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Agricultural Weather Insurance:

Basis Risk Reduction, Behavioral Insurance and Uncovering Quality Risks

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presented by

Tobias Paul Franz-Josef Dalhaus

MSc. Agricultural and Food Economics,
Rheinische Friedrich-Wilhelms-Universität Bonn

born on 26.09.1989

German citizen

Accepted on the recommendation of

Prof. Dr. Robert Finger

Prof. Dr. Joshua D. Woodard

Prof. Dr. Yann de Mey

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Zusammenfassung

Die landwirtschaftliche Produktion ist einer Vielzahl von Risiken ausgesetzt, welche die Volatilität der erzielten Gewinne erhöhen können. Insbesondere die hohe Variabilität von Wetterbedingungen in einem sich änderndem Klima setzt Landwirtinnen und Landwirte unter Druck. Landwirtschaftliche Versicherungssysteme können hier ein Mittel sein die finanziellen Auswirkungen dieser Risiken zu verringern. Innerhalb dieser Versicherungen haben sich Wetterversicherungen als innovatives Mittel herausgestellt um Klimarisiken zu minimieren. Hier ist die Versicherungsauszahlung nicht abhängig vom Schaden auf dem Feld, sondern wird durch einem unabhängig gemessenen Wetterwert bestimmt, zum Beispiel der Niederschlagssumme an einer nahegelegenen Wetterstation.

Diese Arbeit zielt darauf ab Wetterversicherung für Landwirtinnen und Landwirte attraktiver zu gestalten, indem Auszahlungen besser an die tatsächliche Risikoexposition abgestimmt und auch die Präferenzen der Landwirtinnen und Landwirte berücksichtigt werden. Hierbei liegt der Fokus auf zwei Kernbereichen. Erstens, die Anpassung der Wetterversicherungsauszahlungen an das Pflanzenwachstum auf dem Feld. Die Diskrepanz zwischen Auszahlung und Schaden wir hierbei als Basisrisiko bezeichnet. Nach einer allgemeinen Einleitung in Kapitel 1, zielen die Kapitel 2, 3 und 4 darauf ab das Basisrisiko zu verringern. Zweitens, Präferenzen von Landwirten bezüglich ihrer Versicherungsentscheidung besser in der Ausgestaltung des Versicherungskontraktes zu berücksichtigen. Hierfür wird in Kapitel 5 eine massgeschneiderte Versicherung entworfen, die sich den Präferenzen der Landwirtin anpasst.

Zur Reduktion des Basisrisikos werden in Kapitel 2 verschiedene Ansätze getestet und verglichen, die darauf abzielen, den Versicherungszeitraum möglichst präzise zu bestimmen. Dafür werden Pflanzenwachstumsphasen definiert, die besonders trockenheitsanfällig sind und verschiedene Lösungen gegenübergestellt die das Auftrittsdatum dieser Phasen bestimmen können. Die Ergebnisse zeigen, dass frei verfügbare, regionale Beobachternetzwerke dazu

beitragen das Basisrisiko zu verringern und somit die Attraktivität von Wetterversicherungen erhöhen. In Kapitel 3 werden die monetären Auswirkungen von Spätfrösten während der Apfelblüte quantifiziert. Hier wird deutlich, dass nicht nur die Ertragshöhe sondern auch die Ertragsqualität durch Wetterereignisse beeinflusst wird, was zur substantiellen Minderung von Verkaufspreisen auf Betriebsebene führt. Ein einziger Frosttag führt in dem empirischen Beispiel zu Verlusten von Erträgen (-1% bis -5%), von Qualität und somit auch von Verkaufspreisen (-4% bis -35%) was schlussendlich zu aggregierten Erlösverlusten (- 3% bis - 43%) führt. Die Höhe des Effektes ist abhängig von der Schwere (Tagesminimumtemperatur) des Frostereignisses. In Kapitel 4 wird eine ökonometrische Strategie skizziert mit der Ertragsdaten von verschiedenen Aggregationsstufen (Betriebserträge und regionale Durchschnittserträge) mit Wetterdaten kombiniert werden können, um das Basisrisiko zu verringern. Hierbei dient der regionale Durchschnittsertrag als Prior für die Schätzung des Einflusses von Wetter auf Betriebserträge innerhalb einer Bayesianischen quantilen Regression.

Zur besseren Berücksichtigung von Präferenzen in der Ausgestaltung des Versicherungskontraktes, schlägt eine aktuelle Studie vor, dass die Versicherungsentscheidung von Landwirten mit Erkenntnissen aus „Cumulative Prospect Theory“ und „Narrow Framing“ besser beschrieben werden kann als mit Hilfe der standardmässig angewandten Erwartungsnutzentheorie. Obwohl eine Reihe von weiteren Studien eine Abweichung der Versicherungsentscheidung von erwartungsnutzenmaximierendem Verhalten feststellen, wurde dies bisher nicht in der Ausgestaltung von Agrarversicherungen berücksichtigt. Hierzu werden in Kapitel 5 die Parameter der Wetterversicherung an Cumulative Prospect Theory Präferenzen, wie Verlustaversion und Wahrscheinlichkeitsgewichtung, angepasst. Die daraus resultierende Versicherung wird als 'Behavioral Weather Insurance' bezeichnet und es wird gezeigt, dass insbesondere eine stochastische Mehrjahresprämie eine vielversprechende

Erweiterung der aktuellen Versicherungsausgestaltung sein kann. Somit können Wetterversicherungen gemäss individueller Präferenzen ausgestaltet werden, um optimal auf die Bedürfnisse der Landwirtin zugeschnitten zu sein.

Zusammenfassend greift diese Arbeit bisherige Erkenntnisse zu Wetterversicherungen auf und entwickelt diese in verschiedene Richtungen weiter, sodass Landwirte bei der Absicherung von Wetterrisiken besser unterstützt werden können. Die Berücksichtigung von neuartigen und bestehenden Datenquellen und deren Kombination in einem flexiblen ökonometrischen Rahmen zusammen mit der Quantifizierung von bisher übersehenen Wetterrisiken, zeigt ein grosses Potential auf, um das Basisrisiko zu verringern. So wird die Wetterversicherung zu einer sinnvollen Ergänzung bestehender Versicherungssysteme, besonders in Ländern mit einer Vielzahl ungenutzter Datenquellen. Zudem ist die Berücksichtigung des Entscheidungsverhaltens von Landwirtinnen und Landwirten in der Ausgestaltung von Versicherungen ein logischer nächster Schritt und die hier präsentierten Ergebnisse bieten einen Einstiegspunkt auch weitere Verhaltensweisen zu berücksichtigen.

Abstract

Agricultural production is exposed to a variety of risks that increase the volatility of farm profits. In particular, the high variability of weather, especially in context of a changing climate, is of relevance for agricultural producers. Agricultural insurances contribute to support farmers to cope with these risks. Among these insurances, weather insurances (WI) are an innovative tool to cope with climatic risks in agriculture. Using WI, farmers receive an indemnification not based on actual yield reductions, but are compensated based on a measured weather index, such as rainfall at a nearby weather station.

This thesis aims at making WI more attractive to farmers through two channels. First, by better suiting the weather indexed insurance payout to actual crop performance, i.e. by reducing basis risk, a situation in which WI payout mismatches crop losses. After a general introduction into the topic within chapter 1, chapters 2, 3 and 4 focus on providing a more detailed explanation for farm losses based on weather data. Second, this thesis suggests solutions to adjust insurance contract parameters such as the timing of the premium payment to better tailor WI to farmers' preferences, which are presented in chapter 5.

Chapter 2 tests and compares different approaches to find the occurrence dates of crop growth phases that are especially vulnerable against drought and uses this information to reduce basis risk of WI. The results show, that spatially explicit, public and open databases of phenology reports contribute to reduce basis risk and thus improve the attractiveness of WI. Chapter 3 quantifies the monetary impact of spring frost events during the flowering phase of apple trees. Here it becomes evident that not only crop yields are affected by weather events but also the quality of the harvest can drop, which is translated into substantial losses in farm-gate prices. With respect to the empirical example of apple production, we find that a frost day induces drops in yields (-1% to -5%), quality and thus farm-gate prices (-4% to -35%), and finally leads to lower revenues (-3% to -43%), depending on the severity of the frost event (i.e. the daily

minimum temperature). In chapter 4, we propose an econometric procedure to combine crop yield data on different levels of aggregation with high-resolution weather data to reduce basis risk. Here, we suggest using aggregated crop yield data to serve as the prior for farm-level estimates in a Bayesian regression framework, and the use of quantile regression (QR) to estimate the impact of weather indices on crop yields.

Regarding the second research goal of better tailoring WI to farmers' preferences, we build upon a recent study which found that Cumulative Prospect Theory and narrow framing can offer useful insights to be able to better explain farmers' insurance choice. Although various studies suggest that farmers deviate from standard expected utility maximizing insurance behavior, no study so far took up this knowledge and explicitly designed WI to better fit the observed insurance decision making. To this end, chapter 5 adjusts insurance contract parameters to better tailor farmers' preferences by introducing what we call 'Behavioral Weather Insurance'. It is shown that a stochastic multiyear premium increases the prospect value of weather insurances depending on farmers' preferences, while a zero deductible design does not. Thus, insurance contracts might be tailored to individual preferences to optimally serve farmers' needs, which offers potential benefits for both insurer and insured.

In conclusion, this thesis builds upon current knowledge and develops WI further in various directions to better help farmers manage their weather risk. The combination of open and rich data sources and existing information with the help of a flexible econometric framework together with the uncovering of so far unquantified weather risks shows massive potential for reducing basis risk. This makes WI an attractive supplement to current insurance products, especially in countries with rich sources of unused data. Moreover, the incorporation of farmers' decision making behavior provides a useful extensions of the current literature and might serve as an entry point for further investigation to make insurance a powerful ally in an increasingly instable climate.

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Content

Chapter 1

Introduction

Agricultural production is exposed to a variety of risks that increase the volatility of farm profits (Hardaker et al., 2004). In particular, the high variability of weather, especially in context of a changing climate, is of relevance for agricultural producers (Schlenker & Roberts, 2009). Accordingly, both extreme weather events but also small deviations from optimal conditions at vulnerable stages of plant growth diminish agricultural income and threaten food security, encouraging the development of efficient risk management tools (IPCC, 2014). These can be classified as shown in figure 1.1 (Berg & Schmitz, 2008, Hardaker et al., 2004).

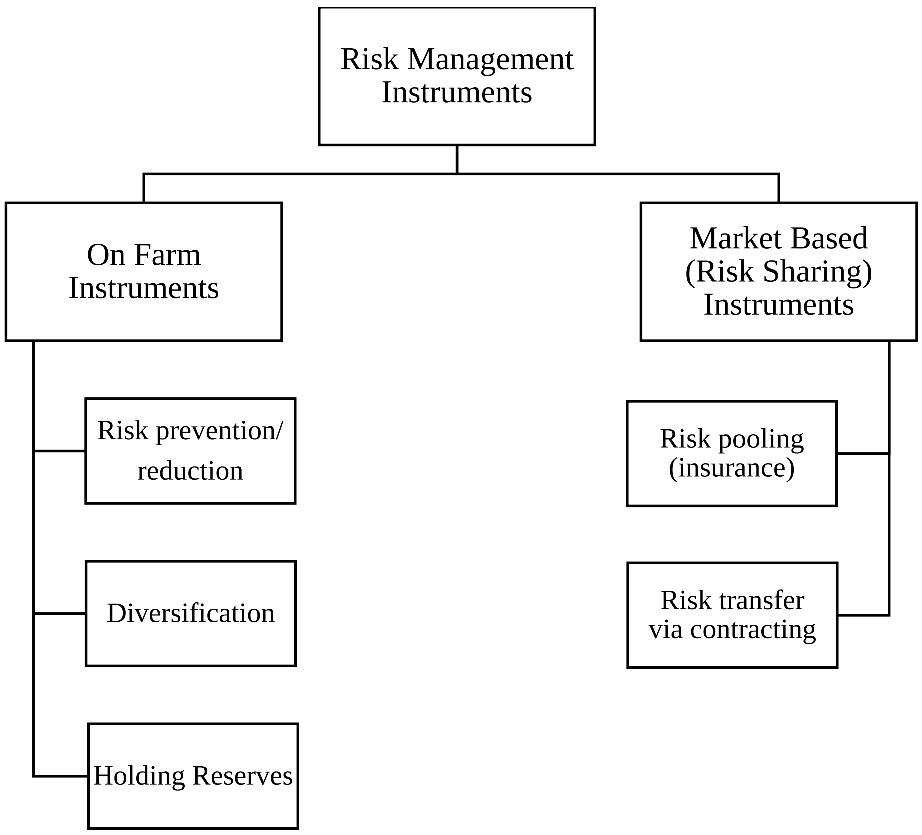

Figure 1.1: Classification of Risk Management Instruments in Agriculture

From the toolbox of strategies, farmers chose their whole farm strategy mix that best fits their preferences. Simultaneously, farmers face substantial alterations in their environment due to e.g. alterations in their risk exposure (e.g. due to climate change) or the increasing availability of information communication technology that affect risk and thus likely also farmers' decision making (Coble et al., 2018 Walter et al., 2017, Howden, et al. 2007). Hence it is indispensable to dynamically adapt and improve risk management instruments to this changing environment. Consequently, it is crucial to best quantify the risk a farmer is exposed to (e.g. by considering newly upcoming (big) data sources) but also a state of the art knowledge of farmers' decision making under risk.

1.1 Crop Insurance

In the context of market based risk management instruments, crop insurances trade farmers' crop production risk to one, or several, insurance companies, which pool the risk of all insured farmers (Chavas, 2004). As summarized in figure 1.2, crop insurance products can be classified into two groups: i) those that indemnify farmers for realized losses (indemnity insurance); and, ii) those that make payments based on some objective measure that is assumed to be highly correlated with realized losses (index insurance).

On the one hand, indemnity insurances provide compensation in case of observed losses caused by predefined perils. Therefore, farmers receive an insurance payout depending on on-farm damage assessment. Insurer and insured must have similar information about the likelihood of a loss and farming practices to avoid moral hazard[1] and adverse selection[2], in order to ensure a functioning insurance market.

[1] Moral hazard indicates the disincentive of farmers to apply good agricultural practice since they are insured against low outcomes.
[2] Adverse selection means that farmers for which the insurance company underestimates the actual risk are more willing to purchase insurance as the premium is cheaper than an actuarially fair premium.

On the other hand, the payout of index insurances does not depend on actual losses but on the performance of a predefined index or trigger value. Standard examples of these include area yield insurance (Skees et al., 1997) and weather insurance (WI) (Martin et al., 2001, Vedenov & Barnett, 2004, Odening et al., 2007).[3] More specifically, this implies that a payout occurs if a critical strike level of the index is undercut or exceeded[4]. Index and on-farm results should have a strong correlation to cover yield losses efficiently (e.g. Conradt et al., 2015a). The rainfall sum within a certain time period is an often used weather index that informs the payout of WI and is potentially closely related to a farm's crop and therefore financial performance. Accordingly, WI pays out in the case the sum of rainfall is lower than the strike level. The payout is then determined by the difference between the actual rainfall sum and the strike level multiplied by a so called ticksize[5] or the payout per missing millimeter of rainfall.

