delta_f(\tilde{p}_{25/75}(z))$ is 4.92%. We observe however for all climatic scenarios that the standard deviation of $\delta_c(p_{c-1}(z))$, or respectively $\delta_c(\tilde{p}_{c-1}(z))$, is bigger than the standard deviation of $\delta_c(p_c(z))$. For the insured, this implies that insuring with non-adjusted contracts is more risky compared to hedging with an adjusted contract.

While expected profits from non-adjusted profit-maximizing contracts are positive (in the medium and future scenario, for certain indices), they are significantly smaller than the profits from offering adjusted profit-maximizing contracts. Non-adjusted profit-maximizing contracts in the future scenario generate profits of 13.8 to 46.4 CHF/ha, which reflects approximately the expected profits in today's conditions. By offering an adjusted contract, the insurer could generate profits that are 3 times higher. $\Pi_f(p_f(z))$ ranges between 88.2 and 163.3 CHF/ha. The standard deviation for all non-adjusted contracts is also quite large compared to the standard deviation of the adjusted contracts. Thus, offering non-adjusted contracts is more risky than offering adjusted profit-maximizing contracts.

To sum up, evaluating the effect of hedging with non-adjusted insurance contracts for the insured revealed that non-adjusted contracts exist that generate higher hedging benefits than their adjusted counterparts in certain scenarios (medium, and strong), but may make the insured worse off in others (future). In some cases, insuring with non-adjusted contracts may make the insured even worse off than in the situation without insurance (moderate).

We show that non-adjusted contracts that generate a higher hedging effectiveness than their adjusted contracts are not going to be offered by the insurer as these contracts create losses. Similarly, for the situation where expected profits from non-adjusted contracts are higher than profits from adjusted contracts (moderate), an evaluation of the hedging effectiveness shows that these contracts (based on Index 1, 2, and 3) produce a negative δ. These contracts would re-distribute wealth from the insured to the insurer and the insured would not buy them. As a result, insurers may not be able to sell non-adjusted weather insurance contracts any longer.

Focusing on non-adjusted contracts that produce simultaneously positive profits and hedging benefits, we find that the insurer (and the insured) could be better off with an

Table 3.14: Profits (in CHF/ha) for adjusted and non-adjusted contracts

			Index 1	Index 2	Index 3	Index 4
today	**adjusted**	optimal	**41.61**	**61.29**	**58.78**	**67.29**
		(std)	*4.24*	*5.84*	*4.96*	*6.42*
moderate	**adjusted**	optimal	**74.80**	**103.08**	**100.94**	**112.56**
		(std)	*6.1*	*5.9*	*6.0*	*5.3*
	non-adjusted	optimal	145.8	310.1	257.7	-332.8
		(std)	*36.4*	*39.6*	*42.6*	*93.4*
		profit	192.9	375.9	321.1	-260.6
		(std)	*36.4*	*39.7*	*42.7*	*93.5*
medium	**adjusted**	optimal	**89.51**	**126.93**	**125.62**	**137.32**
		(std)	*2.94*	*3.85*	*3.58*	*4.64*
	non-adjusted	optimal	-212.8	-79.1	-91.0	-57.1
		(std)	*51.6*	*44.3*	*54.7*	*65.0*
		profit	-146.4	13.0	0.15	45.0
		(std)	*51.6*	*44.3*	*54.6*	*65.0*
strong	**adjusted**	optimal	**92.20**	**142.2**	**141.48**	**153.84**
		(std)	*5.32*	*3.23*	*3.51*	*3.43*
	non-adjusted	optimal	-102.8	-135.4	-132.5	-140.7
		(std)	*36.83*	*16.8*	*36.2*	*48.8*
		profit	-12.6	-47.7	-11.5	-9.6
		(std)	*36.7*	*17.1*	*36.2*	*48.7*
future	**adjusted**	**optimal**	**88.28**	**149.56**	**149.20**	**163.30**
		(std)	*8.0*	*7.42*	*8.30*	*8.0*
	non-adjusted	optimal	-71.9	-95.6	-97.0	-140.6
		(std)	*53.1*	*31.0*	*92.5*	*61.3*
		profit	19.8	46.4	44.4	13.8
		(std)	*53.0*	*30.8*	*92.2*	*61.1*

Note: Expected profits from adjusted and non-adjusted contracts (in CHF/ha) for all indices are shown over time, together with the standard deviation Expected profits from non-adjusted contracts ($\Pi_c(p_{c-1})$, or $\Pi_c(\tilde{p}_{c-1})$,) in a given climatic scenario (c) are derived by calculating the net-payments from offering an optimal ($p_{c-1}(z)$), or a profit-maximizing ($\tilde{p}_{c-1}(z)$) insurance contract from the previous climatic conditions ($c-1$) in c. Crop: maize, location: SHA, model parameters: $ny = 25$, $nz = 50$, $bw(1) = 100$, $bw(2) = 300$, and $\sigma = 2$.

adjusted profit-maximizing contract (optimal contract), because these contracts generate on average similar expected profits (expected δ) at a lower standard deviation. By not adapting weather insurance contracts on time, insurers face the risk of huge losses (as in the strong scenario), and the risk reduction for the insured is no longer guaranteed (as in the moderate scenario).

3.7 Conclusion

We shed light on the consequences of using historical data for designing (and pricing) weather insurance products for the resulting hedging effectiveness for the insured, and the profitability for insurers. The objective of this paper is twofold: First, we evaluate the potential of using weather insurance to manage the climate change induced increase in weather risk. A process-based crop simulation model is used to simulate crop yield data for today's weather conditions, and for a climate change scenario for the time period 2036-2065. The stationarity assumption is not valid for the yield and weather data used in this study. We simulate adjusted weather insurance contracts for today's and future climatic conditions using an insurance model developed by Kapphan (2011). Adjusted insurance contracts are developed using weather data that represents the weather risk to be hedged. We find that the payoff function of adjusted contracts changes its shape over time, and that adjusted contracts are defined over a wider range of so far unprecedented realizations of the weather index. For stylized (linear) weather derivatives, our findings imply that insurance parameters (strike, exit, tick size, and cap) have to be adjusted over time to effectively hedge future weather risk.

We show that the increase in weather risk due to climate change generates a huge potential for the weather insurance industry. In particular, we find that the insurance industry can expect profits to increase by up to 240% (depending on the contract) when offering adjusted contracts. At the same time, the benefits in terms of risk reduction from hedging with adjusted weather insurance contracts almost triple for the insured.

Second, we analyze the effect of offering non-adjusted risk management products to cope with the expected increase in weather risk in light of climate change, i.e. we take into account that the insurance industry prices and designs contracts using historical (backward-looking) data, despite the fact that the stationarity assumption is no longer valid. We demonstrate that the payoff function of weather insurance products requires regular updating in times of climate change in order to guarantee that the product delivers the expected hedging benefits. Otherwise, we find that non-adjusted contracts either create substantial losses, or that profits from non-adjusted contracts are substantially smaller than profits from the corresponding adjusted contracts. While increasing the premiums of today's insurance products helps insurers build up liquidity that can be used to cover the increase in future indemnities, this is not sufficient in order to provide clients with adequate risk management products. In contrast to damage-based insurance products, parametric insurance products require in addition that contract characteristics are regularly adapted in light of climate change.

Our results are driven by the changes in the distribution of the underlying weather index. These changes affect the frequency and extent of payments. Adjusted insurance contracts account for the new climatic conditions by providing higher payments at a higher frequency, and in return charge a higher premium. With non-adjusted contracts, we observe that (depending on the index and the climatic conditions), the insured is either over- or under-compensated relative to the payments needed to cover the actual loss. The different patterns in which payout probabilities of non-adjusted contracts change (relative to the adjusted contracts), cannot be attributed to particular climatic conditions, since multi-peril weather indices were used to predict crop yields. More research is required to analyze how climate change is affecting the risk reduction from univariate weather indices, and how to best adapt (simple) insurance contracts.

Our results have been derived by studying the effect of a single climate change scenario, on one crop, at one geographical location. Future research should extend the methodology outlined in this paper to other crops and other regions using multiple climate projections to assess the effect of climate change on insurance design and risk reduction. The use of a process-based crop simulation in combination with climate projections represents one possible method for dealing with non-stationary yield data. In future work, statistical methods for dealing with non-stationary time series data should be used to replicate our approach for evaluating the effect of hedging with non-adjusted insurance contracts.

Climate change projections are informed by General Circulation Models (GCM) and Regional Circulation Models (RCM), which are subject to uncertainty due to a number of factors such as the representation of the physical system, or the future boundary conditions which depend on the global economic development. From a risk management perspective, the state of the art knowledge on generating local climate change projections should be used to determine the effect of uncertainty in anthropogenic warming estimates on our results, i.e. the effect of emission scenario uncertainty, as well as GCM/RCM model uncertainty on the simulated insurance contract, and respectively the effect of the uncertainty on the hedging effectiveness.

These uncertainties propagate to the crop model, which is subject to very similar uncertainties in itself. In general, not all processes and process interactions affecting crop growth can be fully represented with a process-based crop model. For example, indirect weather-related impacts of pests and diseases are not considered. Also, the calibration of crop parameters is subject to uncertainty. Even if a crop model was found to reflect the patterns of observed yields reasonably well under current climate conditions, it cannot be evaluated how reliable the predictions for changed climate conditions are. In this context it has to be noted that possible impacts of CO2 increase were not considered in this study. Future work should investigate how sensitive the derived weather indices are to uncertainties in climate projections, crop model parameters and model assumptions. Furthermore, it should be analyzed how such uncertainties affect the hedging effectiveness of adjusted contracts.

3.8 Appendix

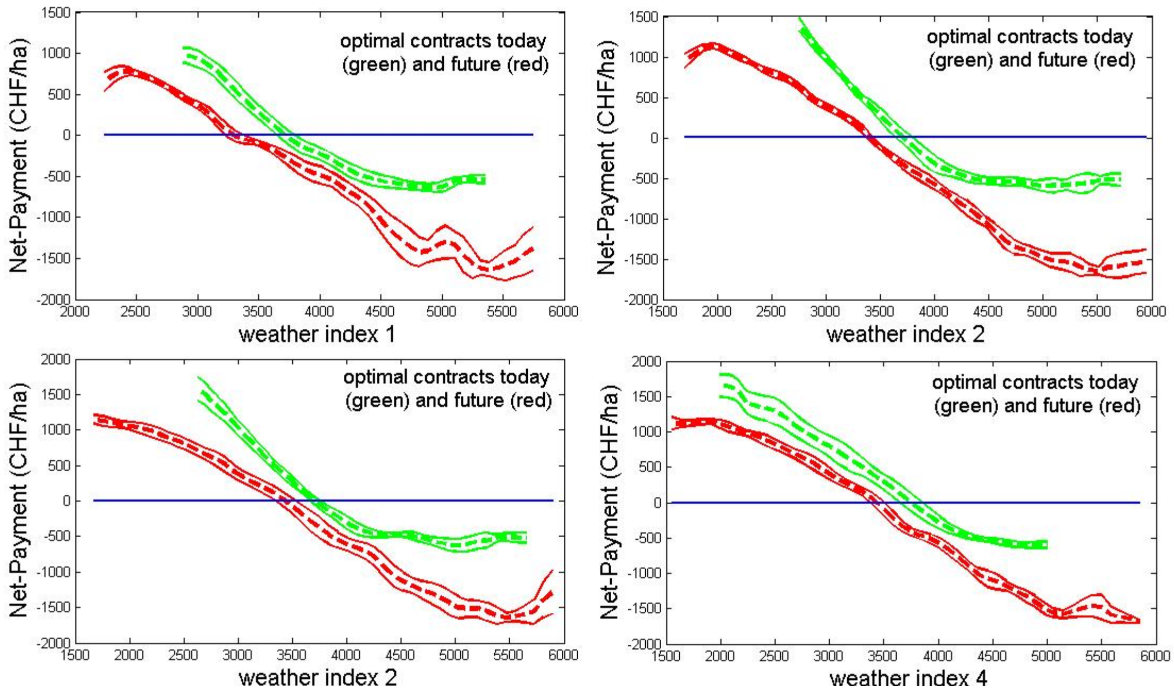

Figure 3.10: Optimal contracts (*dashed line*) with standard deviation (*solid lines*) for today's (*green*) and future (*red*) climatic conditions for all indices.

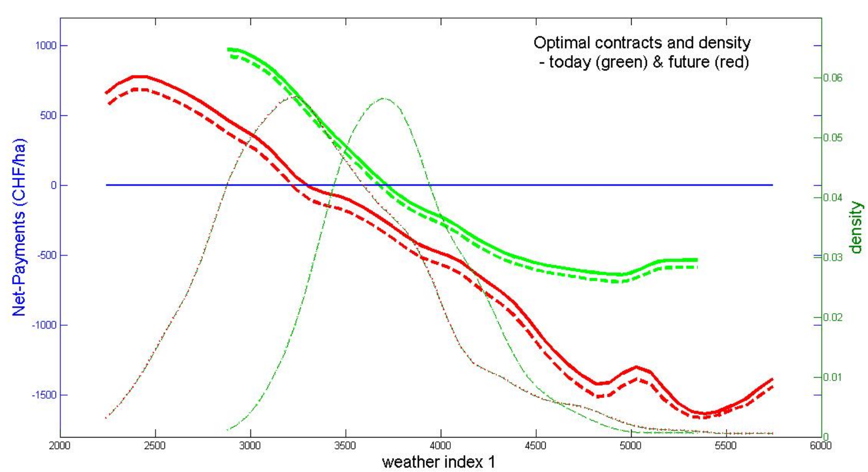

Figure 3.11: Optimal (*solid line*) and profit-maximizing (*dashed line*) insurance contracts for Index 1 with density, for today's (*green*) and future (*red*) climatic conditions.

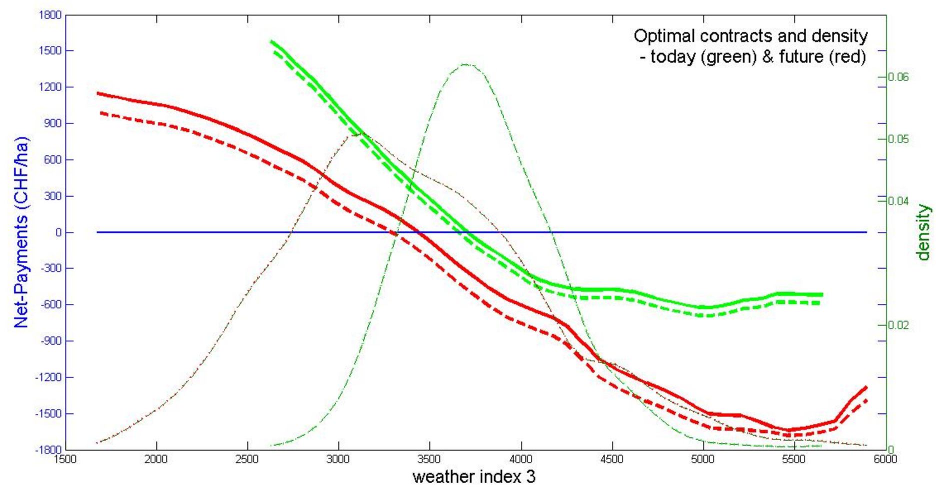

Figure 3.12: Optimal (*solid line*) and profit-maximizing (*dashed line*) insurance contracts for Index 3 with density, for today's (*green*) and future (*red*) climatic conditions.

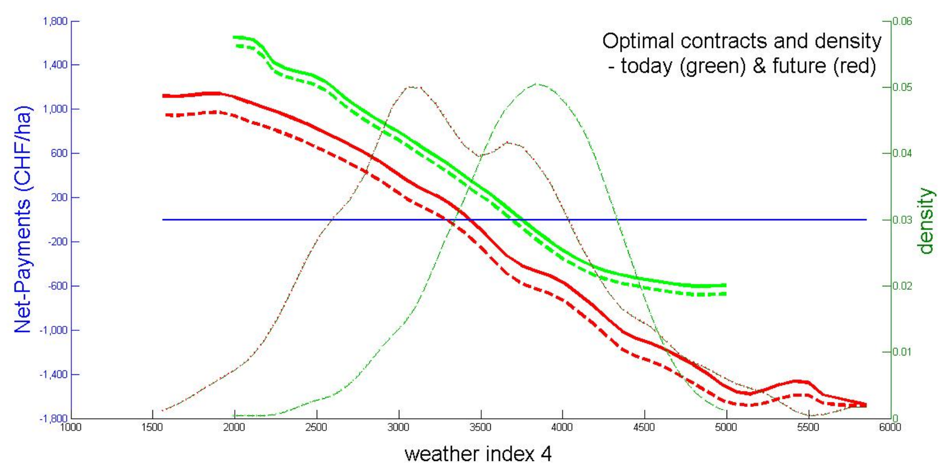

Figure 3.13: Optimal (*solid line*) and profit-maximizing (*dashed line*) insurance contracts for Index 4 with density, for today's (*green*) and future (*red*) climatic conditions.