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[3] WI is sometimes also called weather derivatives, weather index based insurance, or weather index based risk transfer products. In this thesis, the terms weather insurance, weather index based insurance and weather index insurance are used synonymously according.

[4] For example, protection against undercutting the index is drought, i.e. payout in case of a lack of rainfall and against exceeding the index is flooding, i.e. excessive rainfall.

[5] The terminologies strike level and ticksize are derived from financial options literature and common terms in studies focusing on WI

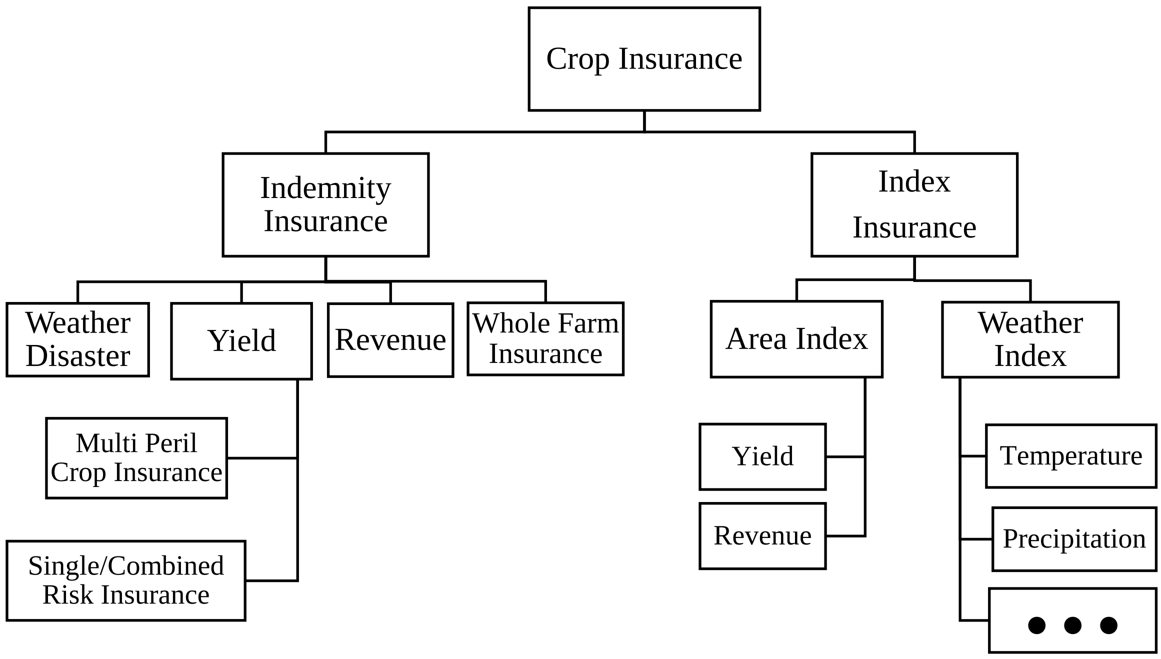

Figure 1.2: Classification of Crop Insurances

The focus of this thesis is on WI because of two reasons. First, WI is able to cope with problems arising from asymmetric information between insurer and insured. Second, the increasing availability of open data which are so far unused, results in a considerably high potential for possible improvements.

However, two important drawbacks remain for index insurance that have not been fully resolved so far and that have led to the failure of former WI markets. First, despite weather having a strong influence on crop yields, low correlation between losses and index value can occur (Woodard et al., 2008). The remaining risk that is not covered by the insurance is called basis risk, which a major adoption hurdle for WI. Second, the uptake of crop insurance in general and WI in particular is rather low without massive subsidization up to the point that insurance has a positive expected value (Glauber, 2013, Coble & Barnett, 2013, Du, Feng & Hennessy, 2017). This deviates from the optimal behaviour of a risk averse farmer under standard expected utility theory, suggesting that current insurance design does not fully take into account farmers' insurance decision making behaviour (Babcock, 2015).

1.1.1 Basis risk

Basis risk describes any occurring discrepancy between WI payout and on-farm loss. More specifically, it describes the situation in which the farmer experiences a loss while the index triggers none or vice versa. Sources of basis risk can be classified into three categories: spatial basis risk, temporal basis risk and design basis risk. The spatial basis risk is caused by the distance between the point of index measurement (e.g., weather station) and the farm's location (Leblois et al. 2014, Ritter et al. 2014). The temporal basis risk captures the imperfect choice of the period for index determination (Deng et al. 2007, Díaz-Nieto et al. 2010). The design basis risk describes the fact that the index value does not include all the relevant information for predicting the targeted farm-level yield, e.g. through choice of the underlying weather variable or estimation strategy.

Spatial basis risk

To accurately estimate the impact of weather conditions on yields on a single farm basis, precise weather information is essential. If insured weather condition mismatch on-farm weather, spatial basis risk occurs. Regarding this, Woodard and Garcia (2008) suggest using weather data obtained from a weather station as close as possible to the farm. This is of particular relevance for precipitation indices since the correlation between the index and losses quickly declines with increasing distance (Odening et al. 2007, Norton et al. 2012). To overcome the problem of low weather station density, other authors (Heimfarth and Musshoff 2011, World Bank 2013) suggest either interpolating weather station data to on-farm locations or creating a portfolio of contracts from different stations in the farm's region. For instance, kriging techniques have been used to estimate on-farm rainfall based on nearby weather stations' data

(Paulson et al. 2010) and to explain the relationship between rainfalls at the two locations (Norton et al. 2015). Along these lines, the World Bank (2013) used a model to interpolate station data to a grid of 9 km × 9 km resolution covering Guatemala and Honduras. Other studies suggest creating a portfolio of several weather options based on the data from different weather stations using a geographic cross hedging effect (Berg and Schmitz 2008, Woodard and Garcia 2008, Ritter et al. 2014). Norton et al. (2012) detected that weighting this portfolio by geographical parameters, such as longitude, latitude, altitude, or distance, further decreases spatial basis risk. In a case study on German wheat production, Dalhaus & Finger (2016) found that using open and transparently produced rainfall grid data potentially decreases transaction costs of drought index insurance while holding risk reducing properties constant compared to weather station data. In this thesis we build up on findings of Dalhaus & Finger (2016) and use weather grid data for WI design because here "it is no longer necessary to find an appropriate weather station […] and the time series of grid data weather information is always complete and technical failure is less likely".

Temporal basis risk

Temporal basis risk mainly results from choosing index measurement time windows that are imperfect for two reasons. First, the chosen time windows that are based on general calendrical definitions—that is, choosing the cumulative rainfall in a specific month—are just proxies for critical vegetation periods. In reality, these growth phases vary across space and time. Only a few studies have incorporated growing seasons explicitly (e.g., Kapphan et al. 2012, Leblois et al. 2014b, Conradt et al. 2015b, Kumar et al. 2016). While Kapphan et al. (2012) extracted information on vegetation phases from a crop model; Leblois et al. (2014) and Conradt et al. (2015b) used growing degree-days (thermal time) to specify vegetation periods. Kumar et al. (2016) identified heat-sensitive growth stages from experimental data based on observed phenological phases. Second, the start and end dates of these windows of index measurement are usually fixed; that is, they are identical in every year (e.g., start and end dates of months). This choice ignores the fact that the timing of single-growth stage periods vary from year to year. These fixed time windows are, however, chosen in all previous studies on weather index insurances. As an exception, Conradt et al. (2015b) used flexible weather index definitions based on vegetation periods defined using growing degree-days (GDD), allowing index measurement windows to be specifically suited to the vegetation phase and to vary from year to year. This flexible index definition was found to be superior to a fixed index definition (Conradt et al. 2015b). However, the definition of vegetation phases based on GDD faces several challenges, for example, that assumptions must be made on the occurrence of vegetation periods based on GDD across various crops and varieties used, and that precise knowledge of sowing dates might be required (Conradt et al. 2015b). Therefore, Dalhaus & Finger (2016) find that using observations from a phenological network of farmland in the farms' region to find winter wheat's occurrence dates of stem elongation, ear emergence and milk ripeness flexibly improves WI compared to fixed time periods. So far, no study has compared different approaches to consider crop growth phases in WII design.

Design basis risk

Besides spatial and temporal basis risk, design basis risk indicates low explanatory power of the chosen index for losses due choosing a wrong model design in general. More specifically, the influence of the index value on farms' key performance indicator is biased through one of three reasons.

First, the choice of an index underlying (weather variable) that constitutes a weak predictor for losses (e.g. temperature vs. precipitation). Concerning this matter, recent studies found that the weather variable should be individually specified according to regional specific weather risks (See Leblois & Quirion, 2013 for an overview of different applications). Second, the chosen key performance indicator does not include all relevant weather induced losses. In this context, all studies so far concentrated on weather induced yield quantity (as key performance indicator) losses, although weather related quality drops result in major price reductions (Kawasaki & Uchida, 2016). Consequently, a WI that covers both yield quality and quantity losses is urgently needed. Third, the strategy for quantifying the indexes' influence on farms' key performance indicator is designed inappropriately (e.g. choice of econometric model). Here, two areas have been considered recently: i) modelling weather influence on low yield outcomes (losses) rather than general influence of weather on yields (e.g. Conradt et al. 2015a); ii) handling of aggregation bias and spatially correlated risk exposure for single farm risk assessment and insurance pricing (see e.g. Finger, 2012, Heimfarth et al. 2012, Goodwin & Hungerford, 2015, Woodard et al., 2016). However, modelling weather influence on yield losses on a single farm basis considering spatially correlated risk exposure at higher levels of data aggregation has not been considered so far.

1.1.2 Considering farmers' behavior in insurance design

Participation in currently existing crop insurance schemes is generally low without massive subsidization, although farmers are risk averse (Glauber, 2013, Du et al. 2017, Pope & Just, 1991). This empirical reality is not consistent with standard expected utility characterizations of risk aversion suggesting that farmers' risk preferences and insurance decision-making do not follow classical assumptions of expected utility (EU) theory. Expected utility suggests that WI uptake decreases with basis risk (Clarke, 2016), increases with premium subsidization (Glauber, 2013) and increases with farmers' risk aversion[6] (Just et al., 1999). One of the reasons for this may be that some farmers do not assign insurance premiums and payouts to fluctuations in crop income, but rather experience insurance as a stand-alone investment (Babcock, 2015).

[6] In fact, Clarke (2016) finds that an increase in risk aversion can also lead to a decrease in WI demand due to basis risk, as WI enables a scenario of exacerbating an unfortunate financial situation (farmer experiences a loss, WI does not pay out and farmer still has to pay the premium).

Recent evidence suggests here that cumulative prospect theory (CPT) (Tversky & Kahneman, 1992) may be a better predictor than EU theory of farmers' insurance decision-making (Du et al., 2017, Babcock, 2015, Bulut, 2018, Bougherara & Piet, 2014). CPT extends EU theory in three dimensions. First, it distinguishes outcomes into gains and losses with respect to a certain reference point. Second, the slope of the value function is steeper in the loss domain compared to the gain domain indicating loss aversion. Third, individual outcomes are weighted following a weighting function accounting for decision makers' distortions of probability values. So far, no study exists that focuses on developing WI contracts that better fit farmers' CPT preferences, while covering losses effectively.

1.2 Research objective

The above drawbacks reveal two overarching entry points for further investigation, which are needed to make WI more attractive and agricultural income more robust against meteorological threats. Hence, the overall goal of this thesis is to contribute improvements of existing WIs:

i) by reducing basis risk by including further data sources and uncovering undetected weather impacts

ii) and by designing contracts that consider farmers' insurance decision making behavior

1.3 Study outline & major contributions

The following four main chapters address the two overarching research goals. Regarding the reduction of basis risk by incorporating more data, chapter 2 deals with incorporating better information on crop phenology and chapter 4 on using a Bayesian quantile regression approach that incorporates different aggregation levels of yield data. Concerning the reduction of basis risk by uncovering undetected weather impacts, chapter 3 shows that weather not only reduces yields but also prices through quality reductions. With respect to considering farmers' insurance decision making behavior, chapter 5 introduces a so called behavioral weather insurance (BWI), which includes a stochastic multiyear payment and a zero deductible design to better fit farmers' preferences.

1.3.1 Basis Risk

Regarding crop production, chapter 1.1.1 summarizes that temporal basis risk occurs if WI does not reflect the actual growth stage that is sensitive to specific weather. More specifically, in case of a WI that aims at reducing farmers' financial exposure to drought risk, the rainfall sum within a growth stage that is insensitive to water shortages. Two major approaches have been suggested for flexibly incorporating shifts of the occurrence dates of vulnerable crop growth stages over time and space. First, by using a thermal time model using growing degree days (GDD) that estimates the occurrence dates of critical growth stages based on required temperature loads that (Kapphan et al. 2012, Conradt et al., 2015b). Second, by using actually observed growth stages, i.e. phenology observations, provided by a public and independent institution (Dalhaus & Finger, 2016). Chapter 2 tests and compares different approaches to find the occurrence dates of these phases and uses this information to reduce temporal basis risk of WI. We find spatially explicit, public and open databases of phenology reports to contribute to reduce basis risk and thus improve the attractiveness of WI. In contrast, we find growth stage modelling based on growing degree days (thermal time) not to result in significant improvements.

Weather impacts both crop yield quality and quantity and is thus a driving force of farm income volatility (Lesk et al., 2016). While yield quantity risks and their determinants are usually well documented, yield quality risk is often unspecified although it is an important driver of price risks (Grunert, 2005). Here, the agronomic mechanisms for how weather can negatively influence crop quality are well known, while the monetary consequences of such quality losses on the farm level remain unexplored so far. The quantification is important for a better understanding of how weather impacts farmers' income but also to develop WI that incorporates monetary consequences of weather induced quality and thus price losses, i.e. to reduce design basis risk. In chapter 3 we use the example of late spring frost events in apple production to quantify the monetary impact of weather events on farmers' revenues. By disentangling the effect of late spring frosts on both yield and price components we are able to distinguish quality and quantity losses, which is usually impossible due data restrictions (e.g. Bozzola et al., 2017). We find that a frost day induces drops in yields (-1% to -5%) and quality implying farm gate price reductions (-4% to -35%), which finally leads to lower revenues (- 3% to -43%).

Design basis risk occurs if the insured weather index is generally a poor predictor for losses, e.g. through missing an important weather variable, a weather impact (such as in the case of quality risks) or using an uninformed econometric strategy. The econometric estimation of the impact of weather on crop yields informs the design of the WI and both strike level and ticksize can be derived from regression results. Here, Conradt et al. (2015a) found that using quantile regression (QR) reduces the design basis risk of WI compared to standard linear ordinary least squares (OLS) regression. QR differs from OLS in two major dimensions. First, it minimizes the absolute distance between the fitted and observed values rather than the squared deviation, which makes the estimation more robust against outliers in the data. Second, QR allows for differences in the impact of weather across quantiles of the crop yield distribution. For example, QR can estimate different impacts of rainfall on yields depending on whether the yield is high or low. Here, figure 4.1 shows exemplarily that the impact of one millimeter of rainfall on winter wheat yields is more severe when yields are low. To account for farm-specific drivers of yield variability, farm-level data on both weather and crop yields are indispensable for designing a tailored WI. However, the availability of insufficiently long time series of historical yield records is often limited at the farm-level. In contrast, longer and more wide-spread regional level yield data are often freely available provided by public bodies. However, the yield variability of aggregated yield data is substantially lower (e.g. Marra and Schurle, 1994, Finger, 2012, Woodard and Garcia, 2008). Thus, aggregated data is not able to capture idiosyncratic risks and therefore are also less suited to identify the marginal impacts of different weather shocks on crop yields. To overcome these challenges, we explore the use of Bayesian Quantile Regression (BQR, Yu & Moyeed, 2001) to design WII in chapter 4. This allows for combining of data on different levels of aggregation and accounting for spatial and temporal basis risk. Here we propose using aggregated crop yield data to serve as the prior for farm-level estimates in Bayesian regression framework, and the use of quantile regression (QR) to estimate the impact of weather indices on crop yields. Our results show that, although BQR helps to design structures to effectively reduce farmers' financial exposure to drought risk, basis risk remains unaffected in this case study context.