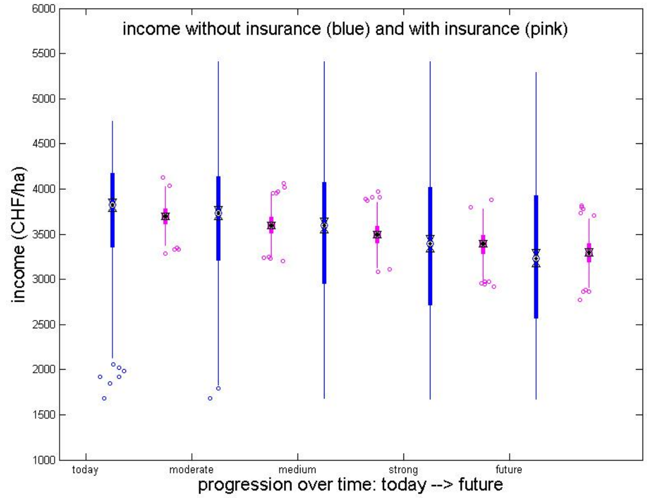

Figure 3.14: Transition of boxplots from the income distributions without and with optimal insurance for Index 3.

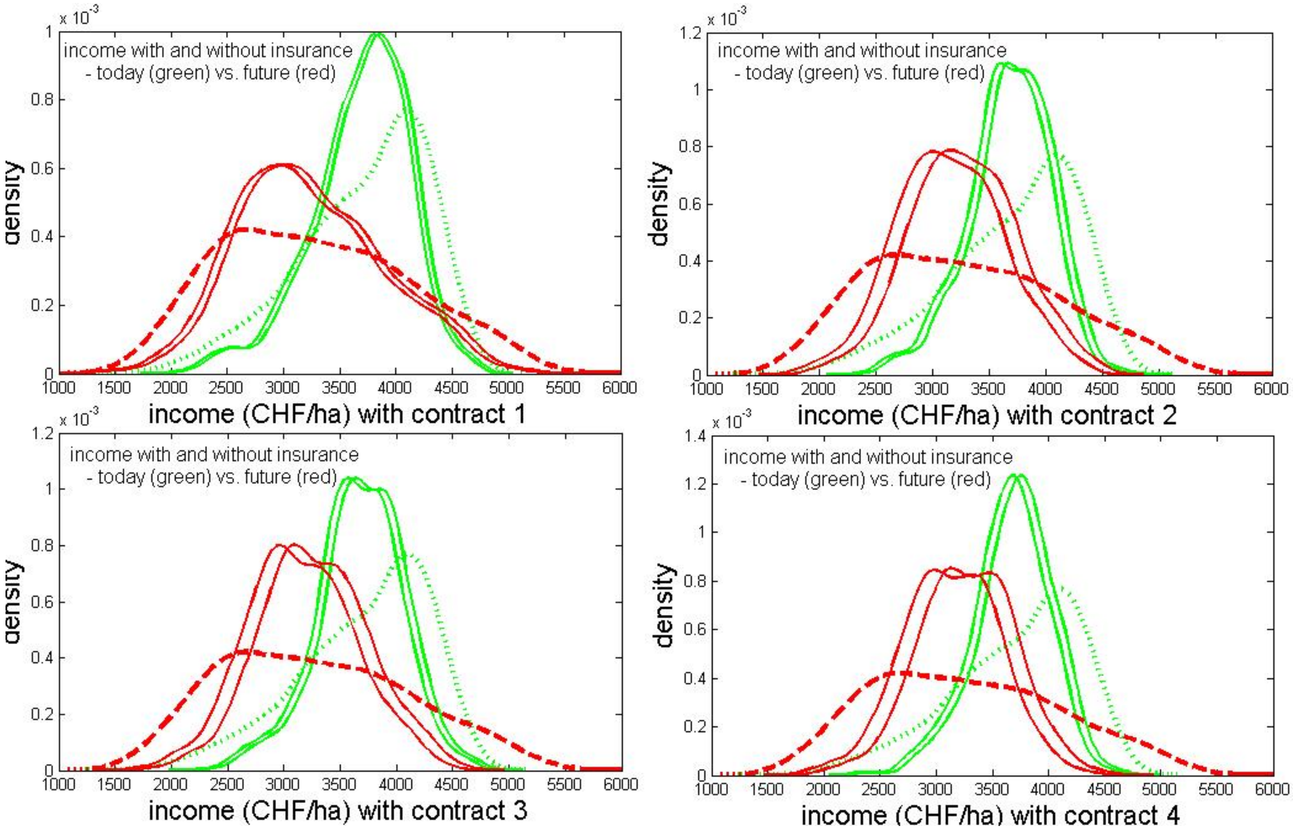

Figure 3.15: Income distributions with optimal (*solid line*) and profit-maximizing (*dashed line*) insurance, for all indices, and without insurance (*pointed line*) for today's and future climatic conditions.

Table 3.15: Weather-yield regression outputs for today's and future climatic conditions

Model	Index 1		Index 2		Index 3		Index 4	
Climate	Today	Future	Today	Future	Today	Future	Today	Future
m.precip.2	969.8^{***}	559.44^{***}	13.6^{***}	8.52^{***}			4446.2^{***}	1724.1^{***}
m.precip.3			224.5^{***}	165.1^{***}			430.2^{**}	105.1^{***}
m.precip.4			304.2^{**}	237.6^{***}			975.5^{**}	142.9^{***}
m.tmin.1			-13.3^{*}	-3.35^{*}				
m.tmin.2			214.2^{**}	123.6^{***}				
m.tmax.3			34.6^{*}	-18.3^{***}				
m.tmax.4			108.6^{**}	-39.1^{**}				
P.ETo.2					12.8^{***}	7.9^{***}		
P.ETo.3					15.5^{*}	12.2^{***}		
P.ETo.4					6.9^{**}	6.7^{***}		
RDI.2							-111810.6^{***}	-61239.0^{***}
RDI.3							-3949.2^{*}	5683.2^{**}
RDI.4							-2447.5^{**}	6112.5^{*}
m.precip.2^2							-282.7^{***}	-54.2^{***}
m.precip.3^2							-16.2^{***}	0.2^{*}
m.precip.4^2							-51.8^{**}	6.24^{**}
Adj.R^2	37.1	40.7	49.3	69.3	47.1	68.8	62.5	74.9

Note: $***$ significant at the 1% level. $**$ significant at the 5% level. $*$ significant at the 10% level.
m.precip is the mean of daily precipitation values.
m.tmax and m.tmin are, respectively, the means of daily maximum and minimum temperatures.
P.ETo(Priest) is the difference between daily precipitation and daily evapotranspiration (ETo), where ETo is measured using the Priestley-Taylor formula. m.precip^2 are the squared daily mean precipitation values.
RDI(Hamon) is the Reconnaissance Drought Index derived using daily potential evapotranspiration, where ETo is measured using the Hamon formula.

Table 3.16: Descriptive statistics of weather indices

Climatic scenarios	today *1981-2001*	Scenario 1 *moderate*	Scenario 2 *medium*	Scenario 3 *strong*	future *2036-2065*
Index 1					
mean	3792	3700	3591	3477	3381
std	346.1	456.7	517.7	531.7	558.9
skewness	0.450	0.091	0.359	0.396	0.831
Index 2					
mean	3785	3705	3589	3477	3369
std	400.4	533.7	635.6	681.4	720.4
skewness	0.428	0.023	0.131	0.271	0.553
Index 3					
mean	3779	3700	3585	3478	3371
std	386.7	524.9	631.3	677.9	718.9
skewness	0.401	-0.125	0.015	0.209	0.425
Index 4					
mean	3797	3696	3588	3468	3353
std	467.1	563.1	665.2	714.3	729.9
skewness	-0.274	-0.453	-0.105	0.112	0.316

Note: Mean (in kg/ha), standard deviation (in kg/ha), and skewness of all weather indices for all climatic scenarios.

Table 3.17: Descriptive analysis of income distribution with and without insurance

Climatic scenarios		Today *1981-2001*	Scenario 1 *moderate*	Scenario 2 *medium*	Scenario 3 *strong*	Future *2036-2065*
mean	no insurance	3.696	3.598	3.497	3.387	3.294
(CHF/ha)	optimal	3.696	3.598	3.497	3.387	3.294
	profit	3.630	3.497	3.371	3.245	3.145
std	no insurance	186.3	273.3	300.3	301.1	279.4
(CHF/ha)	optimal	120.0	130.9	137.0	141.3	146.3
	profit	120.1	130.9	137.0	141.3	146.5
skew	no insurance	-0.222	-0.813	-0.375	-0.020	0.061
	optimal	-0.03	0.019	0.09	-0.12	-0.01
	profit	-0.03	0.019	0.09	-0.12	-0.01
quantile	no insurance	3.449	3.210	3.083	2.998	2.937
10%	optimal	3.541	3.435	3.323	3.207	3.109
	profit	3.475	3.334	3.198	3.065	2.959
25%	no insurance	3.574	3.455	3.267	3.168	3.106
	optimal	3.611	3.509	3.402	3.288	3.194
	profit	3.545	3.408	3.276	3.146	3.045
50%	no insurance	3.704	3.640	3.534	3.385	3.292
	optimal	3.697	3.598	3.492	3.392	3.297
	profit	3.631	3.497	3.366	3.250	3.146
75%	no insurance	3.835	3.791	3.724	3.611	3.485
	optimal	3.777	3.684	3.586	3.484	3.398
	profit	3.711	3.584	3.461	3.343	3.248
90%	no insurance	3.932	3.911	3.858	3.787	3.644
	optimal	3.852	3.764	3.671	3.556	3.482
	profit	3.787	3.663	3.545	3.415	3.332

Note: Statistical moments of the income distribution without insurance and for the situation with optimal and profit-maximizing insurance for all climatic scenarios.

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Chapter 4

Approximating Optimal Weather Insurance Contracts

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4.1 Introduction

The agribusiness sector is exposed to meteorological weather events that affect output and cause inter-annual yield variability. In the U.S, for instance, the agricultural GDP (in 2000 US$) varies by 12.1% due to weather variability (Lazo et al., 2011).[1] Global climate change may induce the variability of the agricultural productivity to increase. With climate change, average temperature conditions and the weather variability are on the rise, which manifests itself as an increase in the number of extreme events such as floods, heatwaves, and prolonged drought conditions (IPCC, 2007). As a result, the frequency and severity of weather-related crop losses are expected to increase in all regions. Farm-level adaption strategies and improvements in plant breeding can mitigate some impacts, but nevertheless, agricultural production is becoming more risky over time (Trnka et al., 2011). To manage the residual weather risk, sound risk transfer products are needed. The aim of this paper is therefore to compare the hedging benefits of the linear weather risk transfer products available to farmers in the OTC market with the insurance contracts recently developed by Kapphan (2011), who proposes a methodology to derive optimal index-based weather insurance.

[1] For comparison, the inter-annual variability of the utilities sector that is attributable to weather is 7.0%, and the weather variability of the entire U.S. economy is 3.4% (Lazo et al., 2011).

4.1.1 Overview of Index-based Weather Products

Even without the threat of climate change, agricultural production is inherently risky due to its weather exposure. Historically, farmers have managed weather risk using a wide range of agricultural insurance products. Named and multi-peril damage based insurance, or revenue insurance, are used to compensate crop yield shortfalls, and to smooth income fluctuations over time (Coble et al., 2000). Since these insurance schemes are plagued by problems of asymmetric information, governments often subsidize premiums (Hazell, 1992; Skees et al., 1999). Recently, index-based, or parametric, weather insurance has received attention as an innovative risk management instrument to deal with weather risk.

Compared to traditional agricultural insurance, such as the multi-peril crop insurance (MPCI) scheme in the US, parametric weather insurance determines payments based on the difference between an underlying weather index and a pre-specified threshold (measured during a pre-defined period). Index-based weather insurance exploits the fact that weather events are predictors for crop losses, and are exogenously verifiable events. Since payouts are determined by the realized weather, problems of moral hazard and adverse selection are eliminated as the insured retains an incentive to mitigate crop losses (Miranda and Vedenov, 2001). Another advantage of index-based weather insurance is that crop loss verifications are no longer needed to determine the eligibility of a claim, which reduces the administrative cost of providing insurance (Richards et al., 2004). A major drawback of an index-based product is that the index may not perfectly track the crop losses of the insured, which leaves the insured with so-called basis risk.[2]

The idea of using an index to predict yield losses and to determine payouts goes back to Halcrow (1949), and was further developed by Miranda (1991), and Skees et al. (1997), who propose area-based yield insurance as an alternative to the U.S. federal crop insurance programm. The principle of using an area-based index to trigger payouts was later extended from area yields to rainfall (Skees et al., 1999). At that time, a market for weather derivative started to originate in the energy sector (Dischel, 1998; Brocket et al., 2005). In 1997, energy suppliers first used (temperature-based) weather derivatives to hedge against abnormal weather conditions, which cause electricity demand, and hence electricity prices, to spiral. Similar to index-based weather insurance, weather derivatives provide protection against weather-related changes in production quantity. From

[2] Basis risk results due a difference between the weather measured at the station, and the weather that prevails at the farming site. Ideally, a weather derivative should be written on an index that is measured at the same location where the derivative is used, thereby completely eliminating basis risk (Vedenov and Barnett, 2004).

a risk management perspective, weather derivatives are essentially equivalent to index-based weather insurance since both products can be used to hedge weather risk. With each, the buyer pays a premium and receives a commitment of compensation from the seller if predefined conditions occur. Weather derivatives are financial products, which can be bought at an exchange, like the Chicago Mercantile Exchange (CME), or are available in the over-the-counter (OTC) market. Exchange-traded contracts are standardized and available for a number of major cities (in the North America and Europe) and simple weather indices, whereas in the OTC market customers can obtain derivative contracts custom-tailored to their particular hedging needs. Due to its flexibility to structure contracts that address complex weather risks, the OTC market grew by almost 30% in 2010, while the overall market for weather derivatives grew by 20% (WRMA, 2011).

Despite the advantages of index-based weather insurance, and the rapid development of the weather market, the penetration of index-based weather products in agriculture, is rather low, especially when compared to other weather-dependent sectors. Basis risk is often the main argument used to explain the slow uptake of index-based insurance products in agriculture, as the risk remains with the grower (World Bank, 2011). Another possible explanation why farmers hesitate to adopt weather risk management, either in the form of an insurance product or weather derivatives, is the unfamiliarity with the weather marketplace.

4.1.2 Hedging with Index-based Weather Products

Obtaining a customized weather hedge requires that the insured selects a measurement station, a weather index, possibly thresholds defining the index, a time period, and the parameters that define the payoff function (Zeng, 1999; Vedenvo and Barnett, 2004). The payoff structure of a generic derivative contract is characterized by a strike and exit value, a tick size and cap. The choice of each component affects the resulting contract, the premium charged by the seller, and most importantly the weather coverage obtained. To obtain a desired coverage, a buyer needs to assess a number of possible combinations of index, location, and contract parameters with respect to their hedging benefits. Leaving aside the possible combinations of insurance parameters, Vedenov and Barnett (2004) already note that "various combinations of weather variables, (crops), and weather measurement stations create an enormous number of potential weather derivatives, ... " need to be considered for an informed decision.

In general, the design of a parametric weather hedge can be decomposed into two steps: creating an index, and structuring the payoff function. Finding an index that explains crop losses well matters for reducing meteorological basis risk, i.e. the risk of the index not triggering any payments despite the fact that crop losses occurred. The design of the payoff structure matters for minimizing structural basis risk, i.e. the risk of receiving inadequate payments that do not fully cover the realized losses. Ideally the contract is structured such that the insured receives a compensation from the insurer that reflects the actual accrued crop losses. To structure such a contract both sources of basis risk need to be minimized.

In the energy sector, simple indices, such as heating degree days (HDD) and cooling degree days (CDD), are good predictors of electricity demand. In agriculture, the relationship between crop yields and weather is more complex as manifold weather events affect the plant development throughout the growing period. Therefore, agriculture specific indices have been proposed to minimize basis risk. (Steinmann et al., 2005; Tsakiris et al., 2005; Narasimhan et al., 2005; Keller et al., 2011; Kapphan, 2011). While the underlying indices have been adapted to the agricultural context, the generic payoff structure, that originated from the energy sector, has so far been adopted.

Numerous studies exist that evaluate the potential of index-based weather insurance at a given location, for one ore more crops (Turvey, 2001; Breustedt et al. 2008; Torriani et al., 2008; Zant, 2008; Berg et al., 2009; Musshoff et al., 2009; Leblois et al., 2011). Often these studies propose a few indices and compare them based on their hedging benefits, while relying on one methodology to structure the payoff function. The findings from these studies are hence location- and crop-specific, and more importantly, depend on the chosen structuring method. All contributions, however, share the assumption of a linear payoff function. The issue of addressing structural basis risk has so far been neglected in the literature. I aim to fill the gap by comparing for the first time -for a given crop and location - different structuring methodologies with respect to their hedging effectiveness.

In particular, I assess the loss in risk reduction from hedging with linear weather insurance contracts compared to optimal weather insurance contracts, which are non-linear as the payout function reflects the agronomic relationship between weather and yields, developed by Kapphan (2011). As the weather market offers at the moment only linear (standardized) contracts, I first derive methodologies to approximate the optimal and profit-maximizing insurance contracts. By approximating I derive the insurance parameters (trigger, tick size, and cap) that define the payoff function of an approximated optimal, and respectively, profit-maximizing contract. I then compare the hedging benefits of the optimal with the approximated counterpart, and thus derive the loss in risk reduction from hedging agricultural weather risk with linear weather derivative contracts.

For the empirical analysis, simulated crop yield and weather data for Schaffhausen, Switzerland, derived from a process-based crop simulation model in combination with a weather generator, representing today's climatic conditions and a climate scenario is used. Using the same weather and crop yield data, as well as the same underlying indices as in Kapphan et al. (2011) allows me to compare the benefits of hedging today's weather risk with a linear contract ($\delta_t(a_t(z))$) with the risk reduction potential of linear contracts with climate change ($\delta_f(a_f(z))$), and to assess the findings of Kapphan et al. (2011) using a different insurance design method.[3] Moreover, in light of climate change, the loss in risk reduction from hedging agricultural weather risk with linear contracts (compared to non-linear optimal contracts) is evaluated over time.

The remaining paper is structured as follows: In Section 4.2, I propose two methodologies for approximating the optimal and profit-maximizing insurance contracts, and explain the approach taken to estimate the loss in risk reduction (for the insured), and the loss in profits (for the insurer). Section 4.3 outlines the yield and weather data sets used in this study, and describes the underlying weather indices. In section 4.4.1, the properties of the optimal contract and the approximated counterparts are described, and in section 4.4.2 the loss in risk reduction from hedging with approximated contracts compared to optimal contracts is assessed for both climatic conditions. The sensitivity of the results is evaluated in section 4.5. In section 4.6, I offer a conclusion and outlook of the potential application of the insurance design lessons learnt in this paper.

4.2 Theoretical Approach

4.2.1 Optimal and Profit-Maximizing Insurance Contracts

The objective of this section is to propose a robust methodology for deriving the insurance parameters (trigger, exit, cap and tick size) from the optimal and profit-maximizing insurance contracts, that are needed to define a linear weather derivative payoff structure. Before the approximation methods are explained, I offer a brief review of the optimal weather insurance design.

The model developed by Kapphan (2011) is used to numerically derive the payoff structure of an index-based weather insurance contract with optimal hedging effective-

[3] Kapphan et al. (2011) assessed the benefits from hedging weather risk with optimal insurance contracts for today's and future climatic conditions. The authors find that with climate change the benefits from hedging, as measured by δ, almost triple for the insured, and that insurers can expect profits to increase by about 240% from offering optimal adjusted weather insurance contracts (for a relative coefficient of risk aversion of $\sigma = 2$). An adjusted insurance contract accounts for the changes in the crop yield and the weather distributions that are due to climate change.

ness for the insured and with maximum profits for the insurer. Yields are represented by y and z measures the corresponding realization of the weather index in a given climatic scenario c, with $c \in \{t, f\}$ and t representing today's and f future climatic conditions.[4] The influence of weather on yields under given climatic conditions is captured through the conditional distribution of yields with cdf $F_c(y|z)$ with density $f_c(y|z)$, which are estimated parametrically using Gaussian kernel function. The distribution of the weather index $z \in \mathcal{Z}_c \equiv [\underline{z}_c, \overline{z}_c]$ is characterized by the cdf $G_c(z)$ and density $g_c(z)$. The optimal weather insurance payoff structure $p_c(z)$ is derived by maximizing the expected utility of the insured subject to the constraint that the risk-neutral insurers charge an actuarially fair premium. As only the payout after the premium P_c matters to the insured, $p(z)$ represents the net-payout, so that $p_c(z) = I_c(z) - P_c$ for all $z \in Z$, with $I_c(z)$ representing the indemnity, or gross payment, for a given z. Following Kapphan (2011), the insured is risk-averse and has preferences over consumption, θ, with $\theta = y + p_c(z)$, which are characterized by constant relative risk aversion (CRRA), i.e. $u(\theta) = \theta^{1-\sigma}/1 - \sigma$ with $\sigma > 0$. Formally, $p_c^*(z)$ maximizes the expected utility of the insured

$$\max_{p_c(z)} \int_{\mathcal{Z}_c} \int_{\mathcal{Y}_c} u(y + p_c(z)) dF_c(y|z) dG_c(z) \tag{4.1}$$

subject to the constraint

$$\int_{\mathcal{Z}_c} p_c(z) dG_c(z) = 0. \tag{4.2}$$

Constraint (4.2) implies that insurers make on average zero profits, i.e. the premium is actuarially fair. Furthermore, a profit-maximizing contract $\tilde{p}_c^*(z)$ solves

$$\max_{\tilde{p}_c(z)} \Pi_c \equiv - \int_{\mathcal{Z}_c} \tilde{p}_c(z) dG_c(z) \tag{4.3}$$

subject to the constraint that the insured's expected utility is equal to or greater than his expected utility in an uninsured situation, i.e.

$$\int_{\mathcal{Z}_c} \int_{\mathcal{Y}_c} u(y + \tilde{p}_c(z)) dF_c(y|z) dG_c(z) \geq \int_{\mathcal{Z}_c} \int_{\mathcal{Y}_c} u(y) dF_c(y|z) dG_c(z). \tag{4.4}$$

I thus consider the realistic situation where insurers add a loading factor to the premium to cover transaction costs of providing weather insurance. From the profit-maximizing insurance contract, the loading factor at which the insured is indifferent between hedging his weather risk and not obtaining any protection can be derived by comparing the pre-

[4] Alternatively, y_c can represent revenues from selling crop yields at a given price p with z representing predicted revenues.

mium of the optimal contract $p_c^*(z)$ with the premium of the profit-maximizing contract $\tilde{p}_c^*(z)$.

4.2.2 Approximating Optimal and Profit-Maximizing Contracts

For the optimal and profit-maximizing contracts, I propose 2 different methods to derive a piecewise linear contract, that approximate those optimal contracts. I then evaluate how well the approximated contract, that looks more like a classical weather derivative payoff, reduces the risk compared to the optimal contract. For the profit-maximizing contract, I also propose an approximation, and evaluate how well the approximated counterpart maximizes the insurer's expected profits compared to the profit-maximizing contract.

To approximate the optimal and profit-maximizing insurance contracts, trigger τ_c and exit η_c values are chosen with respect to the statistical moments of the index distribution $g_c(z)$. The optimal approximated contract is represented by $a_c(z)$, and the approximated profit-maximizing contract by $\tilde{a}_c(z)$.

In a baseline approximation scenario, the trigger is set to be equal to the z value of the 90% quantile of $g_c(z)$, denoted as $\tau_{c,90\%}$. The exit level is set to be equal to the 20% quantile of $g_c(z)$, denoted by $\eta_{c,20\%}$.[5] Later, a sensitivity analysis is performed to analyze the effect of the selection of the approximation parameters on the results (see section 4.5). Finally, to fully characterize the approximated payoff functions, the payouts corresponding to the trigger and exit values, denoted by μ_c and κ_c respectively, need to be defined. This also implies a tick size (slope) of

$$\phi_c = \frac{\kappa_c - \mu_c}{\tau_c - \eta_c}. \tag{4.5}$$

The net-payout at τ_c, given by μ_c, is referred to as the minimum payment ("minpay"), and the net-payout at η_c, given by κ_c, is called the "cap." Figure 4.1 illustrates the insurance parameters of the approximated contract. In the following, I propose two different methods to derive these insurance parameters.

Method 1: For given trigger and exit values, the corresponding net-payout values are determined from $p_c(z)$, and respectively $\tilde{p}_c(z)$, via interpolation as the optimization problem is solved in its discrete form as described in Kapphan (2011). The optimal net-payout value at τ_c^1 is represented by μ_c^1 and the profit maximizing net-payout by $\tilde{\mu}_c^1$. The net-payout values corresponding to η_c^1 are then given by κ_c^1 and $\tilde{\kappa}_c^1$, respectively. The tick

[5] For the indices used in this study, the yield outcome improves for higher levels of the index. Therefore the weather insurance contract has to trigger payments as soon as the weather index falls below a critical threshold. Consequently, $\tau_c > \eta_c$ as the contract follows a put option-style payout. For call option-style payouts with $\tau_c < \eta_c$, the trigger could be set equal to the 10% quantile and the exit could be defined by the 80% quantile of $g_c(z)$.

size of the optimal approximated contract ϕ_c^1 is then given by (4.5).

While the resulting contract parameters (ϕ_c^1, τ_c^1, and η_c^1) fully define a contract, the resulting payoff function no longer necessarily satisfies the zero-profit condition.[6] For the approximated optimal contract $a_c^1(z)$ to still be actuarially fair, I shift the entire function vertically such that the zero-profit constraint is exactly satisfied. Similarly, the payoff function resulting from $\tilde{\phi}_c^1$, $\tilde{\tau}_c^1$, and $\tilde{\eta}_c^1$ is shifted to generate an approximated profit-maximizing contract such that the insured's expected utility from hedging with $\tilde{a}_c^1(z)$ is equal to the expected utility from not hedging.

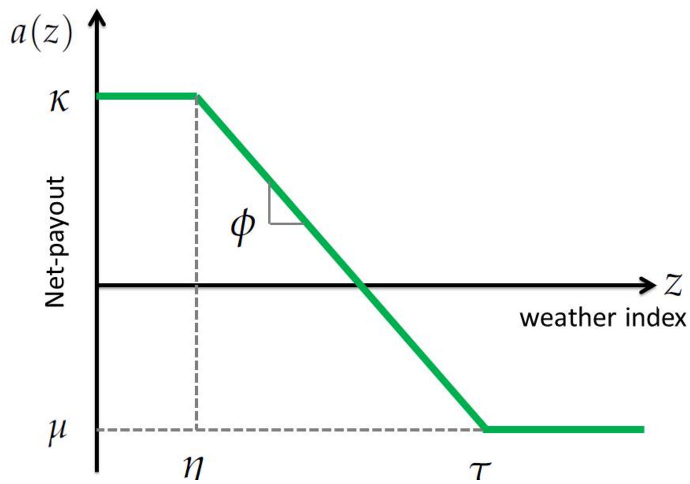

Figure 4.1: Notation of the insurance parameters defining the approximated contract.

Method 2: Alternatively, to approximate the optimal contract $p_c(z)$, I propose a second method to determine the cap κ_c^2, i.e. the maximum payout corresponding to the exit value η_c^2, and the min-payout μ_c^2, corresponding to the trigger level τ_c^2. In a first step, the linear trend between yields y and the index z of the corresponding climate scenario is estimated using OLS regression, i.e. $y = \alpha_c + \beta_c z + \varepsilon_c$. The slope ϕ_c^2 of the approximated optimal contract is then given by the estimated $\hat{\beta}_c$. Next, the net-payout values at the exit (η_c^2) and at the trigger value (κ_c^2) are determined using the fitted relationship. As before, the resulting payoff function is shifted to ensure that the approximated optimal contract $a_c^2(z)$ is actuarially fair. Similarly, an approximated profit-maximizing contract $\tilde{a}_c^2(z)$ can be derived by shifting the resulting payoff function such that the insured's expected utility from hedging with $\tilde{a}_c^2(z)$ is equal to the unhedged situation.[7]

[6] Note that the optimal contract $p_c(z)$ by construction generates zero profits. However, this is not necessarily true for the approximated optimal contract as defined so far, since the approximation may lead to profits that deviate from exactly zero.

[7] As it turns out that Method 1 better approximates the optimal contract, and that the magnitude of the loss in the risk reduction from approximating optimal contracts via Method 1 and Method 2 are quite similar, I do not show the loss in profitability for Method 2. Additional results are available from the author

The difference in the two approximation methods is that the slope (ticksize) ϕ_c^1 is the result of the selection of μ_c^1 and κ_c^1, whereas μ_c^2 and κ_c^2 are determined by evaluating $\hat{y} = \hat{\alpha} + \hat{\beta}z$ at $\tau_{c,90\%}$ and respectively $\eta_{c,20\%}$. The second approximation method allows us to evaluate the sensitivity of the results with respect to the chosen approximation method. Furthermore, Method 2 is inherently similar to the method proposed by Karuaihe et al. (2006), Berg et al. (2009), and Leblois et al. (2011) to derive the payoff function of an index-based weather insurance contract. This strand of literature computes the expected utility of the insured for a given set of the critical insurance parameters (τ_c,μ_c, ϕ_c), and then evaluates the choice of the insurance parameters based on the certainty equivalent gain. The set of τ_c,μ_c, and ϕ_c that yields the highest certainty equivalent gain constitutes the optimal contract, given the functional form assumption that $a_c(z)$ is linear between τ_c and η_c, and that $a_c(z)$ is capped once $z < \eta_c$.

In order to compare the payout function of the approximated contracts, that are defined by the insurance parameters, with the optimal and profit-maximizing contract, I also derive a trigger, exit, cap, and minimum payout for the optimal and profit-maximizing contract. The premium P_c, which is equivalent to μ_c, is given by the minimum of $p_c(z)$. The exit levels, η_c and $\tilde{\eta}_c$, are given by the minimum of $g_c(z)$. The trigger value τ_c is derived by evaluating the gross payout function $I_c(z) = p_c(z) + P_c$, at $I_c(z) = 0$, i.e. the trigger value is given through the index value z where $p_c(z) = P_c$. To derive $\tilde{\tau}_c$ the (gross) payout function is evaluated at $\tilde{I}_c(z) = 0$. As for the approximated contracts, κ_c and $\tilde{\kappa}_c$ correspond to the highest payout of $p_c(z)$ and $\tilde{p}_c(z)$ respectively. Table 4.1 summarizes the notation of insurance parameters corresponding the approximated and optimal contracts.

Table 4.1: Notation of contract parameters for optimal and approximated contracts

Approximation		Contract	Trigger	Exit	Cap	Minpay	Tick
	optimal	$p_c(z)$	τ_c	η_c	κ_c	μ_c	n.a.
	profit	$\tilde{p}_c(z)$	$\tilde{\tau}_c$	$\tilde{\eta}_c$	$\tilde{\kappa}_c$	$\tilde{\mu}_c$	n.a.
Method 1	optimal	$a_c^1(z)$	τ_c^1	η_c^1	κ_c^1	μ_c^1	ϕ_c^1
	profit	$\tilde{a}_c^1(z)$	$\tilde{\tau}_c^1$	$\tilde{\eta}_c^1$	$\tilde{\kappa}_c^1$	$\tilde{\mu}_c^1$	$\tilde{\phi}_c^1$
Method 2	optimal	$a_c^2(z)$	τ_c^2	η_c^2	κ_c^2	μ_c^2	$\tilde{\phi}_c^2$

Note: The notation proposed to characterize optimal and profit-maximizing contracts, together with their corresponding approximated contracts applies to put option-style ($\eta_c < \tau_c$) and call option-style ($\tau_c < \eta_c$) payoff structures. By construction $\tau_c^1 = \tau_c^2 = \tilde{\tau}_c^1$, and that $\eta_c^1 = \eta_c^2 = \tilde{\eta}_c^1$.

upon request.

4.2.3 Loss in Risk Reduction and Profitability

To compute the loss in risk reduction from hedging with linear (weather derivative) contracts instead of using an optimal weather insurance contract, I first evaluate the risk reduction of the insured from hedging with a particular contract. Similarly, to derive the loss in profits from offering approximated contracts compared to profit-maximizing contracts, the expected profits of the different contracts are derived.