1.3.2 Considering farmers' behavior in insurance design

In many countries, farmers' participation in crop insurance schemes is facilitated with massive subsidization, so that high levels of crop insurance uptake have required premium subsidies to the point that insurance purchasing often has a positive expected value (Glauber, 2004, Coble & Barnett, 2013, Du, Feng & Hennessy, 2017). In contrast, the uptake of unsubsidized crop insurance is often low.[7] Assuming a standard expected utility (EU) framework, this observation is not consistent with the optimal behavior of risk averse farmers. A potential explanation for this anomaly is that a share of farmers do not assign insurance premiums and payouts to fluctuations in crop income, but rather narrowly frame insurance as a stand-alone investment (Babcock, 2015). Recent evidence also suggests that cumulative prospect theory (CPT) (Tversky & Kahneman, 1992) may be a better predictor of farmers' insurance decision-making

[7] A small number of countries with functioning non-subsidized crop insurance markets, such as Switzerland (e.g. Finger and Lehmann, 2012), represent exceptions and do not preclude this general tendency.

than EU theory (Du et al., 2017, Babcock, 2015). To this end, in chapter 5 we adjust insurance contract parameters to better tailor farmers’ preferences by introducing what we call behavioral weather insurance. We test BWI across various scenarios of real-world elicited CPT preferences on loss aversion and probability weighting (Bocquého et al., 2014, Bougherara et al., 2017). We find that a stochastic multiyear premium increases the prospect value of weather insurances depending on farmers’ preferences while holding the risk reducing properties constant.

1.4 Discussion & Outlook

1.4.1 Basis Risk

Chapter 2 is the first study that explicitly compares WIs that consider single stages of plant growth, i.e. by using either phenological observations or GDD modelling (Dalhaus & Finger, 2016, Conradt et al., 2015b, Kapphan et al., 2012). It therefore provides an overview of current knowledge of how to better incorporate crop growth stages in WI design. The results presented here can serve as an important basis for further research but also as a reference tool for insurance analysts. More specifically, depending on the data availability and the crop to be insured either modelling or phenology observations can be an optimal solution to be implemented. It also suggests entry points for further research that could add additional options to find occurrence dates of growth stages for insurance purposes such as ‘biometeorological time’ or ‘physiological days’ as suggested by Saiyed et al. (2009) or satellite imagery Sakamoto et al. (2005). Going even further, also social media posts, which can be surprisingly easy accessed and analysed in large amounts, can provide information on the actual timing of growth stages (Zipper, 2018). Thus, temporal basis risk might be further reduced also in countries where phenological observations data is scarce. For Germany, concept of using phenological observations has already stimulated further research in WI in Doms et al. (2018) and Möller et al. (2018).

In chapter 3, our results regarding the impact of spring frost on apple yields are consistent with the literature and are commonly observed in many regions (Rodrigo, 2000, Menapace et al., 2013). Recent studies even suggest to implement WI that aims to reduce farmers' spring frost risk exposure (Ho et al., 2018). However, our findings that frost leads to significant reduction of farm gate prices and subsequent revenue losses add a new perspective on how spring frost impacts apple production. More generally, a major lack of evidence exists on the quantification of monetary consequences of quality losses. As notable exception, Kawasaki & Uchida (2016) find that economic impacts of weather on rice quality can outweigh those on quantity of yields, however they are unable to quantify the effect in terms of revenues. WI practice should take this into account and develop products that include weather's impact on crop quality. Future research should also take up our findings when estimating the impact of climate change on agricultural production. Especially, when simulating farmers' behavior under future climate scenarios, the consideration of the overall effect of weather on revenues through quantity and quality might influence the results compared to a focus on yields only.

In chapter 4, we find that WI based on farm-level data is able to reduce the drought risk exposure of wheat producing farms in Eastern Germany. However, this only holds if farm-level yield data is sufficiently available for a long time period. In contrast, our results indicate that WI designed using county average yields instead of farm-level yields, are unable to reduce farmers' financial exposure to drought risk. This is in line with literature on aggregation bias (e.g. Marra and Schurle, 1994, Finger, 2012). Although the Bayesian quantile regression framework presented here did not improve the risk reducing properties of WI, Bayesian inference has been proven to be supportive in crop insurance pricing (Shen et al. (2015)). These findings and results presented by März et al. (2016), who found Bayesian quantile regression to be superior in estimating farmland rental rates, might encourage future research to extend the findings presented here to other weather perils. In case of threats that occur more systemically, e.g. temperature or joint indices of temperature and rainfall, the BQR framework might present more promising results. Moreover, BQR needs to be tested in a framework where larger differences exist between farm-level and county-level data availability. In our case study, reliable county-level yields were available from 1992 onwards only, due to the end of the German Democratic Republic. In case of longer time series on county yield records, more extreme events and systemically occurring shocks might be available serving as better priors for estimating farm-level risk.

1.4.2 Considering farmers' behavior in insurance design

Babcock (2015) shows that loss aversion can lead to a reduction of optimal crop insurance coverage levels and thus to less protection against potential income losses. The BWI proposed in chapter 5 aims to counteract this tendency by accounting for CPT properties of farmers' preferences while holding risk reduction potential constant. This includes transforming single year premiums into multiyear premiums and letting farmers experience frequent small gains (insurance payouts) as a result of having no deductible. We find that the BWI with both Adjustments implemented jointly, is unable to increase the prospect value as compared to TWI. However, when switching off the zero deductible option, BWI increases the prospect value compared to TWI for some CPT specifications. More specifically, higher risk aversion over gains and risk seeking over losses, such as observed in these specifications increases preferences for BWI compared to TWI. This is due to the fact that this variation of BWI enables stochastic multi-year premiums rather than deterministic yearly premiums as is the case with traditional weather insurances, satisfying the risk seeking behaviour over losses. Hence, stochastic multiyear premiums potentially increase the insurance demand of prospect value maximizing farmers. In contrast, a zero deductible design does not benefit farmers in terms of prospect value as it increases the total amount of premium payments which are framed as losses in the CPT setting. This holds in the situation when both Adjustments are fulfilled and when only the zero deductible design is implemented. This result is in line with Babcock (2015) who shows that prospect value maximizing farmers with relatively low risk aversion and average loss aversion prefer insurance with higher deductibles. Consequently, a stochastic multiyear premium, although being itself prospect value increasing, is not able to counteract the overweighting of premium payments framed as losses. Future research should take into account that WI parameters can be adjusted to increase WI's prospect value according to farmers' preferences and test whether this increases the demand. Moreover, also other insurance decision making processes can be accounted for in the design on WI.

1.5 Conclusions

With respect to the overarching research goal of this thesis, namely to reduce basis risk and include farmers insurance decision making in the design of WI, the here presented chapters offer various entry points for making WI more attractive to farmers.

The incorporation of innovative and open data sources of phenology observations as presented in chapter 2 was found to be highly basis risk reducing in our case study context. The availability of such data also in other countries indicates the relevance also for other perils and regions. Moreover, the increasing availability of data that is collected by e.g. on-farm machinery, drones or satellites can be useful and this thesis offers insights of how to incorporate such information to improve WI. Regarding this, especially the Bayesian quantile regression framework presented in chapter 5 offers a useful tool for combining various data sources into a tailor made single farm insurance contract. In addition, chapter 3 includes the first study that explicitly quantifies the effect of weather on idiosyncratic price movements, i.e. occurring only at single farms. This adds a whole new layer of quality related income risk that needs to be accounted for not only in WI context. In a broader context, studies that asses the risk of future climate and its implications for farmers' behaviour and thus food security should take into account that weather induced quality losses can be a driving factor of a farms success.

Regarding the Behavioral Weather Insurance presented in chapter 4, this thesis pointed out that a stochastic multiyear premium can help to increase an insurance's prospect value if farmers narrowly frame it as stand-alone investment. The incorporation of insights that are coming from behavioral economics into the design of agricultural insurance is novel and offers entry points also for further adjustments. More specifically, also other insurance decision making processes might exists within a farmer's population that should be incorporated in the insurance design. The work presented here can then be considered as a starting point of a development that can lead to insurance products that are highly tailored to single farmer's individual preferences.

1.6 Chapter Abstracts & Author contributions

CHAPTER 2: Phenology Information Contributes to Reduce Temporal Basis Risk in Agricultural Weather Index Insurance

Abstract

Weather risks are an essential and increasingly important driver of agricultural income volatility. Agricultural insurances contribute to support farmers to cope with these risks. Among these insurances, weather index insurances (WII) are an innovative tool to cope with climatic risks in agriculture. Using WII, farmers receive an indemnification not based on actual yield reductions but are compensated based on a measured weather index, such as rainfall at a nearby weather station. The discrepancy between experienced losses and actual indemnification, basis risk, is a key challenge. In particular, specifications of WII used so far do not capture critical plant growth phases adequately. Here, we contribute to reduce basis risk by proposing novel procedures how occurrence dates and shifts of growth phases over time and space can be considered and test for their risk reducing potential. Our empirical example addresses drought risks in the critical growth phase around the anthesis stage in winter wheat production in Germany. We find spatially explicit, public and open databases of phenology reports to contribute to reduce basis risk and thus improve the attractiveness of WII. In contrast, we find growth stage modelling based on growing degree days (thermal time) not to result in significant improvements.

Author Contributions

T.D. and R.F. wrote the main manuscript and designed the study. T.D. carried out the underlying statistical analysis and prepared all figures. O.M. provided the underlying farm-level yield data and commented on various former versions. All authors reviewed the final manuscript.

CHAPTER 3: Economic impact of weather on yield quantity and quality: The case of spring frost in Swiss apple production

Abstract

Weather extremes impacting crop yield quantity and quality are essential drivers of farmers' income risk. However, weather induced changes in quality and resulting monetary implications remain often unexplored. Here we use the case of late spring frost in apple production to quantify that a frost day induces drops in yields (-1% - -5%), quality reduction implying farm gate price reductions (-4% - -35%), and finally leads to lower revenues (-3% - -43%). We base our analysis on a panel dataset of 2'389 observations of Swiss apple orchards. Our findings reveal that quantity and quality need to be accounted for when quantifying climate impacts on agriculture.

Author Contributions

T.D. and R.F. wrote the manuscript and designed the study. T.D. conducted statistical analysis and prepared all figures. M.B. reviewed and commented on various versions of the manuscript. E.B., D.D., S.S. and T.D. collected and prepared data. All authors read and approved the final manuscript.

CHAPTER 4: Bayesian quantile regression for weather index insurance design: Insuring idiosyncratic risk under data scarcity

Abstract

Crop insurance plays a key role in managing farmers' financial exposure to weather risks. Recent developments have shown that weather index insurance (WII) can help to overcome problems of asymmetric information in classical indemnity based crop insurance. However, basis risk, i.e. the discrepancy between WII payouts and on-farm losses, presents the largest adoption hurdle for WII. Farm-level yield records are necessary to design and assess the effectiveness of WII contracts, but are more scarcely available than longer and more wide-spread regional level yield data. We explore using Bayesian quantile regression (BQR, Yu & Moyeed, 2001) to estimate WII structures, thus allowing the use of both county-level yield data as informative prior in conjunction with farm-level yields and weather in designing the insurance. We develop an empirical application of insuring drought risk in Eastern German winter wheat production. Our results show that, although BQR helps to design structures to effectively reduce farmers' financial exposure to drought risk, basis risk remains unaffected in this case study context. Further research might expand the use of BQR approach to other perils with higher spatial dependence and regions with longer records of county yields.

Author Contributions

T.D. and R.F. wrote the main manuscript and designed the study. T.D. carried out the underlying statistical analysis and prepared all figures. J.D.W. commented on various former versions. All authors reviewed the final manuscript.

CHAPTER 5: Behavioral weather insurance: Applying cumulative prospect theory to agricultural insurance design under narrow framing

Abstract

Experience across many countries has shown that, without large premium subsidies, crop insurance uptake rates are generally quite low. In this article, we propose to use cumulative prospect theory in designing weather insurance products, for situations in which farmers narrowly frame insurance as stand-alone investment. To this end, we adjust insurance contract parameters to better tailor farmers’ preferences by introducing what we call behavioral weather insurance. We find that a stochastic multiyear premium increases the prospect value of weather insurances depending on farmers’ preferences, while a zero deductible design does not. We suggest that insurance contracts be tailored to optimally serve farmers’ needs, which offers potential benefits for both insurer and insured.

Author Contributions

T.D. and R.F. wrote the main manuscript and designed the study. T.D. carried out the underlying statistical analysis and prepared all figures. B.J.B. commented on various former versions. All authors reviewed the final manuscript.

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Chapter 2

Phenology Information Contributes to Reduce Temporal Basis Risk in Agricultural Weather Index Insurance

Tobias Dalhaus, Oliver Musshoff, Robert Finger

Keywords: Risk Management, Weather Index Insurance, Crop Phenology, Temporal Basis Risk, Crop Modelling, Quantile Regression

Abstract

Weather risks are an essential and increasingly important driver of agricultural income volatility. Agricultural insurances contribute to support farmers to cope with these risks. Among these insurances, weather index insurances (WII) are an innovative tool to cope with climatic risks in agriculture. Using WII, farmers receive an indemnification not based on actual yield reductions but are compensated based on a measured weather index, such as rainfall at a nearby weather station. The discrepancy between experienced losses and actual indemnification, basis risk, is a key challenge. In particular, specifications of WII used so far do not capture critical plant growth phases adequately. Here, we contribute to reduce basis risk by proposing novel procedures how occurrence dates and shifts of growth phases over time and space can be considered and test for their risk reducing potential. Our empirical example addresses drought risks in the critical growth phase around the anthesis stage in winter wheat production in Germany. We find spatially explicit, public and open databases of phenology reports to contribute to reduce basis risk and thus improve the attractiveness of WII. In contrast, we find growth stage modelling based on growing degree days (thermal time) not to result in significant improvements.