To quantify the risk reduction potential, for instance, of an optimal insurance contract, I compute the percentage increase of all income realizations in the situation without insurance that makes the insured equally well-off (in expected utility terms) as in the situation with the optimal insurance (see Kapphan, 2011). Formally, this percentage increase $\delta_c(p_c)$ solves

$$\int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Y}_c} f_c(y|z) \frac{(p_c(z)+y)^{1-\sigma}}{1-\sigma} dydz = \int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Y}_c} f_c(y|z) \frac{((1+\delta_c(p_c))y)^{1-\sigma}}{1-\sigma} dydz, \tag{4.6}$$

with solution:

$$\delta_c(p_c) = \left(\frac{\int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Y}_c} f_c(y|z)(p_c(z)+y)^{1-\sigma} dydz}{\int_{\mathcal{Z}_c} g_c(z) \int_{\mathcal{Z}_c} f_c(y|z) y^{1-\sigma} dydz} \right)^{\frac{1}{1-\sigma}} - 1. \tag{4.7}$$

For given climatic conditions, the benefits from hedging with an approximated optimal insurance contract are derived, $\delta_c(a_c^1(z))$ and $\delta_c(a_c^2(z))$, and compared to the benefit from hedging with an optimal contract $\delta_c(p_c(z))$.[8] Similarly, I derive the profits an insurer can expect to earn from offering a particular insurance contract (for given climatic conditions). For the profit-maximizing insurance contracts, expected profits are determined by solving:

$$\Pi_c(\tilde{p}_c) = -\int_{\mathcal{Z}_c} \tilde{p}_c(z) dG_c(z). \tag{4.8}$$

For the insurer, the benefits from offering the profit-maximizing contract, $\Pi_c(\tilde{p}_c)$, are compared to the benefits from providing linear profit-maximizing contracts, $\Pi_c(\tilde{a}_c)$. The loss in risk reduction is then given by

$$\Delta_c^j = \frac{\delta_c(p_c(z)) - \delta_c(a_c^j(z))}{\delta_c(p_c(z))}, j = 1, 2. \tag{4.9}$$

[8] Furthermore, to evaluate the benefits from hedging with different types of weather insurance contracts, I compare the statistical moments of the income distribution without insurance to the statistical moments of the situation with different contracts.

Δ_c^j measures (in percent) the loss in risk reduction from hedging weather risk with linear approximated contracts (using Method 1 ($j = 1$), or Method 2 ($j = 2$) compared to hedging with optimal weather insurance contracts.

For the insurer, the loss in profits from offering linear weather insurance contracts, $\tilde{a}_c^1(z)$, compared to the profit-maximizing contracts, $\tilde{p}_c(z)$, is then given by

$$\Theta_c^1 = \frac{\Pi_c(\tilde{p}_c(z)) - \Pi_c(\tilde{a}_c^1(z))}{\Pi_c(\tilde{p}_c(z))}. \tag{4.10}$$

Table 4.2: Notation for profits and deltas from optimal and approximated contracts

		Contract	Delta	Profits	Loss of δ	Loss of Π
	optimal	$p_c(z)$	$\delta(p_c(z))$	0		
	profit	$\tilde{p}_c(z)$	0	$\Pi_c(\tilde{p}_c(z))$		
Method 1	optimal	$a_c^1(z)$	$\delta(a_c^1(z))$	0	Δ_c^1	0
	profit	$\tilde{a}_c^1(z)$	0	$\Pi_c(\tilde{a}_c^1(z))$	0	Θ_c^1
Method 2	optimal	$a_c^2(z)$	$\delta(a_c^2(z))$	0	Δ_c^2	0

Note: The insured's benefit (δ_c) from hedging weather risk in a given climate scenario ($c = t, f$) depends on the contract type ($p_c(z)$, and $a_c^1(z)$ or $a_c^2(z)$). Insurer's profit (Π_c) in a given climate scenario depends on the contract offered ($\tilde{p}_c(z)$, or $\tilde{a}_c^1(z)$). By construction, the benefits for the insured from hedging with a profit-maximizing contract, $\delta_c(\tilde{p}_c)$, or an approximated profit-maximizing contract, $\delta_c(\tilde{a}_c^1)$, are zero. Similarly, the insurer's expected profits from offering an optimal insurance contract, $\Pi_c(p_c)$, or form offering an approximated optimal contract, $\Pi_c(\tilde{a}_c^1)$, are equal to zero by construction.

Table 4.2 summarizes the notation used for the loss in risk reduction for the insured and the loss in profits for the insurer. Comparing Δ_t^j with Δ_f^j allows us to then assess whether climate change alters the loss in risk reduction. Similarly, whether the loss in profits for the insurer from approximating profit-maximizing contracts is becoming worse or better can be evaluated by comparing Θ_t^1 with Θ_f^1.

4.3 Data and Weather Indices

The same weather and yield data as in Kapphan et al. (2011) is used. The data set consists of $1,000$ simulated maize (*Zea mays L.*) yield realizations, which are generated with CropSyst, a process-based crop simulation model (Stöckle et al., 2003) in connection with $1,000$ years of daily synthetic weather data, generated with a stochastic weather generator LARS-WG (Semenov, 1997; Semenov et al., 2002), for today's climatic conditions and a climate scenario. The climate change scenario (2036-2065) represents regional projections for Europe developed by Vidale et al. (2003) with the CHRM regional model in the framework of the PRUDENCE project on the basis of a A2 emission scenario (Nakicenovic et al., 2000). Observed daily weather data from 1981 to 2010 at Schaffhausen, Switzerland, (SHA: latitude: 47.69, longitude: 8.62) was used to condition LARS-WG. The baseline statistics of LARS-WG were then modified to represent the climate change scenario and a daily weather series of a $1,000$ years was generated.

The CropSyst calibration for maize is based on Torriani et al. (2007a, 2007b) and was adapted to the newer CropSyst version 4.13.09. The synthetic weather series representing today's and future climatic conditions were fed into CropSyst (Stöckle et al., 2003) to simulate maize yields under both climatic conditions. With climate change, average maize yields decrease from 9,266 kilogram per hectare (kg/ha) to 8,190 kg/ha, while the coefficient of variation increases from 0.157 to 0.257. Without adaptive measures, growing maize in Schaffhausen is becoming more risky and less profitable. Further details on the parametrization of CropSyst and of LARS-WG, the climate change scenario, together with descriptive analysis of the simulated maize yields for today's and future climatic conditions can be found in Kapphan et al. (2011).

Furthermore, I use the same underlying weather indices as in Kapphan et al. (2011) to simulate optimal and the corresponding approximated insurance contracts. In particular, the 4 indices take either single or multiple weather events into account that occur during the growing season. All indices are derived from weather-yield regression models where the estimated coefficients serve as weights to construct a multi-peril index. Index 1 uses mean precipitation during vegetative period of maize growth to measure the water supply, and explains 37.1% of the yield variability in today's climatic conditions, and 39.2% with climate change. Considering in addition the influence of heat stress, as measured by the average maximum temperatures during the grain filling period, Index 2 explains 50.3%, and with climate change 68.3%. Index 3 measures the actual water availability, i.e. the difference between mean precipitation and potential evapotranspiration, and explains 46.3%, and 67.8% in the climate change scenario, of the yield variability. Taking the influence of multiple weather events at different phenology stages into account, Index 4 explains the largest fraction of the yield variability with 62.5%, and 74.5%. All weather indices represent predicted yields (measured in kg/ha), and are converted into predicted revenues (in CHF/ha) using the crop price of 0.41 CHF/kg for maize (CHF/kg).[9] For a detailed description of the index selection and design, see Kapphan et al. (2011), Table 4.3 summarizes the goodness of fit of the 4 indices for today's and future climatic conditions.

[9] The average price for maize from 2006 to 2009 in Switzerland, which was 41.00 CHF/100kg (SBV, 2010) is used, as in Kapphan (2011), and Kapphan et al. (2011).

Table 4.3: Descriptive statistics of weather indices

	in %	Index 1	Index 2	Index 3	Index 4
Today	Corr	60.8	70.9	68.1	78.9
	adj. R^2	37.0	50.3	46.3	62.2
Future	Corr	62.6	82.6	82.3	86.3
	adj. R^2	39.2	68.3	67.8	74.5

Note: Today's weather indices are selected based on the Spearman rank correlation coefficient (Corr) and the adjusted R-Square (adj.R^2) from the weather-yield regression for today's conditions. Future weather indices are constructed using the same weather variables, measured during future phenology phases, and using the coefficients from future weather-yield regressions as weights.

4.4 Results

4.4.1 Comparison of Optimal and Approximated Insurance Contracts

For the baseline approximation scenario, Figure 4.2 (left) shows the optimal, $p_t(z)$, and approximated, $a_t^1(z)$, insurance contract for today's weather conditions based on Index 2. The shape of $p_t(z)$ reflects the changes in the riskiness of the respective conditional yield distributions, $f_t(y|z)$, as explained in Kapphan (2011), and is non-linear along the entire range of the index realizations. Payouts of $p_t(z)$ and $a_t^1(z)$ are increasing with lower values of the weather index, as these realizations correspond to low predicted revenues. The optimal payout function flattens for very high index realizations, as they indicate high revenues. At the point where $p_t(z)$ and $a_t^1(z)$ are equal to zero, the insured fully recovers the premium. The break-even point is defined as ξ. For $z \leq \xi$, the insured's indemnifications $I(z)$ exceed the premium and net-payouts are positive. For $z > \xi$, net-payouts are negative, i.e. the insured receives payments that are smaller than the premium. The premium is given by the minimum of $p_t(z)$, and $a_t^1(z)$ respectively. By definition, the approximated contract $a_t(z)$ has a linear slope between τ_t and η_t, and maximum payments, κ_t, are capped once $z < \eta_t$ is reached. Similarly, net-payouts of $a_t(z)$ do not further decrease for $z > \tau_t$, i.e. for index realization that are higher than the trigger, it follows that $I_t(z) = 0$, or $\mu_t = P_t$. Figure 4.2 (right) shows the pdf of the underlying index z together with the trigger, τ_t^1, and exit, η_t^1, levels of my baseline approximation scenario.

The most notable differences between $p_t(z)$ and $a_t^1(z)$ are that 1) the maximum payout of the approximated contract is much lower compared to optimal, 2) the premium of the approximated contracts is slightly smaller, and 3) the approximated contract tends to over-compensate the insured for index realizations between the trigger and exit. These observations hold for all the other indices.[10]

[10]In the Appendix B, Figure 4.9 shows the optimal and profit-maximizing contracts with their approxi-

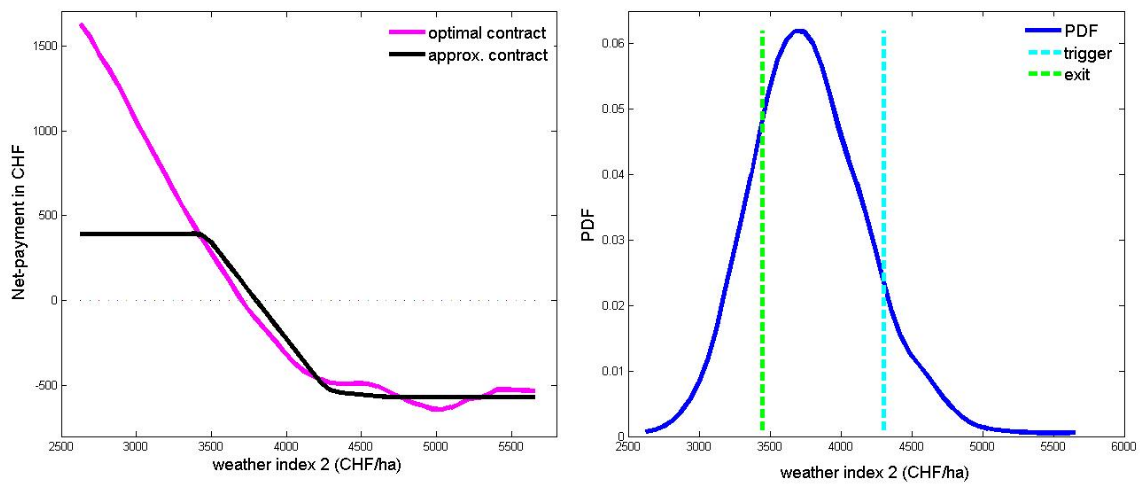

Figure 4.2: Optimal and approximated (based on Method 1) weather insurance contracts for today's climate scenario derived for Index 2 (*left*), pdf of the Index 2 together with the exit and trigger levels for the baseline approximation scenario (*right*). Both the weather index and net-payouts are measured in CHF/ha.

In particular, $a_t^1(z)$ (based on Index 2) starts to pay out once (predicted) revenues τ_t^1 fall below 4300.0 CHF/ha. Once η_t^1 of 3449.9 CHF/ha is reached, net-payouts are capped at 426.3 CHF/ha. The premium for $a_t^1(z)$ is 566.6 CHF/ha. In contrast, the maximum payout of $p_t(z)$ is with 1672.1 CHF/ha much higher, while the exit level is with 2627.8 CHF/ha much lower. The profit-maximizing contract $\tilde{p}_t(z)$ also offers a higher maximum payout of 1557.4 CHF/ha, relative to $\tilde{a}_t^1(z)$, which caps net-payouts 359.0 CHF/ha. By construction, the difference between $\tilde{\eta}_t$ and $\tilde{\eta}_t^1$ is the same as for η_t and η_t^1. I also observe for $p_t(z)$ and $\tilde{p}_t(z)$ that these contracts possess higher strike values compared to their approximated counterparts. As soon as $z < \tau_t = 5036.8$ CHF/ha, the optimal (gross) contract triggers payments. Given that these payments do not let the insured break even as long as $z > \xi$, the difference in $\tau_t \geq \tau_t^1$ can be neglected from a risk reduction perspective. Table 4.4 summarizes the insurance parameters (τ_c, η_c, κ_c, ϕ_c, and P_c) of $p_c(z)$, $a_c^1(z)$, $a_c^2(z)$, and for $\tilde{p}_c(z)$ and $\tilde{a}_c^1(z)$ based on Index 2 for both climatic scenarios.

Furthermore, I observe that $a_t^1(z)$ tends to overcompensate the insured (relative to $p_t(z)$) for all weather events between τ_t and η_t, i.e. the insured receives a slightly higher payout for $z \in [\eta_t, \xi_t]$, or has to make slightly smaller payments for $z \in [\xi_t, \tau_t]$ to the insurer, than suggested by the optimal contract. Thus, $a_t^1(z)$ and $\tilde{a}_t^1(z)$ provide less coverage in years where the weather is really bad, and hence revenues are low, compared to $p_t(z)$ and $\tilde{p}_t(z)$. While extremely bad weather events are rare, these are the events when adequate compensation is needed the most. Furthermore, the linear payout structure of

mated counterparts for all indices.

Table 4.4: Contract parameters for Index 2

TODAY	$p_t(z)$	$a_t^1(z)$	$a_t^2(z)$	$\tilde{p}_t(z)$	$\tilde{a}_t^1(z)$
P_t	-641.9	-566.6	-510.1	-711.2	-618.8
(std)	*(23.8)*	*(16.3)*	*(20.5)*	*(97.9)*	*(28.8)*
τ_t	5036.8	4300.0	4300.0	4953.8	4300.0
(std)	*(46.9)*	*(23.1)*	*(23.1)*	*(41.4)*	*(23.1)*
η_t	2627.8	3449.9	3449.9	2627.8	3449.9
(std)	*(89.7)*	*(11.2)*	*(11.2)*	*(89.7)*	*(11.2)*
κ_t	1627.1	426.3	344.6	1557.4	359.0
(std)	*(172.3)*	*(32.2)*	*(29.6)*	*(171.1)*	*(33.3)*
ϕ_t	n.a.	1.13	1.01	n.a.	1.13
(std)	n.a.	*(0.05)*	*(0.03)*	n.a.	*(0.05)*
FUTURE	$p_f(z)$	$a_f^1(z)$	$a_f^2(z)$	$\tilde{p}_f(z)$	$\tilde{a}_f^1(z)$
P_f	-1688.6	-1047.7	-946.5	-1725.5	-1187.9
(std)	*(67.8)*	*(97.7)*	*(43.3)*	*(59.60)*	*(106.6)*
τ_f	3933.9	4364.3	4364.3	3272.9	4364.3
(std)	*(96.1)*	*(56.85)*	*(56.85)*	*(83.52)*	*(56.85)*
η_f	1657.7	2780.8	2780.8	1657.7	2780.8
(std)	*(102.1)*	*(21.37)*	*(21.37)*	*(102.1)*	*(21.37)*
κ_f	1191.9	709.0	625.5	1022.1	544.7
(std)	*(62.7)*	*(34.46)*	*(20.27)*	*(70.04)*	*(43.06)*
ϕ_f	n.a.	1.09	0.99	n.a.	1.09
(std)	n.a.	*(0.06)*	*(0.02)*	n.a.	*(0.06)*

Note: Contract parameters (τ_c, η_c, κ_c, ϕ_c) of optimal ($p_c(z)$) and approximated insurance contracts ($a_c^1(z)$, $a_c^2(z)$), and profit-maximizing ($\tilde{p}_c(z)$) and approximated profit-maximizing ($\tilde{a}_c^1(z)$) together with the premium (P_c) for Index 2 under today's and future climatic conditions. All contract parameters are measured in CHF/ha. By construction $\tau_c^1 = \tau_c^2 = \tilde{\tau}_c$, and $\eta_c^1 = \eta_c^2 = \tilde{\eta}_c$. Estimates of the standard deviation for $p_t(z)$ and $a_t(z)$, and thus for the contract parameters, are obtained by 10 times randomly drawing 900 observations with replacement from the data, and solving (4.1) subject to (4.2) as described in section 4.2. For more information, see Kapphan et al. (2011).

$a_t^1(z)$ for $z \in [\eta_t, \tau_t]$ neglects the non-linear influence of weather on yields, and tends to overcompensate these losses. The extended coverage of $p_t(z)$ and $\tilde{p}_t(z)$ during bad years is available at slightly higher premiums of $P_t = 641.9$ CHF/ha, and $\tilde{P}_t = 711.2$ CHF/ha respectively, compared to $P_t^1 = 566.6$ CHF/ha, and $\tilde{P}_t^1 = 618.8$ CHF/ha.[11] The difference between $P_t(z)$ and $P_t^j(z)$ is mostly explained by $\kappa_t^o > \kappa_t^j$, since more coverage in bad years causes premiums to rise. However, the fact that $a_t^1(z)$ provides excess coverage for

[11] As suggested by Kapphan (2011), premiums do not necessarily have to be paid upfront at the beginning of the growing season. Instead, the insurer offers the insured a swap contract, which specifies the net-payoff function and the underlying index. At the end of the growing season, once the weather is realized, payments are exchanged. If the farmer has experienced a good harvest, he pays the insurer ex-post for assuming the downside weather risk. Alternatively, in a bad year, the insured receives an indemnification from the insurer.

weather events between τ_t and η_t causes P_t^1 to be higher compared to an approximated contract with κ_t and μ_t that followed the net-payoff structure of $p_t(z)$ for $z \in [\eta_t, \tau_t]$.

Approximated Contracts and Climate Change

Deriving the optimal weather insurance contract, $p_f(z)$, for the climate change scenario, I observe that the $p_f(z)$ covers additional weather events, and that the magnitude of payments decreases for those weather realization that existed already today. Figure 4.3 (left) shows the optimal, $p_t(z)$ and $p_f(z)$, and approximated, $a_t^1(z)$ and $a_f^1(z)$, weather insurance contracts based on Index 2 for today's and future climatic conditions. The change in the shape of $p_f(z)$ and the extended coverage for drier weather conditions is explained by the change in the pdf of the underlying weather index.[12]

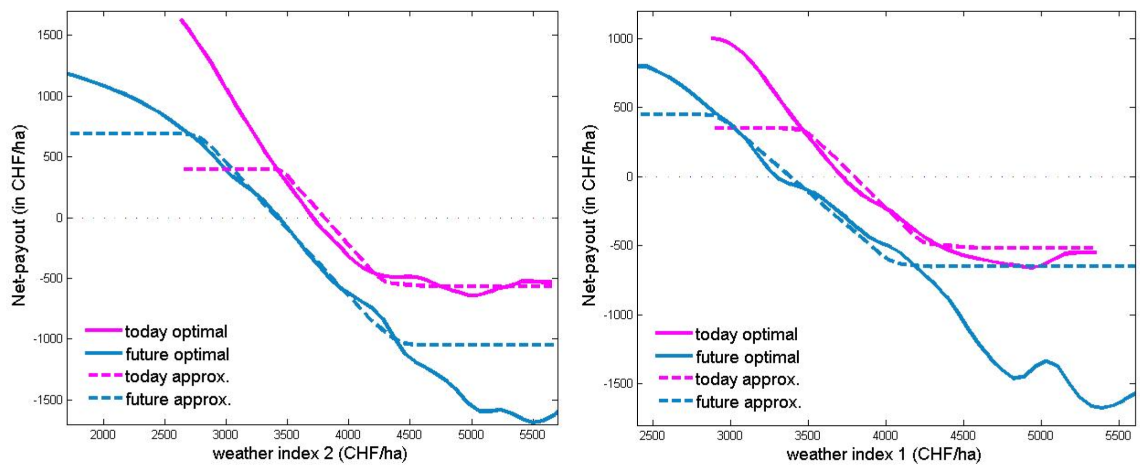

Figure 4.3: Optimal and approximated (Method 1) weather insurance contracts for today's climatic conditions based on Index 2 (*left*) and Index 1 (*right*). Both the weather index and net-payouts are measured in CHF/ha.

The approximated contract $a_f^1(z)$ covers similar to $p_f(z)$ a wider range of weather events. In particular, the future optimal contract offers an extended coverage against drier conditions since z takes on even smaller values with climate change. Therefore, η_f is smaller than η_t, which is then also reflected by $eta_f^1 > \eta_t^1$ for the approximated contract. At the same time, I observe that $\kappa_f > \kappa_t$, and correspondingly $\kappa_f^1 > \kappa_t^1$ for the approximated contract, which results in $P_f^1 > P_t^1$, and correspondingly in $\tilde{P}_f^1 > \tilde{P}_t^1$. While these observations hold for all indices, the direction of change for the trigger level is not consistent across indices. For Index 2, I observe that $\tau_f^1 > \tau_t^1$, while for Index 1 $\tau_f^1 < \tau_t^1$.

[12]For a complete analysis and discussion of the changes in the optimal weather insurance contract due to climate change, see Kapphan et al. (2011).

Figure 4.3 shows the the optimal and approximated contracts for both climate scenarios based on Index 2 (left) and Index 1 (right). These observations confirm, as suggested by Kapphan et al. (2011), that the insurance parameters of the stylized linear contract (τ_f^1, η_f^1, and κ_f^1) need to be a adjusted with climate change. In order to approximate the future optimal contract, the direction of change for τ_f and η_f depends on the change in $g_f(z)$ with respect to $g_t(z)$ of the underlying index.

Comparison of Approximation Methods

While the two approximated contracts have by definition the same strike, $\tau_c^1 = \tau_c^2 = \tau_c$, and exit, $\eta_c^1 = \eta_c^2 = \eta_c$, the two contracts differ in κ_c, i.e. the net-payout at which payments are capped once $z \leq \eta_c$. Figure 4.4 shows $a_t^1(z)$ and $a_t^2(z)$ based on Index 2 for today's weather conditions.[13] Comparing the insurance parameters, I find that $a_t^1(z)$ possesses a higher cap than $a_t^2(z)$ for all indices. While the probabilities of receiving the maximum payments are the same for both approximated contracts, the fact that $\kappa_t^1(z) > \kappa_t^2(z)$ explains why $P_t^1(z) > P_t^2(z)$. Given that the $p_t(z)$ and $\tilde{p}_t(z)$ provide even higher payouts in very bad years, this already suggest that Method 1 is better suited to approximate the optimal and profit-maximizing contracts. In order to determine which method is better suited, the loss in risk reduction for the insured when hedging with $a_c^1(z)$, as measured by Δ_c^1, will be compared to the loss in risk reduction from hedging with $a_c^2(z)$, given by Δ_c^2, for both climatic scenarios in the next section 4.4.2. The method which minimizes the loss in risk reduction is better suited to approximate the optimal contract.

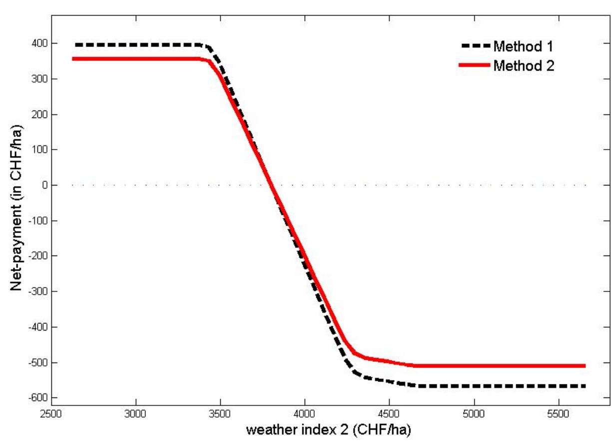

Figure 4.4: Comparison of approximated optimal insurance contracts for Method 1 and 2 based on Index 2 for today's climate scenario.

[13]For the climate change scenario, the difference in the approximation methods described here are the same.

4.4.2 Loss in Risk Reduction and Profitability

I evaluate the risk reduction for the insured from hedging with the optimal $p_c(z)$ and the approximated optimal $a_c^j(z)$ contracts by deriving $\delta_c(p_c(z))$, $\delta_c(a_c^1(z))$ and $\delta_c(a_c^2(z))$ for all indices.[14] Furthermore, I assess the expected profits for the insurer from offering the profit-maximizing contract $\tilde{p}_c(z)$ and the approximated profit-maximizing contract $\tilde{a}_c^1(z)$ by deriving $\Pi_c(\tilde{p}_c(z))$ and $\Pi_c(\tilde{a}_c^1(z))$. The trigger and exit values of $a_c^j(z)$ and $\tilde{a}_c^1(z)$ represent the baseline approximation scenario outlined in section 4.2. In Table 4.5, I report the deltas and profits of all contracts and indices and both climate scenarios. Figure 4.5 (left) shows the boxplots of $\delta_t(p_t(z))$, $\delta_t(a_t^1(z))$ and $\delta_t(a_t^2(z))$ based on Index 4, and Figure 4.5 (right) shows the boxplots of $\Pi_t(\tilde{p}_t(z))$ and $\Pi_t(\tilde{a}_t^1(z))$.

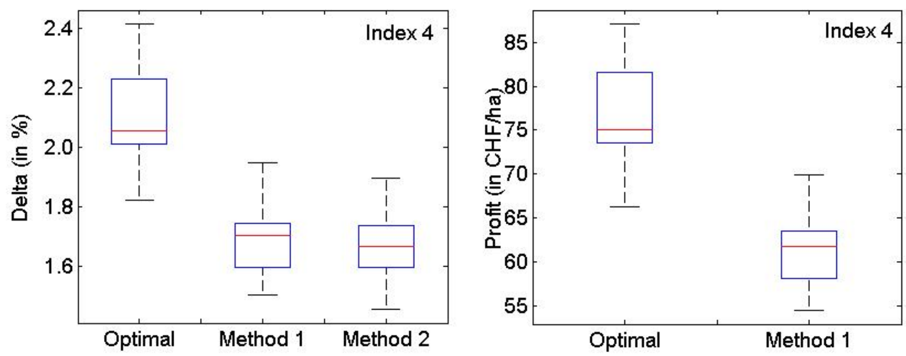

Figure 4.5: Boxplots of risk reduction, as measured by δ in %, for $p_t(z)$ (Optimal), $a_t^1(z)$ (Method 1), and $a_t^2(z)$ (Method 2) based on Index 4 (*left*). Boxplots of expected profits, as measured by Π in CHF/ha, for $\tilde{p}_t(z)$ (Profit) and $\tilde{a}_t^1(z)$ (Method 1) based on Index 4 (*right*).

For today's climate scenario, buying $p_t(z)$ is equivalent to increasing the income of the uninsured in all states of the world by $2.39 - 2.11\%$, with standard deviation of $0.12 - 0.17\%$, depending on the index. I find that when hedging with $a_t^1(z)$, this increase is only $1.11 - 1.70\%$, with standard deviation of $0.10 - 0.13\%$ (depending on the index). The insured attributes an even lower value to hedging weather risk with $a_t^2(z)$, i.e. $\delta_t(a_t^2(z))$ is $1.06 - 1.67\%$, with standard deviation of $0.10 - 1.13\%$. The differences between $\delta_t(a_t^1(z))$ and $\delta_t(a_2^1(z))$ are rather small, but indicate that Method 1 is slightly better suited to ap-

[14]The benefits of insurance for the insured could alternatively be assessed using a different risk measure, such as the 5%-Value at Risk ($VaR_{5\%}$), the Conditional $VaR_{5\%}$, which is also known as the expected shortfall, or as suggested by Kapphan et al. (2011), the relative $VaR_{5\%}$. Since δ evaluates the effect of insurance on the entire income distribution compared to the other risk measures, which only consider the effect on the lower end of the income distribution, δ is my preferred risk measure. Qualitatively, it can be shown that the results obtained from using δ also hold for the other risk measures. In the Appendix A, the statistical moments from hedging with $p_t(z)$ and the approximated optimal $a_c^j(z)$ are shown for Index 4.

proximate the optimal contract as it achieves a slightly higher hedging effectiveness for the insured. For the insurer, I find that offering $\tilde{p}_t(z)$ yields expected profits of $50.2 - 76.8$ CHF/ha, with standard deviation of $4.4 - 6.0$ CHF/ha depending on the index, and that expected profits from $\tilde{a}_t^1(z)$ range only between $39.9 - 61.7$ CHF/ha, with standard deviation of $3.5 - 4.7$ CHF/ha.

Table 4.5: δ (in %) and Π (in CHF/ha) for different contracts

TODAY	$\delta_t(p_t(z))$	$\delta_t(a_t^1(z))$	$\delta_t(a_t^2(z))$	$\Pi_t(\tilde{p}_t(z))$	$\Pi_t(\tilde{a}_t^1(z))$
Index 1	1.39	1.11	1.06	50.28	39.95
(std)	*(0.12)*	*(0.10)*	*(0.10)*	*(4.45)*	*(3.52)*
Index 2	1.86	1.42	1.36	67.70	51.43
(std)	*(0.15)*	*(0.10)*	*(0.10)*	*(5.21)*	*(3.34)*
Index 3	1.92	1.52	1.45	69.9	54.94
(std)	*(0.15)*	*(0.10)*	*(0.11)*	*(5.47)*	*(3.69)*
Index 4	2.11	1.70	1.67	76.8	61.73
(std)	*(0.17)*	*(0.13)*	*(0.13)*	*(6.04)*	*(4.75)*
FUTURE	$\delta_t(p_f(z))$	$\delta_f(a_f^1(z))$	$\delta_f(a_f^2(z))$	$\Pi_f(\tilde{p}_f(z))$	$\Pi_f(\tilde{a}_f^1(z))$
Index 1	3.0	2.46	2.48	91.33	75.44
(std)	*(0.20)*	*(0.24)*	*(0.19)*	*(5.62)*	*(5.48)*
Index 2	5.0	4.64	4.50	152.97	141.24
(std)	*(0.25)*	*(0.30)*	*(0.24)*	*(8.50)*	*(9.60)*
Index 3	4.99	4.61	4.52	153.34	141.48
std	*(0.24)*	*(0.25)*	*(0.23)*	*(7.61)*	*(7.74)*
Index 4	5.42	5.07	4.91	167.41	156.28
(std)	*(0.26)*	*(0.28)*	*(0.27)*	*(8.21)*	*(8.77)*

Note: The trigger values of the approximated contracts are defined by $\tau_{c,90\%}$, and the exit values for the approximated contracts are given by $\eta_{c,90\%}$, for $c \in t, f$.

For the climate change scenario, I find that the insured attributes a higher value to hedging weather risk compared to today's conditions. For $p_f(z)$, the hedging effectiveness, as measured by $\delta_f(p_f(z))$, increases to $3.0 - 5.42\%$, with standard deviation of $0.20 - 0.26\%$. Similarly, I observe that $\delta_f(a_f^1(z))$ increases to $2.46 - 5.07\%$. This confirms findings of Kapphan et al. (2011), that hedging weather risk becomes more viable for the insured with climate change. The increase in δ_f compared to δ_t is observed across indices and insurance contract types, i.e. the insurance design method does not drive the results of Kapphan et al. (2011).

For the insurer, I find that with climate change offering $\tilde{p}_f(z)$ yields expected profits of $91.3 - 167.4$ CHF/ha depending on the index, and that the insurer can expect to earn profits of $75.4 - 156.2$ CHF/ha with $\tilde{a}_f^1(z)$. Again, this confirms findings of Kapphan et al. (2011), that with climate change insurers can expect to earn higher profits due to the increase in weather variability, and that the increase in Π_f compared to Π_t holds for all indices and contract types.