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2.1 Introduction

Agricultural insurance solutions are an important tool for farmers to manage risks. Among a wide set of available insurance solutions [1] weather index insurances (WII) have recently emerged as promising alternative to classical damage based insurance solutions. For WII the payout made to the farmer is based on a measured index, e.g. precipitation at a weather station, and is not directly based on yield or income losses experienced by the farmer. Thus, WII overcome asymmetric information problems of classical insurance schemes, because farmer and insurance company have equal information about the weather risk and are unable to manipulate the insured value (the weather) [2]. In addition, compensation of farmers only requires information of weather records and is thus fast and cheap. Hence, WII have a large potential in both developed and developing countries and can contribute to better farm-level risk management and more efficient use of natural resources [3, 4]. However, index insurances not necessarily lead to accurate compensation of yield losses and thus might fail to payout if farmers experience income losses. This phenomenon is denoted as basis risk and constitutes a significant adoption hurdle of these products by farmers. Basis risk can be separated into three components: 1) Geographical/spatial basis risk occurs if index is measured with spatial distance to production location [5]. 2) Design basis risk is a result of taking an index that is an inadequate predictor of yield losses [6]. 3) Temporal basis risk captures the imperfect choice of the time frame for index measurement [7, 8]. In this paper, we suggest novel approaches to reduce temporal basis risk.

Temporal basis risk mainly occurs because WII does not reflect the actual growth stage that is sensitive to specific weather, e.g. droughts. The measurement period for the weather index has to be specified in the insurance contract by both parties before the growth period of the crop starts. As the most straightforward procedure, periods over which the index is measured are thus often chosen to reflect particular calendar periods (e.g. specific weeks or months). These fixed time windows can only roughly approximate crop specific growth phases [9]. Moreover, the occurrence dates of growth phases are not constant across time and space, because weather conditions can cause large shifts in the actual occurrence of these periods [10, 11]. The resulting misspecification of insurance periods results in biased WII payout determination and therefore weak risk reducing properties hampering insurance uptake across risk averse farmers [12]. So far, only few studies have suggested approaches aiming to reduce temporal basis risk of WII, following more flexible index designs, i.e. by considering shifts of crop growth phases over time and space [13, 14]. In this respect, ‘flexible’ implies to implement yearly changing insurance periods according to the actual occurrence dates of vulnerable growth phases [10]. First, Kapphan et al. [13] used growing degree days (GDD) to model occurrence dates of emergence, vegetative period, grain filling and maturity in corn production based on thermal time. They evaluated the performance of their WII based on simulated corn yield and weather scenarios. Second, Conradt et al. [14] used GDD to simulate occurrence dates of tillering, shooting and ear emergence in spring wheat. They tested the risk reducing properties of the resulting WII based on a case study in Kazakhstan. Both approaches allow for fine scaled estimates of multiple growth phases. Furthermore, Dalhaus and Finger [15] suggest to use observations from a phenological network of farmland in the farms’ region to find winter wheat’s occurrence dates of stem elongation, ear emergence and milk ripeness. They tested their WII based on a case study in central Germany. The latter approach accounts additionally for a maximum of comprehensibility for the farmer, which is considered as key success factor in WII [16,17] So far, no study has compared different approaches to consider crop growth phases in WII design.

We here use an empirical example of a WII against drought risk in winter wheat production in Germany to compare existing and propose new approaches to reduce temporal basis risk. In winter wheat production, especially phases of low water supply during “reproductive and grain-filling” limit the development of the plant [18]. Farooq et al. [18] review outcomes of several contributions concerning yield reduction due to drought taking place at different developmental stages in winter wheat. Their findings indicate, that wheat is most vulnerable to drought during the phase from ‘stem elongation’ to ‘anthesis’ [19, 18]. Within this phase, assimilates are to a large extent used to develop grains [20]. Hence, drought induced leaf senescence [21, 22], reduced carbon uptake due to stomata closure [23] as well as shortening of grain filling period [20] decrease grain number and grain weight, thus reducing final yield outcome.

In this study, we aim to test and compare different approaches to find the occurrence dates of these phases and use this information to reduce temporal basis risk of WII. We focus on the following crop growth stage modeling and different phenology observation networks (see also table 2.1 for comparative features).

Growing Degree Days: Plants are expected to require a plant and growth stage specific temperature load to reach a certain growth stage. The growing degree days approach helps to model this based on observed temperature data. Using the GDD model we are able to estimate the occurrence dates of the drought sensitive period between stem elongation and anthesis of winter wheat.

Yearly Phenology Reporters: Publicly provided open dataset of plant growth stage occurrence dates. The network comes with a high spatial density and a detailed reporting procedure including various different growth stages. Data is published at the end of the calendar year. (denoted as ‘Yearly Reporter’ henceforward) Using yearly reporters’ data we are able to derive region specific information on the actual occurrence dates of the drought sensitive growth stages stem elongation and ear emergence in winter wheat.

Immediate Phenology Reporters: Publicly provided open dataset of plant growth stage occurrence dates. The network however comes with a lower spatial density and less reported growth phases compared to the latter network. Data is published directly after observation. (For a detailed explanation of all three approaches, see section 'Determination of water sensitive growth stages'.) (denoted as 'Immediate Reporter' henceforward) Using immediate reporters' data we are able to derive region specific information on the actual occurrence dates of the drought sensitive growth stages stem elongation and ear emergence in winter wheat.

To this end, we add to the current discussion of utilizing (big) data sources to support more efficient insurance solutions and thus sustainable agriculture [24, 25].

Table 2.1: Characteristics of the different Approaches to account for Drought sensitive growth Stages in WII Design

GDD	Yearly Reporter	Immediate Reporter
• Simulation • 356 Weather Stations • Numerous growth phases • Simulation of Anthesis occurrence possible • Immediate calculation • Vernalization[a] not considered	• Observation • 1,200 reporters • 7 growth phases for winter wheat • Anthesis not reported • Available at the end of the year • See figure 2 for the spatial distribution in the case study region	• Observation • 400 Reporters • 6 growth phases for winter wheat • Anthesis not reported • Available immediately • See figure 3 for the spatial distribution in the case study region

[a] Coolness requirement of winter crops to induce generative growth phases. GDD Approach does not distinguish between winter and spring temperature loads [29, 30]

More specifically we aim to answer the following research questions

> **RQ1:** Which approach to explicitly consider yearly changing insurance periods reduces farmers' financial exposure to drought risk compared to a 'no insurance' scenario?

> **RQ2**: Which approach to explicitly consider yearly changing insurance periods fits best to reduce temporal basis risk of weather index insurance?

We use expected utilities (EU) of insured farmers as risk measure to test for a reduction in the financial exposure to drought risk. We conduct this assessment for different scenarios of farmers' level of risk aversion. Our approach is particularly focused on the relevance of WII to reduce downside risks, i.e. the compensation of extreme yield losses, by utilizing power utility function to calculate expected utilities and the use of quantile regressions to obtain critical parameters of the WII such as tick size [6]. Our empirical example is based on farm-level wheat yield data for northern Germany, with a focus on drought risks. We conclude with a critical discussion on the applicability of the various approaches considered here, with respect to the insured crop, data availability and potential further research paths.

2.2 Results

For summary statistics on differences between the three approaches and WII contracts see the respective section of the online supplementary file.

We test for statistical significance of i) the ability of WII solutions to reduce farmers' financial exposure to drought risk compared to no insurance (RQ1) and ii) differences across the different WII specifications used here (RQ2). Table 2.2 shows Wilcox test results of the risk reducing properties of the different insurance products compared to the uninsured case. This assessment is based on average values of expected utilities across all considered farms and a fair insurance premium. We find that both WII based on phenology reporting data highly significantly increased farmers' expected utility and thus reduce the financial exposure to drought risk. This result holds over all implemented levels of risk aversion. Note that for risk neutrality (risk aversion being equal to zero) no improvement can be obtained from any insurance with fair insurance premiums. Regarding WII based on GDD estimated growth stages we could not detect any significant changes in expected utility compared to the 'no insurance' base scenario. Hence, GDD based WII did not reduce the financial exposure to drought risk in our empirical example of winter wheat production in Germany.

Table 2.2 Results RQ1: Tests for risk reducing properties of different WII compared to 'no insurance' reference scenario

	Yearly Reporter	Immediate Reporter	GDD…
Coefficient of relative risk aversion r_r	H_0:$EU_{year} \leq EU_{noins}$	H_0:$EU_{imm} \leq EU_{noins}$	H_0:$EU_{GDD} \leq EU_{noins}$
	p- value		
0 (risk neutral)	0.62	0.29	0.93
0.5	$3.48 \cdot 10^{-2}$	$6.31 \cdot 10^{-2}$	0.84
1	$2.51 \cdot 10^{-2}$	$7.49 \cdot 10^{-3}$	0.64
2	$6.73 \cdot 10^{-3}$	$9.93 \cdot 10^{-3}$	0.60
3	$5.72 \cdot 10^{-3}$	$1.42 \cdot 10^{-2}$	0.51
4 (extremely risk averse)	$5.28 \cdot 10^{-3}$	$1.31 \cdot 10^{-2}$	0.53

EU_{year}: Vector of expected utility values of insured farmers using yearly phenology reporters' data

EU_{imm}: Vector of expected utility values of insured farmers using immediate phenology reporters' data

EU_{GDD}: Vector of expected utility values of insured farmers using growing degree days modelling

EU_{noins}: Vector of expected utility values of uninsured farmers

Table 2.3 displays the results of comparisons between the different approaches. We find no difference in the risk reducing properties between different phenology reports. This result reveals that the benefits of using phenology reports in WII are independent of the reporting schemes. Compared to WII based on GDD approach, both phenology reporter based WII performed significantly better and thus reduced temporal basis risk.

Table 2.3 Results RQ2: Comparing risk reducing properties between WII

Coefficient of relative risk aversion α	H_0:$EU_{year} \leq EU_{imm}$	H_0:$EU_{year} \leq EU_{GDD}$	H_0:$EU_{imm} \leq EU_{GDD}$
	p-value		
0 (risk neutral)	0.50	0.23	0.17
0.5	0.27	$3.77 \cdot 10^{-2}$	$5.97 \cdot 10^{-2}$
1	0.35	$3.77 \cdot 10^{-2}$	$3.94 \cdot 10^{-2}$
2	0.13	$2.38 \cdot 10^{-2}$	$4.73 \cdot 10^{-2}$
3	0.10	$1.98 \cdot 10^{-2}$	$5.97 \cdot 10^{-2}$
4 (extremely risk averse)	0.10	$1.98 \cdot 10^{-2}$	$8.29 \cdot 10^{-2}$

EU_{year}: Vector of expected utility values of insured farmers using yearly phenology reporters' data

EU_{imm}: Vector of expected utility values of insured farmers using immediate phenology reporters' data

EU_{GDD}: Vector of expected utility values of insured farmers using growing degree days modelling

EU_{noins}: Vector of expected utility values of uninsured farmers

All results presented here show the differences between the three WIIs with respect to their ability to reduce temporal basis risk and thus increase farmers' expected utility. Within our online supplementary file we present results on the magnitude of the here identified effects (see table A4 of the online supplementary file).

2.3 Discussion

This study is the first comparing different WIIs that explicitly consider managing drought risk in single stages of plant growth. In our approach, insurance periods vary across time and space according to the occurrence dates of the growth stages stem elongation, anthesis and ear emergence. Our results reveal improvements for WII schemes by reducing temporal basis risk. Drought risks are expected to become more pronounced for arable farmers in Europe in the future. Thus, developing functioning WII insurance solutions is considered as viable climate change adaptation tool [26,27].

Using phenological observations to suit WII to agronomical plant development highly significantly decreased farmers risk exposure and thus increased farmers' expected utility compared to both, using GDD based WII and to insuring 'no insurance reference scenario. However, both phenology reporting networks did only provide information about the growth stage of 'ear emergence' and not about the highly drought sensitive growth stage of 'anthesis', which can be estimated by the GDD approach [28]. More specifically, GDD based approaches allow a substantially finer assessment of crop growth stages than phenology observations. Nevertheless, the GDD approach failed to properly estimate the occurrence of 'anthesis' and risk reducing properties of the reporters based WII remained strong. The fact that both reporting networks, which have different reporting procedures and network densities, showed a relatively similar performance, underlines the robustness of our results to changes in the reporting procedure and station density. With respect to timely insurance payouts in the case of loss events, we would like to clearly emphasize that immediate reporters, which publish their findings right after occurrence, constitute the preferable option compared to yearly reporters. Timely compensation of losses to avoid illiquidity is considered as key requirement of crop insurances to avoid illiquidity. However, including the growth stage of 'anthesis' in the phenology reporting system would potentially further increase the risk reducing properties.

Concerning the usage of GDD to find appropriate WII periods, we found several drawbacks that have to be considered. Thus, GDD estimate of the occurrence dates of ‘stem elongation’ was considerably too early. As a result, rainfall in the insured period was considerably higher due to a longer insurance period and a shift into a more wet time of the year. Hence, drought risk was underestimated and farmers received fewer payouts resulting in low risk reducing properties (tables 2.1, 2.2, 2.A2 and 2.A3). GDD modes might be improved using expert knowledge or additional experimental data. Furthermore, crop modelling approaches can provide valuable information to derive estimates for the occurrence dates of plant growth stages considering differences in the impact of winter and spring temperature loads (vernalization) and length of the day (photoperiodism) [29, 30, 31, 32]. Thus, methods to reduce temporal basis risk must be selected crop specific, based on their ability to find occurrence dates of growth stages for the specific crop. Yet, these possible advances have to be aligned to findings that more complex WII solutions lead to lower acceptance on farmers’ side [16,17].

Public institutions surveying phenological development of plants, i.e. the occurrence dates of growth stages, exist in many regions that are important crop insurance markets (see van Vliet et al., [33] for Europe or Morellato et al. [34] for South and Central America). However, despite their availability and the fact that all approaches tested could be easily implemented in current practical index insurance schemes, none of them has been considered in practice so far. This reveals a massive potential for improvements especially for WII products. This is particularly valid for countries such as the USA, where the market for WII is well established (premiums paid for WII exceeded 284 m USD in 2016, (www.rma.usda.gov) and various data sources on crop phenology are not yet used in WII (www.usapn.org).

WII currently are tested in many developing countries where the availability of phenology information might be limited and where the impacts of drought might be more severe [35,36]. Here, crop specific methods to find the occurrence dates of sensitive growth stages might be implemented. Whereas, in our case study the availability of cheap real-time phenology observations constitutes the most cost-effective and from farmer's perspective comprehensible tool, it might be worth using more complex approaches in case of phenology data scarcity. In this respect also alternatives to GDD approach such as 'biometeorological time' or 'physiological days' as suggested by Saiyed et al. [37] or satellite imagery [38] could further reduce temporal basis risk. Improving weather-index insurance by integrating crop modelling seems key in developing better insurance solutions for countries where phenology data is scarce. Moreover, validating GDD models using regional phenological observations could be a practical way to bring together advantages of both approaches. Consequently, our study discloses a variety of ways to include temporally flexible index designs.

Moreover, our findings contribute to the ongoing debate on the inclusion of novel (big) data sources in agricultural decision making in general and agricultural insurance in particular [24]. Within the broader picture of smart farming, where "aspects of technology, diversity of crop and livestock systems, and networking and institutions […] are considered jointly" [25], we contribute a practical application that combines large and open datasets, crop modelling and meteorological applications with agronomical knowledge. Our findings are thus expected to stimulate further research but also business opportunities in the field of agricultural risk assessment and risk management.

Finally, our findings contribute to improve risk management options based on WII. But, individual risk management options should be compared and embedded in a whole farm analysis. For estimating the optimal risk management strategy coping with various perils a more holistic framework might be applied, taking into account the whole crop rotation, livestock production, the financial situation as well as off farm income, i.e. whole farm/ household income [39]

2.4 Methods and Data

2.4.1 Design of the Weather Index Insurance

We aim to develop a WII that reduces the exposure to drought risk which frequently affects winter wheat yields in our study region [40] (see section "Farm Level Yield Data" for a description of the underlying dataset). Thus, winter wheat yield *y* is displayed as a function of weather index *r*, in our case the sum of precipitation within a drought sensitive growth stage:

$$y = g(r) + \varepsilon \tag{2.1}$$

More specifically, we implement a cumulative precipitation index r_{tik}^{R}, which represents the sum of precipitation within a specific period [41, 42]:

$$r_{tik}^{R} = \sum_{d=start}^{end} R_{ti}^{d} \tag{2.2}$$

r_{tik}^{R} denotes the precipitation index of farm *i* in year *t* and insurance product $k \in$ [GDD, Yearly Reporter, Immediate Reporter], summing up daily rainfall R_{ti}^{d}. Further, d=d_{start} and d=d_{end} mark start and end-dates of accumulation period and should be tailored to water sensitive growth stages. We especially aim to improve flexible start and end date detection by testing three different approaches to find these dates based on both phenological observation networks and crop growth stage modeling. By specifically suiting the weather index in equation 2.2 to the drought sensitive growth stages, we avoid to include damaging effects of excessive rainfall, which can also be reflected by a rainfall sum index [43,11]

Using a European put option design WII is suited to indemnify losses caused by low precipitation events. European options are financial products that give the owner the right of exercising the option at a specific point in time. The owner then receives a payout depending on a payout function. In the case of a put option, the insurance payout begins if a specific strike level S_{ik} of precipitation is undercut and rises depending on the options' ticksize T_{ik} (payout per missing index value, in our case mm precipitation). The insurance payout π_{tik}^{put} is determined by $\pi_{tik}^{put} = P \cdot [T_{ik} \cdot \max\{(S_{ik} - r_{tik}^{R}), 0\}]$, where P denotes the winter wheat price (Note that we assumed the winter wheat price to be 15.80 €/dt (dt denotes deciton, i.e. 100 kg) [44], our results are robust against changes in P as shown in tables A5 – A8 of the online supplementary file)

Extending equation 1, wheat yield y_{ti} of farm i is assumed to be random and stochastically dependent on weather index r_{tik}^{R} and an error term $\tilde{\varepsilon}_{ti}$:

$$y_{ti} = c_{ik} + \beta_{ik} \cdot r_{tik}^{R} + \tilde{\varepsilon}_{tik} \tag{2.3}$$

c_i is a constant intercept and β_i the slope coefficient of the rainfall index variable that can be interpreted as the influence of rainfall index r_{tik}^{R} on yields y_{ti}, both randomly distributed across the years.

We define strike level S_i as the estimated rainfall value related to the farm individual mean yield $\bar{y}$ ($S_{ik} = g_{ik}{}^{-1}(\bar{y}_{ik})$). More specifically we insert coefficient estimates $\hat{\beta}_{ik}$ (which represents options' ticksize T_{ik}) and $\widehat{c_i}$ together with the mean yield $\bar{y}_i$ into equation 2.3 and solve for the corresponding rainfall index value r_{ik}^{R} that marks the strike level of rainfall S_{ik}.

Both strike level and ticksize are obtained from quantile regression (QR) outcome, recently suggested by Conradt et al. [9], estimated for each farm separately. The estimation problem is defined as:

$$\hat{\beta}_{ik}(\tau) = arg \min_{\beta_{ik} \in \mathbb{R}} (\tau \cdot \textstyle\sum_{y_i \geq \beta_{ik} \cdot r_{ik}^{R}} \left| y_i - \beta_{ik} \cdot r_{ik}^{R} \right| + (1 - \tau) \cdot \textstyle\sum_{y_i < \beta_{ik} \cdot r_{ik}^{R}} \left| y_i - \beta_{ik} \cdot r_{ik}^{R} \right|) \tag{2.4}$$

QR focuses on a quantile of interest defined by τ and is comparably robust to outlier values as it minimizes the absolute distance between fitted values and residuals. We follow Conradt et al. [6] and chose $\tau = 0.3$ and specially suit the regression on low yield outcomes. We use the statistical software environment R-statistics [45] with the additional package 'quantreg' [46]. For a detailed description of using quantile regression in weather index insurance design see Conradt et al. [6] and Dalhaus and Finger [15].

2.4.2 Determination of Drought sensitive Growth Stages

Plant Growth Stage Modelling (GDD)

First, we use a WII conditioned using plant growth stage modelling approach, i.e. growing degree days (GDD) as suggested by Conradt et al. [14]. The occurrence of different crop growth stages are calculated based on required air temperature loads (thermal time). This approach is denoted subsequently as 'GDD'. Therefore, we take average seeding dates and calculate based on these all following growth stages.

$$GDD = \sum_{n=1}^{N} \max(\min\{H_n^{av}, H^{up}\} - H^{base}, 0) \quad (2.5)$$

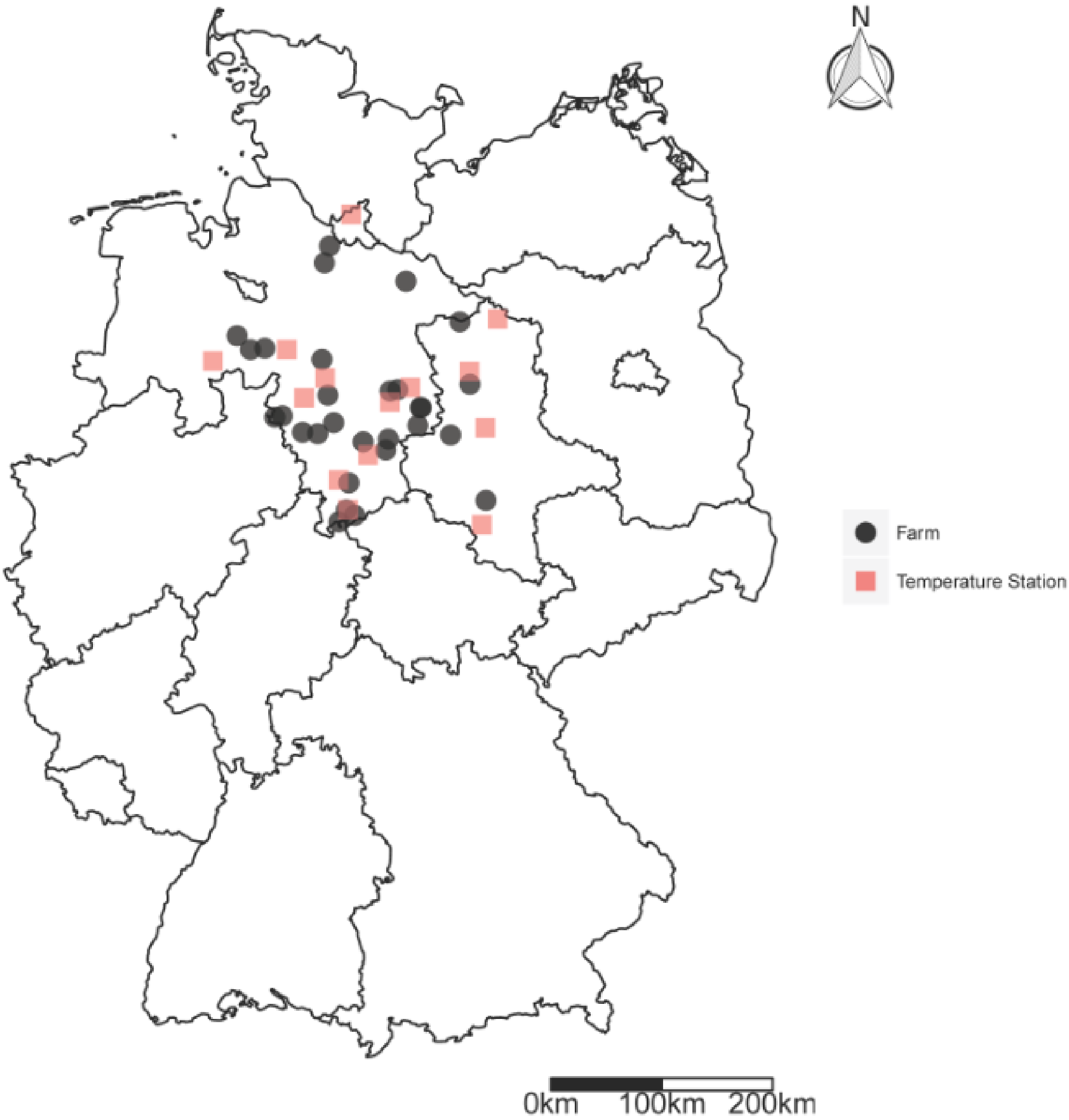
We thus sum up mid-range daily air temperature H^{av} ($H^{av} = \frac{H^{min}+H^{max}}{2}$; with H^{min} and H^{max} being the daily minimum and maximum air temperature respectively) if it is greater than H^{base} = 3°C and lower than H^{up} = 22°C. If H^{av} exceeds H^{up}, we take H^{up} as GDD value, as growth is assumed to remain static then [28]. After reaching a GDD threshold, the plant is assumed to start a new growth stage. For our study region, we rely on literature values of these thresholds, see table 4 for an overview. We consciously decided to rely on literature values only, to ensure a minimum of transaction costs and to propose an easy to implement, highly transparent and cheap insurance product.

Table 2.4: GDD Thresholds for different growth stages

Phase	Assumption	Source
Seeding Date	15th Oct	Chamber of Agriculture North Rhine-Westphalia [60]
Stem Elongation	659 °C	Miller et al. [61]
Anthesis	1,150 °C	Torriani et al. [25]

GDD values are used to identify the start of the ‘stem elongation’ growth stage and obtain the start date $d_{start;GDD}$ for equation 2.5. We then repeat the procedure for the ‘anthesis’ growth period and get the end value $d_{end;GDD}$ for equation 2.5. We decided to use this simple GDD model as this was applied in previous studies on WII [13,14]and it is straightforward in implementation. From farmer’s perspective, the WII must be easy to understand and straight forward in its payout determination, a more complex growth stage model might counteract this requirement [16,17].

Figure 2.1: Location of Temperature measuring Weather Stations and Case Study Farms



The figure was created using the package ggplot2 (version 2.2.1.9) [62] of the statistical software environment R-statistics (version 3.3.2)

Yearly Phenology Reporter

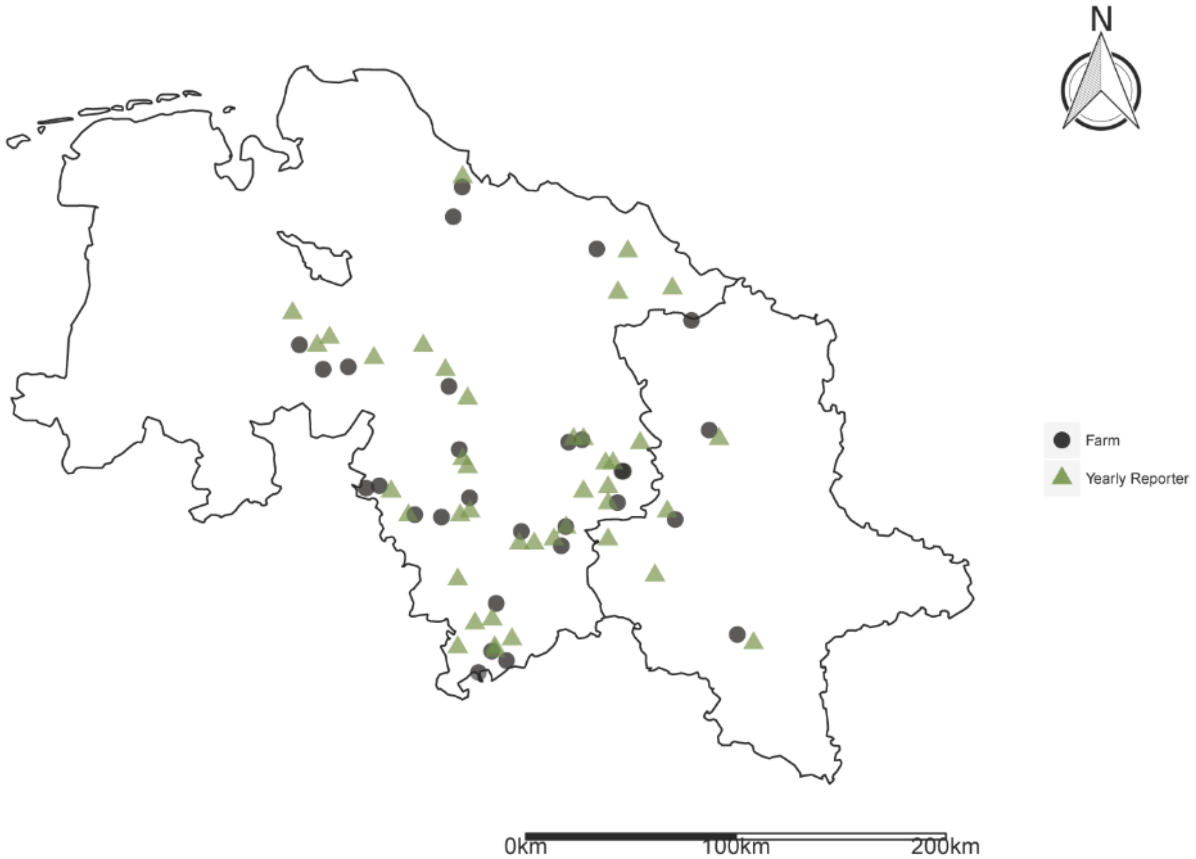
Second, we condition WII based on phenological observations that indicate growth stages in a particular region reported at the end of the year (see figure 2.2 for location information).

Deutscher Wetterdienst provides occurrence dates of growth stages for a variety of plants (ftp://ftp-cdc.dwd.de/). Within a basis network 1,300 reporters report on a yearly basis whereas 390 of these report their findings immediately. For wheat only, the former reporter dataset consist of ~650,000 observations. Taking into account that observations are available for over 20 different crops and immediate reporter data is published in real time, this phenology data constitutes a data source of large potential interest for various agricultural applications. Reports include growing information of wild growing but also agricultural flora cultivated under real-world (i.e. non-experimental) conditions. Observers check their reporting area two to three times a week and on a daily basis in rapid plant development periods. Untypical topographic points as well as unusual field conditions (climatic or cultivation anomalies) should be avoided. The data of single reporters is cross checked with surrounding reporters within the same natural region before publishing [47,48] (within these natural regions plant growth conditions are similar). Similar public networks are available for various other major crop insurance markets (See van Vliet et al., [33] for Europe, Morellato et al. [34] for South and Central America and www.usapn.org for the US).

Our methodology here closely follows Dalhaus and Finger [15]. However, in contrast to this study, we focus solely and more detailed on one source of basis risk (temporal) and compare existing and propose new approaches coping with this issue. This data source provides high quality data, however with the drawback of being reported only at the end of the year. We use phenological observations of stem elongation and ear emergence to determine $d_{start;\, yea}$ and $d_{end;\, yea}$. As the growth stage of anthesis is not reported in the underlying data, we focus on the ear emergence growth stage that is closest to the anthesis stage.