While all contracts, $p_c(z)$, $a_c^1(z)$ and $a_c^2(z)$, achieve positive hedging benefits, the risk reduction realized by the approximated contracts is significantly smaller compared to the risk reduction realized by the optimal contracts in both climate scenarios. To evaluate the loss in risk reduction, Δ_c^1 and Δ_c^2 are derived using (4.9) and the δ_c's reported in Table 4.5. For Index 4, I find that Δ_t^1 is 19.4%, i.e. approximating the optimal contract (based on Index 4) using Method 1 with $\tau_{t,90\%}$ and $\eta_{t,20\%}$ causes a decrease in risk reduction by 19.4%. For today's climatic conditions, the loss in risk reduction is between $19.4 - 23.6\%$ for Method 1 (Δ_t^1), and between $20.8 - 24.4\%$ for Method 2 (Δ_t^2) depending on the index. Table 4.6 shows the loss in risk reduction and profits for all indices and both climate scenarios.

With climate change, I find that the loss in risk reduction from approximating $p_f(z)$ is becoming smaller, i.e. Δ_f^1 is $6.45 - 18.0\%$, for all indices. Thus, the increase in weather risk due to climate change, which causes an increase in the goodness of fit of the weather index (see Table 4.3, section 4.3) reduces the loss in risk reduction, that I observed for today's climatic conditions. Given that $\Delta_c^2 > \Delta_c^1$ for all indices, I conclude that Method 1 better approximates the optimal contracts, and hitherto also the profit-maximizing contracts.

For today's climate, the losses in profits, as measured by Θ_t^1, range between $19.6 - 24.0\%$ depending on the index. With climate change, the loss in profits, Θ_f^1, ranges between $6.6 - 17.3\%$ depending on the index, and is smaller compared than Θ_t^1 . The increase in weather variability makes hedging with linear weather insurance contracts less unattractive compared to hedging with the optimal contracts. Similarly, offering approximated contracts instead of the profit-maximizing counterparts causes a smaller loss in profits with climate change.

Table 4.6: Loss in risk reduction and profits

	Δ_t^1	Δ_t^2	Θ_t^1	Δ_f^1	Δ_f^2	Θ_f^1
Index 1	20.1%	23.7%	20.5%	18.00%	17.33%	17.39%
Index 2	23.6%	26.8%	24.0%	7.20%	10.0%	7.66%
Index 3	20.8%	24.4%	21.4%	7.61%	9.41%	7.73%
Index 4	19.4%	20.8%	19.6%	6.45%	9.40%	6.64%

Note: Loss in risk reduction (in %) for the insured, and loss in profits for the insurer (in %) are derived for the baseline approximation scenario for all indices and both climate scenarios.

4.5 Sensitivity Analysis

Both approximation methods require to select quantiles of $g_c(z)$ to define the exit and trigger value. The choice of τ_c and η_c determines the range of weather events covered by the resulting contract and consequently affects the hedging effectiveness of the contract. Therefore, the loss in risk reduction, as well as the loss in profits, also depends on the choice of the approximation parameters. In order to evaluate the sensitivity of the results outlined in section 4.4, which are derived for the baseline approximation scenario ($\tau_{c,90\%}$ and $\eta_{c,20\%}$), I perform a sensitivity analysis with respect to the approximation parameters.

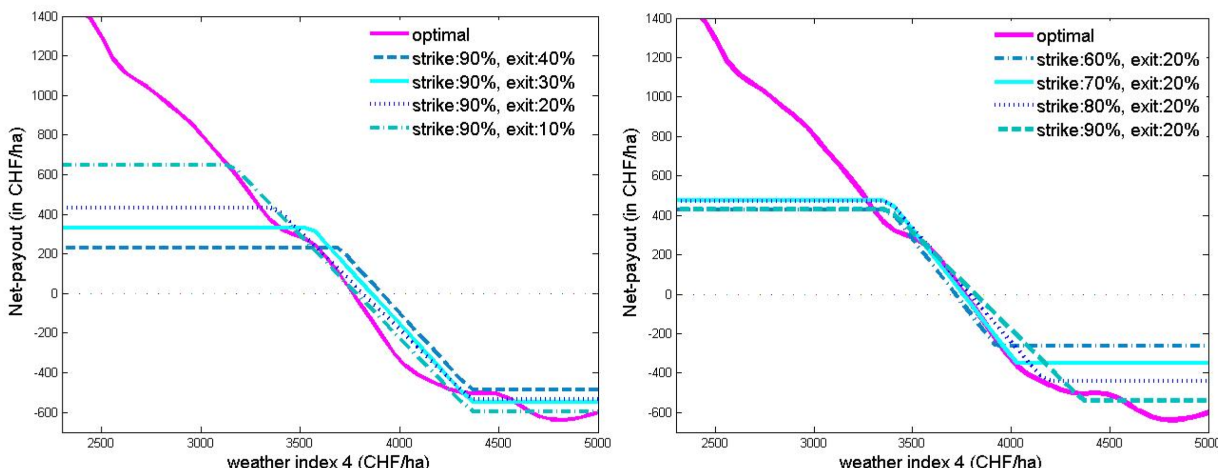

Figure 4.6: Optimal contract with approximated contracts (Method 1) based on Index 2 for today's climatic conditions. *Left:* Approximated contracts share the same strike value ($\tau_{t,90\%}$) and differ in the exit value ($\eta_{t,10\%}$, $\eta_{t,20\%}$, $\eta_{t,30\%}$, and $\eta_{t,40\%}$). *Right:* Approximated contracts share the same exit ($\eta_{t,20\%}$) and differ in the strike value ($\tau_{t,60\%}$, $\tau_{t,70\%}$, $\tau_{t,80\%}$, and $\tau_{t,90\%}$).

Increasing the trigger value, for instance from $\tau_{c,60\%}$ to $\tau_{c,80\%}$ implies that the contract starts to payout earlier, i.e. as soon as predicted revenues fall below the 80% quantile of the weather index z, the insured receives payments. Figure 4.6 (right) shows $p_t(z)$ based on Index 4 together with approximated contracts that share the same $\eta^1_{t,20\%}$ and differ in τ^1_t. Contracts that compensate moderate shortfalls with respect to the highest yield potential (e.g $\eta_{t,90\%}$) come at a higher cost ($P_{t,90\%} > P_{t,60\%}$). Decreasing the exit value, for instance from $\eta_{c,30\%}$ to $\eta_{c,20\%}$ implies that the contract provides more coverage in the event of bad weather. Figure 4.6 (left) shows $p_t(z)$ based on Index 4 together with approximated contracts that share the same $\tau^1_{t,90\%}$ and differ in η^1_t. Since the probability of these bad weather events is small, the increased coverage causes only a marginal increase in premiums. Consequently, increasing both τ^1_c and lowering η^1_c simultaneously creates a weather hedge with extensive coverage and frequent net-payments.

To assess how the insured evaluates the increased coverage given that it comes at a higher premium, I derive δ_c for a range of τ_c and η_c values. In particular, the hedging benefits (as measured by δ_c) for the insured are derived for τ_c equal to the quantiles of $g_c(z) \in [60-95\%]$, and η_c equal to the quantiles of $g_c(z) \in [5-40\%]$. Similarly, the expected profits (as measured by Π_c) for the insurer are derived for the same range of exit and trigger values. Figure 4.7 shows $\delta_t(a_t^1(z))$ and $\Pi_t(\tilde{a}_t^1(z))$ based on Index 4 for today's climatic conditions for a range of possible exit and trigger values.

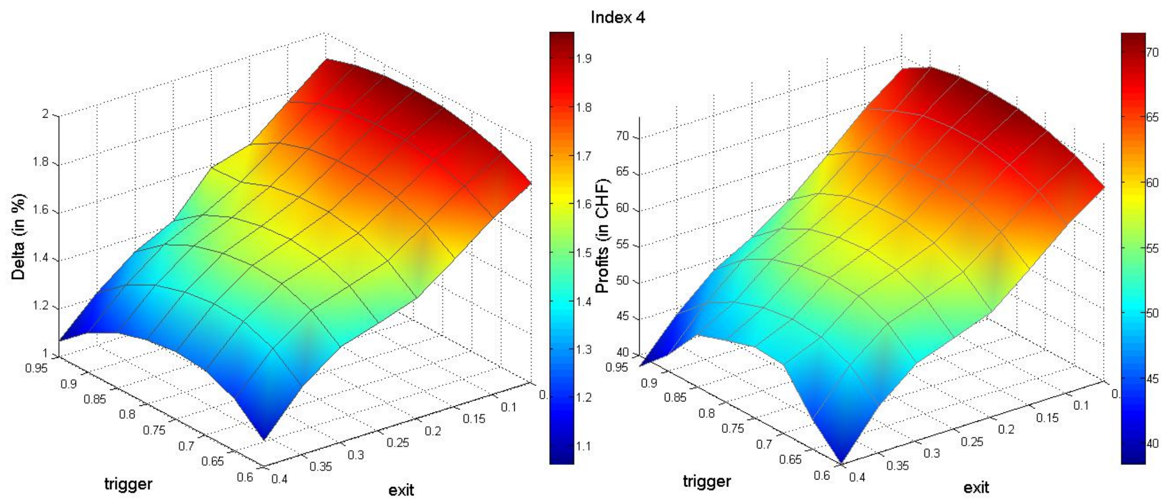

Figure 4.7: Risk reduction from hedging with $a_t^1(z)$ as measured by delta with $\tau_t^1 = g_c(z) \in [60-95\%]$ and $\eta_t^1 = g_c(z) \in [5-40\%]$ (*left*), and expected profits (Π_t) from offering $\tilde{p}_t^1(z)$ with $\tilde{\tau}_t^1 = g_c(z) \in [60-95\%]$ and $\tilde{\eta}_t^1 = g_c(z) \in [5-40\%]$ based on Index 4 (*right*) for today's climatic conditions.

I find that increasing the coverage of $a_t^1(z)$ either by increasing τ_t^1 while keeping η_t^1 constant, or by decreasing η_t^1 while keeping τ_t^1 constant, increases the hedging effectiveness $\delta_t(a_t^1(z))$. To put the results of the sensitivity analysis in context, for the baseline approximation, I found that $\delta_t(a_t^1(z))$ based on Index 4 is 1.70%, and that $\Pi_t(\tilde{a}_t^1(z))$ is 61.73 CHF/ha, see Table 4.5. For a contract that covers, for instance, only moderate deviations from the mean, as defined by $\tau_{t,90\%}^1$ and $\eta_{t,30\%}^1$, the risk reduction as measured by $\delta_t(a_t^1(z))$ is 1.43%. Keeping $\tau_{t,90\%}^1$ constant, and choosing an exit level of $\eta_{t,10\%}^1$ creates a contract that offers more protection against extreme dry conditions. The risk reduction of the extended coverage is equal to 1.81%, i.e. the insured values the extended coverage more despite the fact that it comes at a higher premium. The observation is in line with a fundamental principle of insurance economics, which states that the insured selects full insurance compared to partial insurance if the insurance policy is available at an actuarially fair premium.[15] Similarly, a contract with $\eta^1_{t,35\%}$ that triggers payouts based on $\tau^1_{t,65\%}$ yields hedging benefits for the insured of 1.37%, while the hedging benefits increase up to 1.41% with $\tau^1_{t,80\%}$ (keeping $\eta^1_{t,35\%}$ constant). However, a further increase of the trigger level up to $\tau^1_{t,95\%}$ changes $\delta_t(a^1_t(z))$ only marginally. For all indices, I observe that the change in $\delta_t(a^1_t(z))$ from increasing $\tau^1_{t,60\%}$ to $\tau^1_{t,95\%}$ is marginal compared to the change in $\delta_t(a^1_t(z))$ that can be realized by decreasing $\eta^1_{t,40\%}$ to $\eta^1_{t,5\%}$. The highest $\delta_t(a^1_t(z))$ is equal to 1.94% and is achieved by the approximated contract with $\tau^1_{t,90\%}$ and $\eta^1_{t,5\%}$. Furthermore, I observe that $\Pi^1_t(\tilde{a}^1_t(z))$ responds similarly to changes in $\tilde{\tau}^1_t$ and $\tilde{\eta}^1_t$. Increasing $\tilde{\tau}^1_t$ while holding $\tilde{\eta}^1_t$ constant, or decreasing $\tilde{\eta}^1_t$ while holding $\tilde{\tau}^1_t$ constant, causes expected profits to increase. The highest $\Pi^1_t(\tilde{a}^1_t(z))$ with 71.3 CHF/ha is realized for the approximated profit-maximizing contract with $\tilde{\tau}^1_{t,80\%}$ and $\tilde{\eta}^1_{t,5\%}$.[16]

The analysis thus shows that the magnitude of $\delta_t(a^1_t(z))$ and $\Pi^1_t(\tilde{a}^1_t(z))$ critically depends on the selection of τ^1_t and η^1_t. With the baseline approximation of $\tau^1_{t,90\%}$ and $\eta^1_{20\%}$, I therefore underestimated the risk reduction potential of $a^1_c(z)$. An approximated insurance contract with extended coverage would cause a smaller loss in risk reduction, as measured by Δ^j_c. Similarly, the losses in profits are overestimated by the baseline approximation for $\tilde{a}^1_c(z)$. By altering the approximation parameters, neither the hedging effectiveness achieved by $p_c(z)$ could be replicated with $a_c(z)$, nor the expected profits of $\tilde{p}_c(z)$ could be replicated with $\tilde{a}_c(z)$.

4.6 Conclusion

I compare for the first time the benefits from hedging weather risk in agriculture with a linear payoff structure, such as the weather derivatives that can be obtained in the customized over-the-counter (OTC) market, and a non-linear, optimal payoff structure proposed by Kapphan (2011). The optimal contract mirrors the agronomic relationship between weather and yields and offers the best risk reduction to the insured. To assess the effect of hedging weather risk in agriculture with linear contracts, I propose two different methods to derive the insurance parameters (strike, exit, cap, and tick size) from the optimal contract.

[15] Given that the insured is risk-averse ($\sigma = 2$), it can be shown that a range of loading factors exists at which the insured prefers the extended weather coverage despite the fact that the contract is not actuarially fair. The range of loading factors for which this is true can be determined with the help of the profit-maximizing contract. From $\tilde{p}_c(z)$, the maximum loading factor at which the insured is indifferent between hedging his weather risk and not insuring can be determined. The statement is then true for any loading factor smaller than the maximum loading factor.

[16] The results described here are qualitatively the same for the climate change scenario, and are available upon request from the author.

The proposed methods are used to simulate, for given strike and exit values, a linear contract with an actuarially fair premium that approximates the optimal contract. For the profit-maximizing contract, I propose a method that simulates a linear contract which fulfills the constraint that the insured is indifferent (in expected utility terms) between hedging and remaining uninsured. The methods differ in their selection of the cap and minimum payout. For Method 2, the fitted relationship between weather and yields is used to determine the cap and minimum payout, whereas Method 1 uses the optimal, respectively profit-maximizing contract to guide the payoff structure design.

Next, using maize and weather data from Schaffhausen, Switzerland, that has been simulated with a process-based crop simulation model for today's climatic conditions, and a climate scenario, I simulate optimal and profit-maximizing contracts. For a baseline approximation scenario, the corresponding approximated contracts are simulated. Next, the hedging effectiveness of the approximated contracts is compared to the risk reduction of the optimal contracts for both climatic conditions. Similarly, the expected profits from profit-maximizing contracts are compared to the profits of the approximated counterparts.

For the baseline approximation scenario, I find that approximating optimal contracts reduces the insured's hedging effectiveness by $20 - 23\%$, and diminishes the insurer's expected profits by $20 - 24\%$ given today's climatic conditions. With climate change, the loss in risk reduction (and profits) from hedging with approximated contracts decreases to $6 - 18\%$ (and the loss in profits decreases to $6.6 - 17.3\%$) due to an increase in the weather variability. These findings show that structural basis risk exists and that the hedging benefits, at a particular location and for a given crop, critically depend on the design method.

Since the approximation methods require to select strike and exit values, which affects the weather events covered and thus the hedging effectiveness of the approximated contracts, I perform a sensitivity analysis with respect to the selection of the strike and exit values on the results. To minimize the loss in risk reduction from approximating optimal (put option-style) contracts, I find that the insured needs to select a low exit level, and a high trigger level to obtain an extensive coverage. I show that my findings are robust to changes in approximation parameters.

The analysis provides useful insights for the selection of insurance parameters when buying standardized linear weather derivative contracts. Within the weather insurance industry, the trigger value is often set to represent historical average conditions $\tau_{c,50\%}$ (Vedenov and Barnett, 2004; Musshoff et al., 2009), and the exit is determined by average conditions plus (for call options) or minus (for put options) 1 to 3 standard deviations of the weather index distribution. Weather insurance contracts are then often structured such that the ratio of maximum payout and premium is between 10 and 20%. My analysis shows that such structuring rules-of-thumb are not backed by optimal risk reduction considerations, as the optimal as well as the approximated contracts exceed by far the industry's structuring benchmark.