The Yearly Reporters observe a reference field cultivated under practical conditions and capture a phenological phase, when about 50 % of all plants reached it [47]. The findings are published online at the end of each year. Insurance payout can thus not be triggered directly after weather occurrence, but only when phenology reporters' data is available. In total, there are around 1,200 Yearly Reporters in Germany available for our period of interest.

Figure 2.2: Location of Yearly Reporters



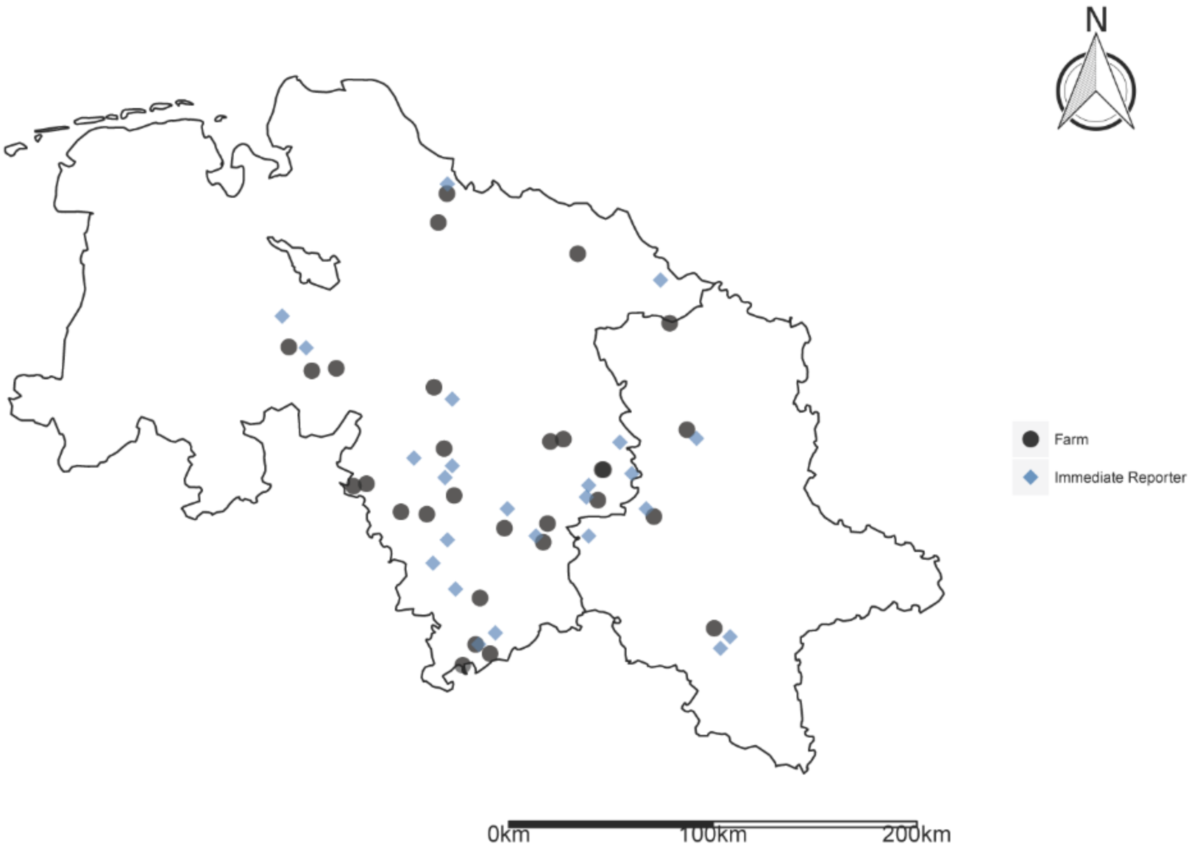
The figure was created using the package ggplot2 (version 2.2.1.9) [62] of the statistical software environment R-statistics (version 3.3.2)

Immediate Phenology Reporter

Third, we use an alternative source of phenological observations that comprises a live publishing reporting network (see figure 2.3 for location information). This third database would thus provide a substantially sooner payout in case of adverse weather events but comes with a considerably lower reporting density [48]. Comparing the Yearly and Immediate Reporter networks thus allows to reflect the balance between quality of the index (reporting density) and the timing of indemnification. Despite its potential, this study is the first considering this latter database in WII context.

The Immediate Reporters' network of the Deutscher Wetterdienst contains around 400 reporters publishing phenological development right after the first occurrence of a growth stage. In contrast to Yearly Reporters, all sites within a radius of up to 5 km are considered, to give an impression of plant development in a wider reporting area. Immediate Reporters report the first occurrence of a growing stage within their reporting area. The Immediate reporting network is especially implemented for the use in agricultural consultancy [47].

Figure 2.3: Location of Immediate Reporters



The figure was created using the package ggplot2 (version 2.2.1.9) [62] of the statistical software environment R-statistics (version 3.3.2)

Table 2.5 summarizes which growth stages are captured within the different reporting networks. Phases with high relevance for drought risks are III Stem Elongation -IV Ear Emergence for both reporting networks. This period captures drought risk during meiosis and reproductive phases.

Table 2.5: Observed Phenological Phases of Immediate and Yearly Reporters

No.	Yearly Reporters	Immediate Reporters
I	Tilling	Tilling
II	Seedling Growth	Seedling Growth
III	Stem elongation	Stem elongation
IV	Ear emergence	Ear emergence
V	Milk ripeness	
VI	Yellow ripeness	Yellow ripeness
VII	Harvest	Harvest

Source: [48]

To precisely account for regional specifics, we use natural regions which were originally defined by Meynen and Schmitthüsen [49] to find farm specific appropriate reporters. For the Immediate Reporters case we dropped four farms from the analysis for which no Immediate Reporters' data was available within the natural region during the whole study period. For cases in which single year phenology reports were not available, an imputation strategy was applied where the mean value of occurrence dates across the available years was used as estimate.

2.4.3 Performance testing

As risk management tool, a WII product is assumed to reduce farmers' financial exposure to weather risk. In this context, the risk reducing properties of the insurance strongly depend on i) basis risk that affects insurance efficacy and ii) decision makers' risk attitude that reflects farmers' individual valuation of risk reducing properties of WII. To test the potential of different WII products to reduce temporal basis risk, we assess farmers' expected utility of their crop production and implement different scenarios of risk aversion. Consequently, the insurance product providing highest expected utility is assumed to provide highest reduction of temporal basis risk. Within this framework, the utility function converts yearly monetary terminal wealth realizations into farm individual utility values, depending on level of risk aversion. Along these lines, we assume decreasing absolute risk aversion and use a power utility function to display farmers' downside risk averse preferences (for recent examples in index insurance context see Dalhaus and Finger, [15], Berg et al. [50], and Leblois et al. [51] and for a general motivation of the utility function Di Falco and Chavas [52, 53] and Finger [54]). To account for these differences we test several coefficients of relative risk aversion $\alpha \in [0, 0.5, 1, 2, 3, 4]$ ranging from risk neutral to extremely risk averse [55]. Assuming that farmers only hold the assets initial wealth W_0, wheat production and index insurance results in yearly terminal wealth W_{tik}:

$$W_{tik} = P \cdot y_{ti} + \pi_{tik}^{put} - \Gamma_{ik} + W_0 \tag{2.6}$$

We used direct payments of 280 €/ha as initial wealth proxy. Hence the farm individual yearly utility is determined by:

$$\mathrm{U}_{k\alpha it}(W_{tik}) = \begin{cases} \frac{W_{tik}^{1-\alpha}}{1-\alpha} & if\ \alpha \neq 1 \\ \ln(W_{tik}) & if\ \alpha = 1 \end{cases} \tag{2.7}$$

This results in an utility value $\mathrm{U}_{k\alpha it}$ for each WII product, year *t*, farm *i* and level of risk aversion α. The mean values across all years reflect the expected utility $E\mathrm{U}_{k\alpha\mathrm{i}}$ of farm *i*, insurance *k* and level of risk aversion α. Subsequently, we test insurance products against each other across different levels of risk aversion. More specifically, we use a non-parametric one sided paired Wilcoxon rank sum test to account for the ordinal nature of utility values [6,13]. More specifically, ordinal nature implies that expected utility values might only be compared with respect to their rank but not with respect to their absolute difference.

Assuming a fair premium, the insurance premium Γ_{ik} is equal to the expected payout. Burn rate pricing is used based on a bootstrapping procedure with 10,000 draws [56]. More specifically, we draw from the historical realizations of the insurance payouts during the period of study and take the average values of those draws. We moreover use a constant premium during the whole period of study as we do not expect changes in the risk exposure, e.g. due to climate change, to change our results. For implementing a marketable insurance product we refer to Kapphan et al. [13], who include climate change scenarios in the pricing of WII.

2.4.4 Weather Data

The underlying weather data was provided by the Deutscher Wetterdienst, an independent state institution. Hence data provision is transparent and comprehensible for policyholders (§ 1, Law of the Deutscher Wetterdienst). For index calculation two weather variables are necessary. First, precipitation data to determine daily rainfall. Second, air temperature data to find growth stages with GDD approach. For both variables we chose nearby weather stations with an average distance between farms and stations of 8.5 km for precipitation and 22.06 km for air temperature stations. All weather data was freely available under ftp://ftp-cdc.dwd.de/. Table 6 gives an overview of precipitation sums calculated using the different approaches of plant growth determination. The considerably higher mean precipitation during the GDD estimated growth phases is a result of the fact that this approach estimates stem elongation date systematically too early. All weather data and code used are available in the online supplementary information.

Table 2.6: Summary Statistics of Precipitation Sums in Growth Phases

Growth Stage determination	Growth Stage	Mean	Standard deviation	Coefficient of Variation
GDD	Stem Elongation – Anthesis	108.77	53.40	0.49
Yearly Reporter	Stem Elongation – Ear Emergence	68.56	36.44	0.53
Immediate Reporter	Stem Elongation – Ear Emergence	68.51	31.88	0.46

Table 2.A1 of the online supplementary file displays a comparison between rainfall determination approaches using Pearson correlation. While precipitation within reported phases of Yearly and Immediate Reporters is relatively closely related (0.58), GDD based precipitation sums are only weakly correlated with these two (0.24; 0.16).

2.4.5 Farm Level Yield Data

Our case study was carried out using winter wheat yield data together with latitude and longitude coordinates of 29 northern German crop farms (see figure 2.1 for location information). To consider technical change during the study period from 1996 to 2010, yield data was detrended using linear trends. For summary statistics see table 2.7. For a more detailed description of the study area see Dalhaus and Finger [15]. Pelka and Musshoff [57] give a more detailed motivation of why linear detrending was used. They conclude from Heimfarth et al. [58] that considering more robust regression approaches [59] did not lead to differences in the results.

Table 2.7: Summary Statistics of Wheat Yields

Summary statistics yield data		
Number of Farms		29
Minimum	[dt[a]/ha]	45.51
Maximum	[dt/ha]	132.00
Mean	[dt/ha]	86.91
Median	[dt/ha]	86.00
Standard deviation	[dt/ha]	14.47
Coefficient of Variation		0.17

Source: Dalhaus and Finger [15]

[a] dt denotes deciton, i.e. 100kg

2.5 Supplementary Information

Table 2.A1: Correlation Matrix: Precipitation in growing phases

	GDD	Yearly Reporter	Immediate Reporter
GDD	1		
Yearly Reporter	0.24	1	
Immediate Reporter	0.16	0.58	1

2.5.1 Summary Results

To give a general overview about the differences across the growth stage estimation approaches, table 2.A2 displays temporal gaps between the estimated timings. Hence, the GDD approach systematically estimates the occurrence of the 'stem elongation growth' stage ($d_{start;GDD}$) around a month earlier than the two reporting networks observe. In single outliers' cases these difference can increase up to 132 days, which leads to unrealistic dates. Note that all estimated

(GDD) and observed (Yearly and Immediate Reporters network) dates are included in the online appendix.

For the second growing stage of interest, GDD estimates ‘anthesis’ ($d_{end;GDD}$) while the reporters only capture the actually earlier but less drought sensitive ‘ear emergence’ growing stage ($d_{end;imm}$ $d_{end;year}$). GDD estimate is still around 20 days earlier than the reporters. However, this misspecification is mainly caused by the former mentioned issue of estimating ‘stem elongation’ timing.

The median difference between Yearly and Immediate phenology Reporters is close to zero days for both phases. However, for single reports this difference can be up to 68 days. These differences arise from distance between single yearly and immediate reporters’ locations as well as different reporting strategies (see section 3.2).

Table 2.A2: Differences in estimated timings in days

Approaches		Stem Elongation	Ear Emergence/ Anthesis
Difference between Yearly Reporters' and GDD Dates			
	Median	37	21
	Min	-6	-23
	Max	132	76
Difference between Immediate Reporters' and GDD Dates			
	Median	33	20
	Min	-26	-19
	Max	123	64
Difference between Yearly and Immediate Reporters' Dates			
	Median	2	0
	Min	-68	-26
	max	54	34

Table 2.A3 summarizes WII contract parameters across the different approaches of growth stage determination. The aforementioned early estimated dates of the GDD approach lead to the fact that the insured rainfall period is longer and shifted into a period in which higher rainfall is more likely. Resulting strike levels that have to be undercut to trigger an insurance payout are higher compared to case when insuring via phenology reporting networks. Medium as well as maximum WII premium rates reflect a high drought risk exposure, as expected in this region. On average, an indemnification of the WII (i.e. net payouts are positive) in 4.10 out 15 years

for the GDD approach, 6.03 years for Yearly and 5.28 years for Immediate Reports. Thus, farmers using WII based on phenology reporters' data receive an indemnification of 29% to 47% more likely compared to GDD case. Even though this might increase transaction costs, not too rare indemnification is seen as important determinant of the success of WII [1].

The differences in the variable 'number of insured farms' are due to the fact that we restricted the insurance only to be concluded if the sign of the estimated relationship between yield and rainfall was positive. That means, if our regression detected a higher negative influence of excessive rainfall compared to low rainfalls' influence in the given growing stage, we dropped these cases as we assumed the farmers not to conclude an insurance contract then. Furthermore, for 8 farms there was no Immediate Reporters' data available in the farms natural region.

Table 2.A3: Summary Statistics of Insurance Contract Parameters for α=1 across all 29 case Study Farms.

Data Source	GDD	Yearly Reporter	Immediate Reporter
Strike Level [mm precipitation/m²]			
Median	191.64	122.91	125.31
Min	128.04	47.20	66.82
Max	1903.23	507.02	360.78
Premium [€/ha]			
Median	61.17	62.74	77.39
Min	7.78	8.89	16.71
Max	162.82	166.64	166.80
Average Number of positive net Payouts (payout minus premium; out of 15 years)			
Mean	4.10	6.03	5.28
Number of insured out of 29 farms*			
	15	24	21

*Note that we assumed the insurance contract to be concluded only if the slope coefficient of QR was positive and if phenology reporters’ data was available.

For full information about the variables see the online appendix.

Table 2.A4: Average Changes of Risk Premium in Percentage Terms, WII compared to uninsured Scenario

Coefficient of relative risk aversion r_r	Yearly Reporters vs. Uninsured	Immediate Reporters vs. Uninsured	GDD vs. Uninsured
0 (risk neutral)			
0.5	- 6.25	-2.19	- 0.34
1	- 6.39	-2.31	- 0.45
2	- 6.66	-2.52	- 0.68
3	- 6.91	- 2.72	- 0.91
4 (extremely risk averse)	- 7.14	- 2.89	- 1.13

2.5.2 Sensitivity Analyses

Table 2.A5 Results RQ1: Tests for risk reducing properties of different WII compared to no insurance (Wheat Price changed to 20€/dt)

Coefficient of relative risk aversion r_r	$H_0{:}EU_{year} \geq EU_{noins}$	$H_0{:}EU_{imm} \geq EU_{noins}$	$H_0{:}EU_{GDD} \geq EU_{noins}$
	p- value		
0 (risk neutral)	0.62	0.29	0.93
0.5	$3.27 \cdot 10^{-2}$	$4.76 \cdot 10^{-2}$	0.85
1	$2.35 \cdot 10^{-2}$	$7.49 \cdot 10^{-3}$	0.60
2	$6.73 \cdot 10^{-3}$	$9.94 \cdot 10^{-3}$	0.60
3	$5.73 \cdot 10^{-3}$	$1.43 \cdot 10^{-2}$	0.56
4 (extremely risk averse)	$4.11 \cdot 10^{-3}$	$1.31 \cdot 10^{-2}$	0.49

Table 2.A6 Results RQ2: Comparing risk reducing properties between WII (Wheat Price changed to 20€/dt)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{imm}$	H_0:$EU_{year} \geq EU_{GDD}$	H_0:$EU_{imm} \geq EU_{GDD}$
	p-value		
0 (risk neutral)	0.50	0.24	0.17
0.5	0.27	$3.77 \cdot 10^{-2}$	$6.32 \cdot 10^{-2}$
1	0.33	$3.77 \cdot 10^{-2}$	$4.46 \cdot 10^{-2}$
2	0.12	$2.24 \cdot 10^{-2}$	$5.02 \cdot 10^{-2}$
3	0.11	$2.11 \cdot 10^{-2}$	$6.32 \cdot 10^{-2}$
4 (extremely risk averse)	0.10	$1.98 \cdot 10^{-2}$	$9.20 \cdot 10^{-2}$

Table 2.A7 Results RQ1: Tests for risk reducing properties of different WII compared to no insurance (Wheat Price changed to 10€/dt)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{noins}$	H_0:$EU_{imm} \geq EU_{noins}$	H_0:$EU_{GDD} \geq EU_{noins}$
	p- value		
0 (risk neutral)	0.62	0.29	0.93
0.5	$4.46 \cdot 10^{-2}$	$8.22 \cdot 10^{-2}$	0.88
1	$3.06 \cdot 10^{-2}$	$9.05 \cdot 10^{-3}$	0.69
2	$7.88 \cdot 10^{-3}$	$9.94 \cdot 10^{-3}$	0.62
3	$6.21 \cdot 10^{-3}$	$1.31 \cdot 10^{-2}$	0.53
4 (extremely risk averse)	$4.88 \cdot 10^{-3}$	$1.31 \cdot 10^{-2}$	0.58

Table 2.A8 Results RQ2: Comparing risk reducing properties between WII (Wheat Price changed to 10€/dt)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{imm}$	H_0:$EU_{year} \geq EU_{GDD}$	H_0:$EU_{imm} \geq EU_{GDD}$
	p-value		
0 (risk neutral)	0.50	0.24	0.17
0.5	0.30	$3.37 \cdot 10^{-2}$	$5.97 \cdot 10^{-2}$
1	0.35	$3.98 \cdot 10^{-2}$	$3.94 \cdot 10^{-2}$
2	0.16	$2.53 \cdot 10^{-2}$	$4.19 \cdot 10^{-2}$
3	0.11	$2.11 \cdot 10^{-2}$	$5.97 \cdot 10^{-2}$
4 (extremely risk averse)	0.11	$1.86 \cdot 10^{-2}$	$7.06 \cdot 10^{-2}$

Table 2.A9 Results RQ1: Tests for risk reducing properties of different WII compared to no insurance (initial wealth changed to 200€/ha)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{noins}$	H_0:$EU_{imm} \geq EU_{noins}$	H_0:$EU_{GDD} \geq EU_{noins}$
	p- value		
0 (risk neutral)	0.62	0.29	0.93
0.5	$3.27 \cdot 10^{-2}$	$4.42 \cdot 10^{-2}$	0.84
1	$2.35 \cdot 10^{-2}$	$8.24 \cdot 10^{-3}$	0.60
2	$6.73 \cdot 10^{-3}$	$9.94 \cdot 10^{-3}$	0.58
3	$5.73 \cdot 10^{-3}$	$1.43 \cdot 10^{-2}$	0.56
4 (extremely risk averse)	$3.78 \cdot 10^{-3}$	$1.31 \cdot 10^{-2}$	0.49

Table 2.A10 Results RQ2: Comparing risk reducing properties between WII (initial wealth changed to 200€/dt)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{imm}$	H_0:$EU_{year} \geq EU_{GDD}$	H_0:$EU_{imm} \geq EU_{GDD}$
	p-value		
0 (risk neutral)	0.50	0.24	0.17
0.5	0.27	$3.77 \cdot 10^{-2}$	$6.32 \cdot 10^{-2}$
1	0.32	$3.77 \cdot 10^{-2}$	$4.73 \cdot 10^{-2}$
2	0.12	$2.24 \cdot 10^{-2}$	$5.02 \cdot 10^{-2}$
3	0.11	$2.11 \cdot 10^{-2}$	$6.32 \cdot 10^{-2}$
4 (extremely risk averse)	0.10	$1.86 \cdot 10^{-2}$	$8.74 \cdot 10^{-2}$

Table 2.A11 Results RQ1: Tests for risk reducing properties of different WII compared to no insurance (initial wealth changed to 350€/ha)

Coefficient of relative risk aversion r_r	$H_0: EU_{year} \geq EU_{noins}$	$H_0: EU_{imm} \geq EU_{noins}$	$H_0: EU_{GDD} \geq EU_{noins}$
	p- value		
0 (risk neutral)	0.62	0.29	0.93
0.5	$3.48 \cdot 10^{-2}$	$7.22 \cdot 10^{-2}$	0.84
1	$2.87 \cdot 10^{-2}$	$9.05 \cdot 10^{-3}$	0.64
2	$6.73 \cdot 10^{-3}$	$1.09 \cdot 10^{-2}$	0.60
3	$5.73 \cdot 10^{-3}$	$1.43 \cdot 10^{-2}$	0.51
4 (extremely risk averse)	$4.86 \cdot 10^{-3}$	$1.31 \cdot 10^{-2}$	0.56

Table 2.A12 Results RQ2: Comparing risk reducing properties between WII (initial wealth changed to 350€/dt)

Coefficient of relative risk aversion r_r	$H_0{:}EU_{year} \geq EU_{imm}$	$H_0{:}EU_{year} \geq EU_{GDD}$	$H_0{:}EU_{imm} \geq EU_{GDD}$
	p-value		
0 (risk neutral)	0.50	0.24	0.17
0.5	0.27	$3.37 \cdot 10^{-2}$	$6.32 \cdot 10^{-2}$
1	0.36	$3.77 \cdot 10^{-2}$	$3.71 \cdot 10^{-2}$
2	0.15	$2.68 \cdot 10^{-2}$	$4.46 \cdot 10^{-2}$
3	0.10	$2.11 \cdot 10^{-2}$	$5.97 \cdot 10^{-2}$
4 (extremely risk averse)	0.11	$1.86 \cdot 10^{-2}$	$7.86 \cdot 10^{-2}$

Table 2.A13 Results RQ1: Tests for risk reducing properties of different WII compared to no insurance (loading 10%)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{noins}$	H_0:$EU_{imm} \geq EU_{noins}$	H_0:$EU_{GDD} \geq EU_{noins}$
	p- value		
0 (risk neutral)	0.99	0.99	1.00
0.5	0.99	0.99	1.00
1	0.99	0.99	1.00
2	0.99	0.99	1.00
3	0.99	0.99	1.00
4 (extremely risk averse)	0.95	0.99	0.99

When adding a loading factor of 10% to the insurance premiums, none of the insurances reduces the financial exposure to risk any longer. This was to be expected, as we only insure a single peril. For a marketable insurance product multiple weather risks should be combined and a whole farm risk management strategy should be developed. As we only compare the different options GDD, yearly reporter and immediate reporter to reduce temporal basis risk of the rainfall component of a WII, results displayed in table 2.A13 do not change the general conclusions drawn in the main paper.

Table 2.A14 Results RQ2: Comparing risk reducing properties between WII (loading 10%)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{imm}$	H_0:$EU_{year} \geq EU_{GDD}$	H_0:$EU_{imm} \geq EU_{GDD}$
		p-value	
0 (risk neutral)	0.92	0.53	0.19
0.5	0.88	0.36	0.17
1	0.81	0.23	0.13
2	0.69	$6.03 \cdot 10^{-2}$	0.10
3	0.46	$4.16 \cdot 10^{-2}$	$7.57 \cdot 10^{-2}$
4 (extremely risk averse)	0.34	$3.19 \cdot 10^{-2}$	0.11

When adding a loading factor of 10% to the insurance premium, the superiority of yearly and immediate reporter based WII compared to GDD vanishes. This is due to the fact, that the GDD based insurance comes with a lower overall absolute premium compared to yearly and immediate reporter based WII as shown in table 2.A3. Hence, the loading factor is more pronounced in the reporter based WIIs as the absolute loading is higher in these cases. The resulting loss in the expected value of revenues is thus higher in the case of yearly and immediate reporter based WIIs, when adding a loading factor. This higher loss in revenues drives the expected utility calculations for table 2.A14. Resulting, the three insurances are no longer comparable when adding a loading factor. Tables 2.A15 and A16 show the results when adding an absolute loading of 10€/ha instead of a loading factor, coming to similar results as displayed in the main paper.

Table 2.A15 Results RQ1: Tests for risk reducing properties of different WII compared to no insurance (loading 10€/ha)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{noins}$	H_0:$EU_{imm} \geq EU_{noins}$	H_0:$EU_{GDD} \geq EU_{noins}$
	p- value		
0 (risk neutral)	0.99	0.99	1.00
0.5	0.99	0.99	1.00
1	0.99	0.99	1.00
2	0.99	0.99	1.00
3	0.99	0.99	1.00
4 (extremely risk averse)	0.99	0.99	0.99

Table 2.A16 Results RQ2: Comparing risk reducing properties between WII (loading 10€/ha)

Coefficient of relative risk aversion r_r	H_0:$EU_{year} \geq EU_{imm}$	H_0:$EU_{year} \geq EU_{GDD}$	H_0:$EU_{imm} \geq EU_{GDD}$
	p-value		
0 (risk neutral)	0.87	0.36	0.05
0.5	0.83	$1.31 \cdot 10^{-3}$	$1.68 \cdot 10^{-3}$
1	0.83	$5.80 \cdot 10^{-4}$	$3.05 \cdot 10^{-4}$
2	0.60	$4.27 \cdot 10^{-4}$	$2.14 \cdot 10^{-4}$
3	0.50	$3.05 \cdot 10^{-4}$	$4.27 \cdot 10^{-4}$
4 (extremely risk averse)	0.45	$3.05 \cdot 10^{-4}$	$3.05 \cdot 10^{-4}$

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Chapter 3

Economic impact of weather on quantity and quality: Spring frost in apple production

Tobias Dalhaus, Michael M. Blanke, Esther Bravin, Dominique Dietiker, Sarah R. Stübi and

Robert Finger

Keywords: Agriculture; crop quality; weather risk; apple; spring frost

Abstract

Weather extremes impacting crop yield quantity and quality are essential drivers of farmers' income risk. However, weather induced changes in quality and resulting monetary implications remain often unexplored. Here we use the case of late spring frost in apple production to quantify that a frost day induces drops in yields (-1% to -5%), quality reduction implying farm gate price reductions (-4% to -35%), and finally leads to lower revenues (-3% to -43%). We base our analysis on a panel dataset of 2'389 observations of Swiss apple orchards. Our findings reveal that quantity and quality need to be accounted for when quantifying climate impacts on agriculture.

3.1 Introduction

Weather impacts both crop yield quality and quantity and is thus a driving force of farm income volatility (Lesk et al., 2016). While yield quantity risks and their determinants are usually well documented, yield quality risk is often unspecified. Regarding quality, adverse weather events affect value-adding parameters, such as the outer appearance (Bi et al., 2011, Houston et al. 2017, Zhang et al., 2010), valuable constituents (Kawasaki & Uchida, 2016, Rao et al., 1993) or the textural structure (Sugiura et al., 2013) of the harvest. While the agronomic mechanisms how weather can negatively influence crop quality are well known, the monetary consequences of such quality losses on the farm level remain unexplored so far. As notable exception, Kawasaki & Uchida (2016) find that economic impacts of weather on rice quality can outweigh those on quantity of yields. We here contribute to fill these gaps and propose a novel approach to quantify the impact of adverse weather on crop quality by exploiting that deviations from optimum quality translate into drops in realized producer prices (Grunert, 2005). More specifically, we use the example of late spring frost events in apple production to quantify the monetary impact of weather events on farmers' revenues. By disentangling the effect of late spring frosts on both yield and price components we are able to distinguish quality and quantity losses, which is usually impossible due data restrictions (e.g. Bozzola et al., 2017).

Apples are one of the most consumed fruits both in Europe and worldwide and late spring frost is well recognized as one of the greatest weather risks that can destroy large parts of the apple production (e.g. large parts of European apple production have been destroyed by heavy spring frost in the 2017 season) (Pérez-Jiménez & Saura-Calixto, 2015, Rodrigo, 2000).Within the floral organs of apple blossoms, ice crystals start formation below a temperature of 0°C. The crystals grow from the extra cellular space, through the cell membrane into the reproductive organs' cells, potentially causing multiple cell deaths. Depending on the severity of frost exposure, the affected flowers either continue to develop normally, produce anatomical and morphological damaged apple fruits or fully abort their development. These damages may cause effects to be observed in i) size, ii) appearance or iii) shape of the ripening fruit (Rodrigo, 2000; Blanke & Kunz, 2010; Eccel et al., 2009). While volumetric yield effects of spring frost on apple yields and expected changes in the exposure due to climate change are well documented (Rodrigo, 2000; Blanke & Kunz, 2010; Eccel et al., 2009, Blanke & Kunz, 2009; Stöckle et al. 2010; Fuhrer et al., 2014; Hoffmann & Rath, 2013), its effects on fruit quality have not been quantified, although it is an important driver of economic success (Garatt et al., 2014). This is also due to the fact that the complexity of quality aspects, restricts the quantification of impacts on apple fruit quality. However, the assessment of climatic risks should be based on final aggregated economic effects that are crucial from the farmers' perspective.