One possible explanation of why farmers have been reluctant to use weather products is the lack of understanding of these more complex contracts, and the need to set the insurance parameters based on individual weather exposure. Given that the relationship between weather and yields is rather complex due to the manifold influence that weather can have on crop growth, a data driven decision is advised to make an informed decision when buying weather protection. The algorithm developed by Kapphan (2011) to simulate an optimal weather insurance contract, together with the approximation methods developed in this paper, constitute a decision-support tool for entrepreneurs intending to hedge weather risk. The benefit of this approach is that buyers do not need to specify the critical insurance parameters (strike, exit, and cap) based on subjective knowledge about their weather risk management needs. As long as the OTC market does not offer optimal parametric weather insurance products, the method proposed facilitates the buyers' decision by identifying the insurance parameters such that the best hedging effectiveness with a linear contract is achieved.

4.7 Appendix A

The benefits from hedging with $p_t(z)$ versus $a_t^1(z)$ and $a_t^2(z)$ are compared based on the statistical moments of the income distribution. In a given year, the income of the insured consists of the revenues from selling maize yields plus the net-payout from the insurance contract. In Figure 4.8, the income distribution without insurance and from hedging with $p_t(z)$ and $a_t^1(z)$ based on Index 4 are shown. Compared to the unhedged situation, both insurance products ($p_t(z)$ and $a_t^1(z)$) reduce the risk of realizing very low incomes. I find for all indices that hedging with the optimal contract causes the income distribution to be compressed the most. Without insurance, farmers growing maize in the respective case study region can expect to earn 3788.4 CHF/ha. The average income without insurance varies with a standard deviation of 598.3 CHF/ha. Hedging weather risk with $p_t(z)$ reduces the standard deviation to 351.1 CHF/ha, while preserving the mean income given that the insurance contract is actuarially fair. Hedging with $a_t^1(z)$ reduces the standard deviation to 410.8 CHF/ha, and 413.8 CHF/ha for $a_t^2(z)$ respectively. Table 4.7 shows the statistical moments (mean, standard deviation, skewness, and quantiles) for the unhedged situation and the different weather insurance contracts proposed based on Index 4. While farmers can expect to receive incomes of 2901.9 CHF/ha or lower with a probability of 10%, hedging increases the income in the worst 10%-years to 3352.6 CHF/ha for $p_t(z)$ and to 3223.0 CHF/ha for $a_t^2(z)$. Only the optimal (and profit-maximizing) contract reduces the skewness.

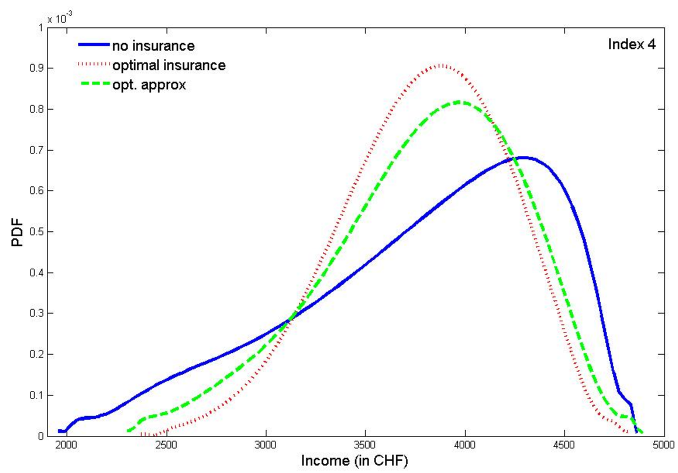

Figure 4.8: Income distribution with optimal (*dotted line*) and approximated (*dashed line*) insurance based on Index 4, and without insurance (*solid line*) for today's climatic conditions.

While hedging with $\tilde{p}_t(z)$ also reduces the standard deviation to 351.1 CHF/ha, the average income with $\tilde{p}_t(z)$ is with 3711.6 CHF/ha smaller. The reduction in the mean income is due to the fact that the insurer generates positive profits from offering $\tilde{p}_t(z)$. Hedging with $\tilde{a}_t^1(z)$ also decreases the standard deviation to the same extent as $a_t^1(z)$, and in addition reduces the mean income, similar to the situation with $\tilde{p}_t(z)$. Analyzing the hedging benefits by means of comparing the statistical moments of the unhedged with the hedged income situation thus yields qualitatively the same results. The optimal insurance contract yields the highest risk reduction compared to the approximated counterparts.

Table 4.7: Income without insurance and with different contracts

	no insurance	$p_t(z)$	$a_t^1(z)$	$a_t^2(z)$	$\tilde{p}_t(z)$	$\tilde{a}_t^1(z)$
mean	3788.4	3788.4	3788.4	3788.4	3711.6	3726.7
std	598.3	351.1	410.8	413.8	351.1	410.6
skw	-0.73	-0.5	-0.7	-0.8	-0.5	-0.72
10%	2901.9	3352.6	3235.7	3223.0	3275.9	3174.1
25%	3422.5	3594.9	3587.3	3586.9	3517.9	3525.4
50%	3909.6	3807.6	3828.9	3833.7	3730.6	3767.0
75%	4253.8	4017.5	4061.6	4062.1	3940.7	3999.7
90%	4459.6	4207.4	4260.8	4258.0	4130.3	4199.0

Note: Descriptive statistics of income without insurance and with different insurance contracts based on Index 4 for today's climatic conditions. Units: CHF/ha.

4.8 Appendix B

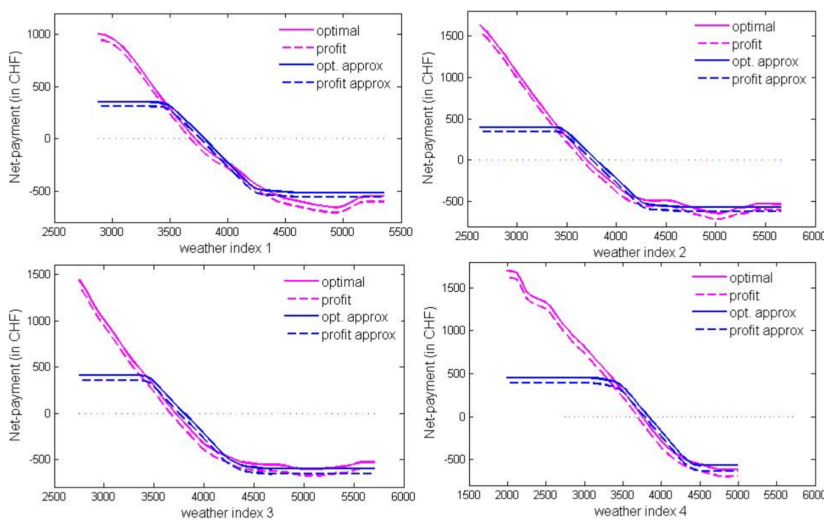

Figure 4.9: Optimal $p_t(z)$ and approximated contracts $a_t^1(z)$ for all indices and today's weather conditions.

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Chapter 5

Insuring Against Bad Weather: Benefits and Challenges in Light of Climate Change

Stanford Institute for Economic Policy Research (SIEPR), Policy Brief, Nov. 2011

5.1 Weather and the Economy

Weather affects almost all industries through both consumption and (directly or indirectly) production. In the power industry, energy demand rises with cooling needs in hot summers, forcing energy companies to produce electricity at higher costs, whereas the beverage industry benefits in hot summers from skyrocketing sales. Every industry faces a different form of weather risk. A recent study by the National Center for Atmospheric Research (NCAR) in Boulder, Colo. shows that the productivity of the entire economy fluctuates with extreme weather events (Lazo et al., 2011). After mining, agriculture is the second most weather-sensitive sector. Weather sensitivity of different sectors ranges from 2.2 percent (for wholesale)to 14.4 percent (for mining). Considering the relatively small share of agriculture in total GDP (1.5 percent), its absolute weather fluctuations amount to US$ 15.4 billion (in year 2000 dollars) and are comparable to what is at stake in the utilities sector (US$ 14.8 billion). The financial sector, accounting for 20 percent of the total GDP, has by far the largest absolute weather sensitivity. If the weather is good in one year for a particular sector, the same weather can mean bad times for another sector. When the sector-specific weather impacts are aggregated nationally, they tend to offset each other to some extent. The overall U.S. weather sensitivity is therefore smaller than the simple average of the individual sectors' weather sensitivities. Overall, the study found that U.S.

economic output varies by up to US$ 485 billion a year, or about 3.4 percent of the 2008 GDP, due to weather variability. NCAR's findings show that adverse weather conditions could push the economy into a recession. In any year, a decline in the GDP by 3.4 percent represents an enormous amount of lost output. While protective action can help to mitigate some losses, other impacts, such as those owing to extreme weather events, may not easily be prevented. Insurance or hedging can reduce the financial impacts from bad weather.

5.2 Insuring Against Bad Weather

Weather risk can be managed either by weather insurance or weather derivatives, index-based financial products where payouts are triggered by an exogenous weather event. For derivatives, payments are not based on actual losses as with traditional insurance, but on observed weather data. Index-based weather insurance exploits the fact that weather observations can be used as a proxy for the losses suffered through reduced sales, lower production, or increased costs due to spiraling input prices. Weather observations obtained from meteorological services are used to determine payouts. Once a predefined threshold (trigger) of the underlying weather index has been reached during a specified time period, the contract starts to pay out. A put option on rainfall, for instance, starts to pay out if cumulative precipitation falls below the trigger. A call on temperature during the winter months pays out if temperatures exceed a predetermined threshold. The buyer of the call pays a cash premium to the counterparty willing to assume the risk that the winter will be mild.

Weather derivatives can be settled quickly compared with loss-based insurance contracts. Weather insurance requires a proof of loss attributable to weather, which can be time-consuming. With weather derivatives, in contrast, the natural buyer has no guarantee that the derivative contract pays out when his business experiences weather-related losses. When using weather derivatives, natural buyers are thus left with so-called basis risk, i.e., the risk of not receiving payments, or inadequate payments, in the event of a loss. Basis risk can arise due to a number of reasons: spatial and temporal discontinuities in weather or an imperfect correlation of the weather index with revenues.

The major advantage of index-based insurance over traditional insurance is that problems arising from asymmetric information, such as moral hazard and adverse selection, are avoided and administrative costs are lower. When payouts are triggered by an exogenous event that is correlated with the insured output, these additional costs can be completely avoided as no incentives exist for the natural buyer to change his behavior. Weather derivatives constitute an innovative risk-transfer product to protect against weather-related revenue fluctuations.

5.3 The Origins of the Weather Derivatives Market

The first official weather transaction occurred between Enron Corporation and Koch Industries (Myers, 2008). The two companies swapped the risk of abnormal temperature conditions in Milwaukee, Wis., during winter $1997 - 1998$, with Koch getting a put on temperature falling below average conditions. Soon after, the Chicago Mercantile Exchange (CME) started to offer standardized weather derivatives in the form of options and futures for a number of major cities in the United States. Today, the CME group offers weather derivatives based on temperature, rainfall, frost, and snowfall for major cities in the U.S., Asia, and Europe. In 2005, the CME expanded its product portfolio with the introduction of hurricane futures and options, providing an alternative for insurers to transfer claims risk to the capital markets.

5.3.1 Over-the-Counter Versus Exchange-Traded Products

Weather derivatives are available for a wide range of weather risks. In addition to the exchange products, the over-the-counter (OTC) market offers alternative opportunities to buy weather derivatives tailored to a particular business need. While standardized derivatives possess the benefit that the exchange (e.g., CME) provides transparency and liquidity and eliminates counterparty risks, they are not ideal solutions for every business. Many companies possess complex weather risk that is uncorrelated with the weather in major cities and desire very specific weather hedges that are now available through the OTC market.

5.3.2 Weather Risk Management at the Corporate Level

The rapid expansion of the weather derivatives market was facilitated by the expanding scientific skill for modeling and predicting weather phenomena. The management of weather and climate risk requires sophisticated and reliable information about weather and its variability. Despite the technological advances made and the increasing number of products available, paired with the need to manage weather risk due to climate change, the number of companies managing weather risk is still low.

CME Group and Storm Exchange Inc., surveyed 205 senior finance and risk managers across a number of weather-sensitive companies in the United States (CME Group, 2008) and found that 82 percent believe that the emergence of climate change with its accompanying volatile weather patterns mandates changes to their corporate risk management approach. And 51 percent admitted that their companies are not well prepared to cope even with the current weather risk, while only 10 percent of the respondents declared that their companies are already managing weather risk. Seldom have executives been so united in recognizing a threat to their businesses and at the same time hesitant about addressing it. One of the reasons companies hesitate to adopt weather risk management practices is the unfamiliarity with the weather marketplace. Companies seem to be uncertain about what type of weather contracts are needed given their unique exposure and in particular how to evaluate the trade-off between costs faced from obtaining protection and the benefits.

5.4 Hedging Effectiveness of Weather Derivatives

For the weather hedge to be most effective, all available information about a company's weather exposure should be used to structure an appropriate contract. In general, structuring a weather hedge can be decomposed into two components: the selection of the index and the parameters that define the payoff structure for a given index. In particular, the hedging effectiveness of weather derivatives depends on the quality of the index in predicting losses and on the parameters that define the payoff function (trigger, tick size, and cap). The "tick size" is the monetary value of one index point. The "trigger" is the threshold level beyond which the contract starts to pay out, and the "cap" specifies the maximum payout per contract.

To select a powerful index, the buyer needs to quantify the time period(s) during which his business suffers most from adverse weather conditions, i.e., which meteorological phenomenon is responsible for the fluctuations and the location(s) at which the weather matters. Based on this information, the underlying weather index can be designed. In order to minimize basis risk, the index has to possess a high correlation with the economic output to be hedged. Often an imperfect correlation of the index with losses is cited as the main drawback of index-based weather products and blamed for not adequately hedging weather exposure. While it is true that there is little scope for weather hedging if it is based on a poorly designed weather index, the way the payoff is structured matters as well for the hedging effectiveness.

The payoff function is determined through the choice of the trigger, tick size, and cap. When structuring the contract, the focus of buyers and sellers alike often lies on the relationship between the premium and the maximum payoff (cap). Contracts tend to be evaluated based on the ratio between the premium and the cap, with a premium ranging between 1/10 to 1/5 of the cap. Thinking about a weather derivative like a lottery, i.e. US$ 1 invested may yield benefits of US$ $5-10$, neglects the fact that the likelihood of getting the maximum payoff depends on the probability of getting hit by really bad weather. Taking a closer look at such rules shows that they are not backed by considerations for efficiently reducing risk.

Weather derivatives are priced by assessing how often the contract would have paid out in the past. To compensate the seller for assuming the risk, a margin is added to the premium. With this logic, increasing a cap implies that more money is paid out in the event of really bad weather, causing the premium to increase. Usually adding tail risk coverage causes premiums to go up only slightly, because the probabilities of tail events are low. Lowering a cap decreases maximum payouts in the event of bad weather. To manage weather risk effectively maximum payoff needs to be adequate to compensate the losses in the event of bad weather.

The choice of the trigger level also affects the pricing of the contract. Increasing (lowering) the trigger level of a put (call) option causes premiums to go up, but it also implies that the insured is more likely to receive (small) payments at a higher frequency. The strike level thus determines the type of losses that are covered by the contract. For businesses with a low tolerance of revenue volatility a contract that generates smaller payments regularly can be valuable in order to smooth fluctuations in cash flows. If the weather hedge is intended to protect only against major events, the trigger can be set such that the contract pays out only under extreme weather conditions.

The buyer needs to assess how much his business suffers in the event of bad weather, i.e., the damages caused by a one-unit change in the weather index. When hedging with a standardized weather derivative from the exchange, this information helps to determine how many contracts to buy since the tick size is predetermined. For instance, at the CME the tick size of temperature-based contracts is equal to US$ 20 per heating degree day (HDD) or cooling degree day (CDD). In the OTC market, the tick size can vary.

Most weather derivative contracts assume a linear relationship between weather and the economic output at stake. For many businesses, it is fair to assume such a linear relationship. In the energy sector, heating and cooling demand varies linearly with weather. Crops are however affected in a non-linear manner by changes in temperature and precipitation conditions. Adequate risk management with weather derivatives for agriculture therefore requires a synthetic financial product that mimics the relationship between weather and yields. By combining for instance weather derivatives with different strikes and tick sizes, a weather derivative portfolio can be created where the portfolio payoffs compensate for the crop losses. Natural buyers thus need to carefully evaluate the outlined trade-offs and obtain a weather contract that efficiently meets the companies' objectives in managing weather risk. For the case of agriculture, Kapphan (2011) has developed a mechanism that accounts for the non-linear impact of weather on crops and that can be used to obtain – for a given index – the parameters defining the payoff structure that delivers an optimal risk reduction.

5.5 Weather Risk Management and Climate Change

With climate change, the number of extreme events and the seasonal variability is expected to increase (WMO, 2011). For weather-sensitive industries, climate change implies that new extreme events are expected to occur, causing damages that may exceed the extent of previously known damages. In addition, the frequency of extreme weather events is increasing and driving up weather-related losses. Munich Re (2011), which maintains a comprehensive database of global natural catastrophes, shows that the number of extreme weather events like windstorms, floods, and forest fires has tripled since 1980 and the trend is expected to persist.

Many industries are seeing the first signs of climate change already today: Ski resorts are faced with less reliable snow conditions; rainfall and temperature variability affect agriculture output; transportation and airline companies experience more business disruption due to an increase in the number of snowstorms and floods.

The number of companies with weather risk on their balance sheets is rising, and the industry will see more natural buyers operating in the market. While these scenarios represent gloomy prospects for the industry, insurers (and reinsurers) are however faced with a new challenge. Climate change is putting an end to stationarity. The assumption that historical (data) records can be used to assess future probability does not hold any longer (McCarl et al., 2008). In particular, the changing occurrence and frequency of extreme weather events imply that historical return periods underestimate the likelihood of losses in the future. Climate change thus undermines a basic assumption that historically has facilitated risk management (Milly et al., 2008).

Traditionally, the insurance industry uses historical data to design and price insurance products. These modeling techniques are, however, illsuited for understanding the implications of climate change (Mills, 2009). Within natural catastrophe modeling, insurers couple climate models with catastrophe models to examine the financial implications of climate change on insured risk. With the current trend, insurers will need to respond by increasing premiums, possibly restricting coverage and increasing deductibles for their damage-based weather insurance products if the number of weather-related losses continues to increase.

Climate change also matters for the design and pricing of weather derivatives. With weather derivatives, the insurer only has to correctly estimate the underlying weather index distribution. Compared with traditional insurance, weather derivatives specify the maximum payout, i.e., the risk taker does not face the uncertainty of future claim payments exceeding historical ones. From the risk taker's point of view, weather derivatives are therefore becoming more attractive. For the insured, however, increased business disruptions due to more severe weather extremes imply that losses beyond the maximum payout specified by the contract are not insured. With climate change, to maintain a given weather risk management objective, the buyer therefore needs to adjust the cap as well as the trigger level over time.

Kapphan et al. (2011) examine the effect of hedging weather risk for maize farmers with weather derivative contracts that are adjusted over time. Adjusted weather derivative contracts are derived by using simulated crop and weather data that includes the climate change signal. For the derivative design, multi-peril weather indices are constructed to predict the fluctuations in maize yields. To hedge the revenue fluctuations of maize growers, assuming a given risk management objective, the payoff structure is designed such that it yields optimal risk reduction (Kapphan, 2011). Weather derivative contracts are simulated for today's (baseline) and future climatic conditions. To maintain a desired risk reduction over time, it turns out that the payoff structure will need to cover a wider range of weather events, i.e., the trigger decreases and the cap increases over time.

The benefits from hedging are then evaluated for a baseline scenario, representing today's climate conditions, and for future climatic scenarios to model the transition from today's climate to the projected climate prevailing around the year 2050. With climate change, the authors find that the benefits from hedging weather risk with adjusted contracts increase over time and more than double in 2050 compared with today's baseline. An increase in weather-related revenue variability makes hedging weather risk more viable. They also evaluate the profitability for the risk taker of assuming weather risk in a changing climate. When incorporating climate change projections in the pricing and design of the contracts, insurers can expect profits to increase by 240 percent from selling adjusted weather derivative contracts.

The hedging effectiveness of adjusted contracts is then compared with the benefits from hedging future weather risk with non-adjusted contracts. Nonadjusted contracts are derived using the current design and pricing approach of the industry, i.e., using backward-looking historical data. Similarly, the profitability of offering nonadjusted weather derivatives is evaluated for the risk taker. Depending on the type of weather risks covered, it turns out that some non-adjusted contracts would make the insured farmers better-off than the adjusted contracts. In those situations, the risk taker generates losses from offering these products. Contracts that cause losses will however not be offered by the risk taker in the long run. The authors also found that some non-adjusted contracts make the insured farmer even worse off than in the situation without hedging. Contracts that do not achieve any risk reduction clearly will not be purchased by farmers.

The study shows that the increased weather variability makes hedging weather risk more worthwhile for both the insurer and the insured. Not adjusting the pricing and design of weather derivatives may not only generate losses for the risk taker, but it possibly undermines the risk reduction that can be achieved with weather derivatives. To capture the benefits of hedging weather risk in a more volatile climate, weather derivative providers need to revise their structuring and pricing in order to offer their clients efficient weather protection.

5.6 Putting an End to the Weather Excuse

In an era with a growing awareness that weather and climate change affect financial performance, companies should no longer be allowed to justify bad performance due to bad weather. Companies with a weather-dependent business can reduce their exposure to weather-related fluctuations by hedging. Weather risk thus should no longer be viewed as an idiosyncratic entrepreneurial risk. Weather management should become an integral part of corporate risk management. Income statements should show the weather exposure, and companies should actively manage weather risk in the same manner as they manage their foreign-exchange, interest-rate and commodity risks.

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Chapter 6

Conclusion and Outlook

6.1 Key Results and Conclusion

With the need to manage weather risk in light of climate change, the current practice for designing weather risk transfer products has been examined, and a novel method has been developed to design index-based weather insurance contracts with optimal hedging effectiveness for the insured. For insurers, the method has been adapted such that the contract maximizes profits while taking the insured's purchasing decision into account. The dual approach of designing index-based weather insurance, using the extremes of an actuarially fair contract and the maximum profit counterpart, offers bookends of the set of possible insurance contracts (for a given level of risk aversion). Maximum loading factors can then easily be derived by comparing the premiums of the two contracts. How gains from hedging weather risk are partitioned, between insurers and the policy holders, is then a matter of market power and depends on the insurer's cost of offering the product.

The structuring method is in particular useful for designing agriculture-specific weather insurance products, since the proposed kernel estimation for deriving the conditional yield density functions captures the non-linear relationship between weather and yield. Apart from agriculture, the method can be applied more generally to determine an index-based weather hedge for any weather-dependent industry. For the case of agriculture, I observe that the indemnity functions of the optimal and profit-maximizing contracts are found to be non-linear due to the agronomy-specific crop response to weather fluctuations.

Optimal contracts are characterized by offering relatively high indemnities in the rare event of extremely bad weather and by frequently providing moderate payments for the common deviations of mean yields. Thus, optimal contracts combine the benefits of catastrophe crop insurance, while off-setting any medium crop losses, which provides the insured with financial stability. Optimal and profit-maximizing contracts share the same shape and differ in the absolute indemnity provided at each index realization. Moreover, the more risk averse the insured, the more protection is being sought for moderate yield shortfalls, which comes at the cost of a higher premium. This observation thus suggests that insurance companies need to offer different payout structures (for the same index) so that policy holders with different risk attitudes can self-select the contract that meets their hedging needs. Insurers benefit from offering index-based weather contracts that differ in the payout frequencies for moderate yield deviations since higher mark-ups can be charged from more risk averse policy holders.

With climate change, the benefits from hedging future weather risk increase significantly. I show that when the weather exposure is hedged with adjusted contracts, which account for the changing distribution of weather and yield distributions in light of climate change, the hedging benefits for the insured almost triple. These results were derived for a moderate level of risk aversion, consequently the benefits can be even larger for higher levels of risk aversion. In the same vein, the insurers' profits increase by almost 240% when an adjusted profit-maximizing contract is offered. Again, the increase in profits can even be higher with more risk averse policy holders.

While these findings are promising given that farmers face an increase in the residual weather risk with climate change, the realization of these benefits depends on the insurance industry. Insurers need to discontinue the practice of using backward-looking data for the design and pricing of weather insurance products. The consequences of using historical data for the structuring, given that climate change undermines the assumption of time series stationarity, were examined. I find that with non-adjusted contracts the hedging effectiveness for the insured is no longer guaranteed, and that insurers even face the risk of losses from selling non-adjusted contracts. With climate change, index-based weather insurance products have to be updated regularly to guarantee that future weather risk is reduced effectively.

In practice, insurers will need to account for the uncertainty in climate change projections, and the uncertainty in crop yield responses due to climate change. Climate change projections are inherently uncertain due to a number of factors such as the representation of the climate system, or the future boundary conditions, which depend on the global economic development and the advancements made in reducing greenhouses gases. To update the pricing and design of optimal index-based weather insurance contracts, the effect of climate change uncertainties on the distribution of the weather index has to be considered. More importantly, the uncertainty regarding the effect of climate change on crop yields, which has implications for the shape of the optimal indemnification structure through the conditional yield densities, has to be evaluated.

By construction, the proposed optimal index-based weather insurance contract implies that no other insurance contract can achieve a higher level of risk reduction for the insured. The advantage is demonstrated by comparing the hedging benefits of an optimal (non-linear) contract with linear weather derivatives available in the OTC market, using the same weather index and yield data. For that purpose, two approximation methods are proposed in order to derive the contract parameters of a generic weather derivative from the optimal (profit- maximizing) contract, such that the approximated counterpart satisfies the assumption of actuarially fair contracts while maximizing the insured's hedging effectiveness (yielding maximum profits while considering the insured's purchase decision). For a baseline approximation scenario, I find that when hedging today's agricultural weather risk with linear contracts, the hedging benefits of the insured decrease by 20 to 23% compared to the optimal contract. Similarly, insurers' profits shrink by 20 to 24% from selling linear contracts to agricultural growers, compared to the profit-maximizing contracts.

To simulate optimal and profit-maximizing insurance contracts, I used 4 weather indices that account for different weather events throughout the growing season, and which differ in their goodness of fit of predicting crop yields. I observe that indices that explain a large fraction of the crop yield variability yield a higher degree of risk reduction for the insured. In addition, I observe that insurers can charge higher loading factors when offering profit-maximizing contracts where the underlying index reliably predicts crop yield losses. With climate change causing an increase in weather variability, I find that the same indices explain a larger fraction of crop yields. Due to the improvement in predicting crop losses in light of climate change, hedging weather risk becomes more viable for the insured and also more profitable for insurers. Furthermore, I observe that the losses in risk reduction from hedging agricultural weather risk with linear weather derivatives decrease with climate change. Since the (linear) relationship between crop yields and weather indices improves in light of climate change, the consequences of approximating optimal (non-linear) contracts become less severe. These observations confirm the general consensus of the literature that minimizing meteorological basis risk, that is improving the index quality, improves the hedging effectiveness.

Since the selection of the approximation parameters (strike and exit) affects the payoff function of the linear weather derivative, and therefore the weather protection provided, a sensitivity analysis was conducted. I find that the losses in risk reduction and profits can be minimized (compared to the baseline approximation scenario) by increasing the strike and decreasing the exit level. The risk reduction realized by the optimal contract could, however, not be replicated even with linear contracts that provide an extensive weather coverage. The same holds true for the profits of the insurer. These findings demonstrate for the first time that – even when using an index that perfectly predicts crop yields - the hedging effectiveness can still be improved through the structuring method. The optimal index-based weather insurance model, in combination with the methods for deriving the contract parameters of a generic weather derivative, is hence a robust decision-support tool, which facilitates the structuring process for buying linear OTC-style weather derivatives.

Alternatively to approximating the optimal contracts with a generic derivative, a synthetic financial weather derivative could be created which replicates the non-linear payoff structure of the optimal contract more closely. The optimal contract could be replicated by combining existing weather derivatives, with different strike and exit levels, into a portfolio of linear weather derivatives. The synthetic payoff may still not perfectly resemble the optimal indemnification structure. Nevertheless, the losses in risk reduction from hedging with the synthetic weather derivative may be smaller than the losses in risk reduction from hedging with a single linear derivative.

The analysis furthermore provided insights for structuring a linear weather derivative. For instance, I observe that the contract parameters have to be set such the contract triggers indemnities as soon as the realized index is smaller than the maximum predicted revenues (index). Furthermore, from the point of view of the insured, capping the maximum payouts is undesirable as this implies that the actual yield losses in extremely bad years are not compensated by the contract. In practice, not capping the payouts in the event of bad weather may be difficult to implement, since this practice serves to keep premiums moderate. Oftentimes, the probabilities of extreme events can only predicted with a high level of uncertainty. Insurers minimize the risk of facing excess payments at an unpredicted rate by capping payouts. These observations can however only be generalized to the extent that the insured relies solely on the index-based weather product to manage his weather-related losses.

To sum up, this dissertation highlights the need to manage agricultural weather risk in light of climate change and shows that hedging with well-designed index-based weather risk transfer products is beneficial for both the insured and the insurer. In particular, a robust decision-support tool has been proposed that can be used to facilitate the structuring process for buying non-linear and linear weather risk transfer products. More importantly, the superiority in terms of risk reduction and profits from hedging agricultural weather risk with optimal index-based insurance compared to linear weather derivatives has been demonstrated. The proposed method for structuring optimal index-based weather insurance can be extended in a number of dimensions.

6.2 Outlook

In future research, it would be interesting to model in more detail some real-world decision factors that affect farmers' insurance purchase. In particular, the decision to transfer risk to an external party is influenced – for agents with preferences marked by constant relative risk aversion – by the policy holder's initial wealth. Agents with high initial wealth tend to hedge a smaller portion of their risk exposure, compared to agents with low wealth (assuming the same risk aversion) and given that insurance is only available at a cost that exceeds the fair premium. The consequences of an initial wealth decomposition, into a weather-sensitive and non-sensitive component, on the shape of the optimal payoff function, could be examined in future work. Moreover, the existence of alternative insurance products, or income from non-farming activities, affects the degree to which farmers seek to reduce their weather risk exposure (from growing a particular crop) with an index-based weather insurance product. In particular, in countries where subsidized farm-level yield (or revenue) insurance programs are available, or where direct payment schemes exit, farmers will only seek to hedge the remaining weather risk that is not already compensated by the damage-based insurance product. In order to design index-based weather insurance products that account for the existence of competing risk management practices, prior information about the wealth set-up of the insured is needed.

Furthermore, the insurance product design should account for the fact that farmers face different sources of weather-related production risk, due to the fact that more than one crop is grown. Different weather risk sources jointly affect the revenues of the insured and as a result the average revenue from farming is less variable – compared to sum of the revenues from individual yields – due to a diversification of weather risk across crops with different weather sensitives. In future work, it would be interesting to consider the diversification effect (from growing different crops) on the degree of protection sought for a particular crop.

Farmers are not only faced with weather-related production risk, they are also confronted with price risk. Climate change with its implications for global food production may lead to a sharp increase in global commodity prices, as demonstrated by the food-commodity crisis in 2008. While revenue insurance schemes address these two risks jointly, classical index-based weather insurance products address only production risk. Future contract design should consider that increased prices function as a "natural hedge" for farmers faced with reduced outputs. Increased prices may partially offset the decrease in revenues. The existence of the "natural hedge" could be used to offer index-based weather insurance at a lower premium. Instead of claiming insurance payments in the situation of reduced yields, an insurer could offer farmers the option to offset their revenue losses by first benefiting from the increased commodity prices. To create incentives for farmers to take advantage of the "natural hedge" revenue compensation, insurers could offer to re-fund part of the premium if farmers decline to receive (full) indemnification. Such a product incorporates aspects of revenue insurance, while still avoiding problems associated with asymmetric information.

The proposed structuring method was calibrated and tested on a large yield and weather time series data set, due to the fact that a biophysical crop growth model in conjunction with a weather generator could be used. The entire data set was used for the contract design and to evaluate the risk reduction benefits, which exposes the results to the risk of over-fitting. Ideally weather insurance contracts should be designed and evaluated on different data sets in order to avoid the risk of over-fitting. However, given the size of the data set, this risk is rated as rather small. This remains to be verified in future work by conducting a cross-validation analysis.

Instead of using simulated crop yield and weather data, optimal index-based weather insurance contracts can also be simulated with historical observations. Historical weather, and in particular yield observations are often only available for 20 to 30 years, which poses a challenge since the use of a non-parametric estimation procedure requires a sufficiently large data set. Clearly, the more weather and yield observations are available, the more precisely one can estimate the weather index density and the conditional yield densities. When working with historical crop yield and weather observations, a panel data set of crop yield observations from farms located in the same region, which were exposed over time to the same weather conditions, can be used for the structuring process. In future work, the size of the data set needed, and the implications for the hedging effectiveness when working with smaller data sets, should be investigated more thoroughly.