We fill this knowledge gap in the literature by quantifying the impact of spring frost during flowering across different temperature ranges on apple yields, revenues and prices received by the farmers, which we use as proxy for frost induced quality losses. Our empirical economic analysis is based on a unique orchard-level panel dataset of apple production in Switzerland, which we match with regional tree phenology and historical daily temperature records. The remainder of this paper is structured as follows. First, we give an overview on the economic orchard information, variety specific tree blooming dates and high resolution weather grid data. Second, we introduce the econometric framework together with various sensitivity analyses. Third, we present our results. The paper ends with a discussion and conclusion.

3.2 Material and Methods

3.2.1 Economic Orchard Data

Economic orchard-level panel data on apple production, constituting the most relevant horticultural production in Switzerland, were provided by the Swiss Federal research station Agroscope (Mouron et al., 2006). The overall dataset includes 2'389 observations containing information on 55 apple varieties planted on 720 orchards across ten cantons (Swiss Federal States) during the years 1997-2014. Observed variables include yields (2’389 observations) [kilogram (kg)/ hectare (ha)], revenues (2’389 observations) [CHF (Swiss Francs)/ ha] (1 CHF = 0.85 EUR), farm gate prices (2’460 observations) [CHF/kg], variety, municipality, a dummy on whether the orchard produces organic and orchard age. The farm-gate prices are orchard specific average realized prices. Thus, a larger share of downgraded apples leads to lower prices. Most common varieties in our sample were Golden Delicious (16% of all orchards), Gala (10%) and Jonagold (8%) (see Figure A2 in the Appendix for histograms on all variables). Data was requested at the Swiss Federal research station Agroscope (www.agroscope.admin.ch).

The investigated farms are located in the Swiss lowland and pre-alpine region, constituting the major apple growing region in Switzerland (Federal Office for Agriculture, 2016). This fruit growing region is characterized by i) small scale farms and orchards, ii) rainfed fruit production in a temperate climate and iii) limited risk management options. Sprinklers, heating/fogging or wind machines, are usually not used yet due to limited economic or technical viability. We thus expect frost related losses in apple production to have a considerably negative influence on revenues while constituting one of the greatest climate related risks.

3.2.2 Tree Phenology Data

Start and end dates of the apple blooming period (i.e. from BBCH 61 to BBCH 69 (Rea & Eccel, 2006)) in each orchard, year and variety specific were employed using phenological records of experimental sites across our study region. More specifically, we obtain our tree phenology data from 33 different experimental stations across Switzerland. The dataset includes location information of the experimental station and occurrence dates of growth stages along the BBCH scale. The data can be accessed via online form at http://www.agrometeo.ch. We use phenology information to find start and end dates of flowering (BBCH 61 to BBCH 69) and chilling (BBCH 97 and BBCH 00; see section on temperature control variables) (Cesaraccio et al. 2004). Dependent on data availability we consider the following four steps of assigning phenology data to single orchards.

- First we match the single orchard information with variety specific phenology data within the same year and canton (here we find 1182 matches). We then use the earliest/latest date within BBCH 61 and BBCH 69 to find the start/end date of flowering for the single orchard.
- Second, in case of insufficient data for step one, we match orchard information with all available variety phenology (except the early flowering variety Boskoop) within the same year and canton (here we find 1029 further matches). We then use the earliest/latest date within BBCH 61 and BBCH 69 to find the start/end date of flowering for the single orchard.
- Third, in case of insufficient data for step two, we match orchard information with variety specific phenology within the same year in all cantons (here we find 141 further matches). We then use the earliest/latest date within BBCH 61 and BBCH 69 to find the start/end date of flowering for the single orchard.
- Fourth, in case of insufficient data for step three, we match orchard information with phenology information within the same year across all varieties from all cantons (here we find 108 further matches). We then use the earliest/latest date within BBCH 61 and BBCH 69 to find the start/end date of flowering for the single orchard.

3.2.3 Weather Data

Daily minimum temperatures within these periods were obtained from a temperature grid with 2.5 x 2.5 km resolution provided by the Swiss Meteorological Office (Frei, 2014). The interpolation method specifically considers Swiss specific texture characteristics and thus nonlinear temperature changes across elevation levels. Furthermore, “valley-scale cold-air pools" can be realistically displayed, taking into account site specific micro climates. In a "flat to hilly terrain", which is representative for our study region, the mean absolute error is 0.5°C. To account for different influences of spring frost on apple yields, revenues and farm-gate prices across different frost regimes, we systematically shifted the frost threshold (i.e. the daily minimum temperature, which designates a day as a frost day) from 0°C to -4.0°C daily minimum temperature. The latter constitutes the lowest observation within the flowering period within our sample showing a rather moderate overall frost risk.

In our regression analysis we use a set of variables to control for other than frost damage effects of temperature. More specifically, we control for damaging summer heat and beneficial winter chill. Regarding the former, we use the number of days with a maximum air temperature above 30°C to control for summer heat spells damaging apple fruits (see Racsko & Schrader (2011) for an overview). Regarding the latter, we control for beneficial cooling effects by including a winter chill control variable. Here we use the available chilling hours (hours with air temperature between 0°C and 7.2°C) between leaf fall and bud development (BBCH 97 and BBCH 00) obtained from the phenology data, according to above matching procedure. For the chilling variable we estimate a sine curve between the daily maximum and minimum temperature variables to derive hourly temperatures (Schlenker & Roberts, 2009). From that we derive the exposure time between 0°C and 7.2°C.

3.2.4 Econometric implementation

We estimate the effects of frost events on three dependent variables, i.e. plot-level apple yield, price and revenue. First, we quantify the impact of frost on yields by estimating the model displayed in equation 3.1.

$$\log(y_{it}) = \beta_{y1}\, frost_{it} + \beta_{yX} X_{ti} \; + \mu_{yi} + \varepsilon_{yit}, \tag{3.1}$$

where y_{it} is the apple yield of orchard *i* in year *t*. Furthermore, $frost_{it}$ is the number of days during flowering with a daily minimum temperature below the frost threshold, whereby we shift this threshold systematically from 0°C to -4°C. The Matrix X_{ti} denotes an orchard and year specific set of control variables including chilling hours, heat spells and orchard age. All time invariant information (such as variety, production method (i.e. organic), surface texture or microclimate) are included and controlled in plot level fixed effects μ_{yi}. The estimated frost effect is thus not affected by those information.

β_{y1} denotes the change in apple yields given a one day change in the frost exposure. As we use the logarithm of yields, the estimated change is in relative terms with respect to the single orchard average yield.

Second, in a similar empirical framework and assuming frost events to cause drops in apple quality, we estimate apple prices p_{it}, as a function of $frost_{it}$ and control variables X_{ti}. Equivalent to equation 3.1, we estimate the impact of frost across a continuous scale from 0°C to -4°C. We further include a year fixed effect υ_{pt} as we expect prices to be highly correlated within a year across all orchards. These dummies capture all effects of price developments commonly faced by all farms. We thus implicitly also control for market induced price changes.

$$\log(p_{it}) = \beta_{p1}\, frost_{it} + \beta_{pX} X_{ti} + \mu_{pi} + \upsilon_{pt} + \varepsilon_{pit} \tag{3.2}$$

Third, we expect final apple revenues r_{it}, i.e. the product of yields y and prices p, to be a function of $frost_{it}$, control variables X_{ti} and orchard μ_{ri} and year fixed effects υ_{rt}, resulting in a similar model as already introduced for prices in equation 2.

$$\log(r_{it}) = \beta_{r1}\, frost_{it} + \beta_{rX} X_{ti} + \mu_{ri} + \upsilon_{rt} + \varepsilon_{rit} \tag{3.3}$$

We estimate the above functions using a linear fixed effects panel estimator (Schlenker & Roberts, 2009; Schauberger, 2017). Furthermore, we apply a multivariate outlier detection procedure to identify and exclude outliers in our data. We thus exclude 2 out of originally 2'389 data points, resulting in 2’387observation which we include in our analysis (Billor et al., 2000; Weber, 2010).

3.2.5 Sensitivity Analyses

Yearly fixed effects (YFE) constitute dummy variables for each year, each of which becomes one if the respective observation occurs in the year of interest. By including YFE we are able to disentangle which effects occur only on single orchards (are idiosyncratic) and which affect all orchards as a whole (are systemic). More specifically, when including YFE in the model, the remaining estimated effects are not impacted by systemically occurring events. In the above specification of the model we exclude YFE from the yield model (Equation 3.1) as we expect frost events to occur jointly across a larger region. By including YFE we expect the yield effect to be absorbed as this event happens jointly at multiple orchards. Within the price and revenue model we include YFE in the above specification (Equations 3.2 & 3.3) as we expect that also prices can be highly correlated within one year through overall market movements, while we are interested in idiosyncratically occurring price drops. By including YFE we are specifically able to detect the drivers of single orchard deviations from overall market prices, which results from downgraded quality.

We here change the YFE specification and include YFE in the yield equation and exclude them in the revenue and price equations respectively. According to equations 3.1 to 3.3 displayed in the main text, we here estimate equations 3.1.1 to 3.3.1 as follows:

$$\log(y_{it}) = \beta_{y1}\, frost_{it} + \beta_{yX}X_{ti} + \mu_{yi} + \upsilon_{yt} + \varepsilon_{yit} \tag{3.1.1}$$

$$\log(r_{it}) = \beta_{r1}\, frost_{it} + \beta_{rX}X_{ti} + \mu_{ri} + \varepsilon_{rit} \tag{3.2.1}$$

$$\log(p_{it}) = \beta_{p1}\, frost_{it} + \beta_{pX}X_{ti} + \mu_{pi} + \varepsilon_{pit} \tag{3.3.1}$$

Besides changing the fixed effect specification of our model we show the robustness of our results also across different subsamples of our data. We therefore first split our data into years before and after 2004 (resulting in a nearly 50:50 split) to show the robustness of our results across time. Moreover, we split the sample in early (before April 24th – Table A4) and late (after April 24th – Table A5) flowering observations across all years.

All data processing including, accessing, matching and processing weather grid with economic and phenology data was done using the statistical software environment R (version 3.3.2) and R Studio (version 0.99.902). Moreover, figures were produced in R and R Studio and edited in Adobe Illustrator (CS6). All statistical analysis was made in Stata (version 14).

3.3 Results

3.3.1 Main results

Table 3.1: Relative marginal impact of below -2°C frost on apple yield, revenue and farm-gate price

		Log Yield [kg/ha]	Log Revenue [CHF/ha]	Log Price [CHF/kg]
<-2°C Frost [days]	β_1	-0.05***	-0.15***	-0.12***
Chilling [hours]	$\beta_{chilling}$	0.002*	0.000	-0.004
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.00	0.00
Orchard age [years]	$\beta_{orchard\ age}$	0.05***	-0.06***	-0.12***
Orchard Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		No	Yes	Yes
Adjusted. R^2		0.11	0.15	0.20

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

Using exemplarily the -2°C as upper threshold, Table 3.1 shows results for the relative impact of a <- 2°C frost on yields, prices and revenues (further sensitivity analysis are presented below). The exposure to one day with a daily minimum temperature below -2°C significantly reduced harvested apple yields (by 5%) and revenues (by 15%). The driving force for the latter effect can be found in the estimation results for apple prices. Hence, farm-gate apple prices decrease by 12 % for every <-2°C frost occurring. Hence, frost related yield drops are intensified by lower farm gate prices. Other variables such as heat spells, chilling hours as well as orchard age, serve as controls.

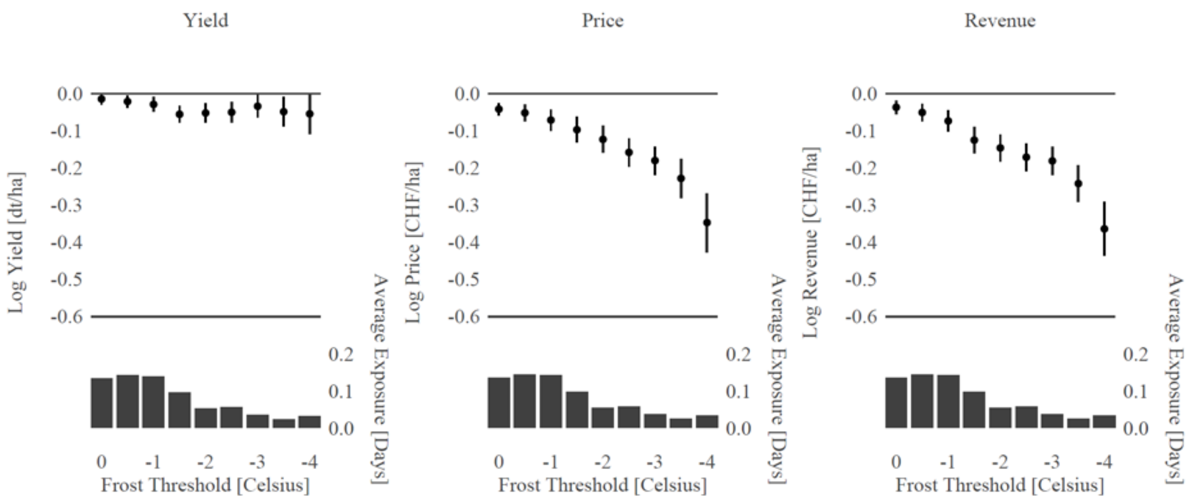


Figure 3.1: Marginal impacts of frost across different frost regimes. Graphs in the upper part of the figures show the marginal impact of frost (exposure to a daily minimum temperature below the frost threshold on the x-axis) on log yield, log price and log revenue respectively. The error bars constitute the 95% cluster robust confidence interval. The histograms in the lower part of the figures display the average frost exposure during flowering in days, across all orchards and years, for the respective temperature interval (0°C to -4°C in 0.5°C steps).

Besides the impacts of frost for a single frost threshold (-2°C) shown in table 3.1, figure 3.1 displays frost impacts when systematically shifting the threshold from 0°C to -4°C. The grey shaded area marks the 95% robust confidence band and the histograms at the bottom indicate the average yearly exposure per farm across the different frost regimes (0°C to -4°C in 0.5°C steps). Quality losses causing the downgrading of apples is the major determinant of overall effects on farmers' revenues. While this effect is found across all temperature ranges, it becomes even more pronounced with lower temperature thresholds. Within our regression analysis we specifically control for systemic effects that affect all farmers simultaneously. Thus the displayed price and revenue drops are orchard individual and thus quality related through declassification.

3.3.2 Sensitivity Analyses

Table 3.2: Relative Marginal impact of below -2°C Frosts on apple yield, revenue and producer price (year fixed effects changed)

		Log Yield [kg/ha]	**Log Revenue [CHF/ha]**	**Log Price [CHF/kg]**
<-2°C Frost [days]	β_1	**-0.02**	**-0.15*** **	**-0.10*** **
Chilling [hours]	$\beta_{chilling}$	0.004***	-0.003	-0.006***
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.00	0.00
Orchard age [years]	$\beta_{orchard\ age}$	0.05***	-0.00	-0.05***
Orchard Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		Yes	No	No
Adj. R^2		0.23	0.04	0.05

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

Compared to our main results, the effect of frost on yields is no longer significant when including year fixed effects in the yield equation (as displayed in table 3.2). Thus yield reducing frost events occur systemically, affecting multiple regions simultaneously.

Moreover, tables 3.3 and 3.4 show split sample results with respect to years before and after 2004. The differences in the estimated spring frost impact results from differences in the frost exposure across years. However, these constitute solely changes in the magnitude, not in the sign of the effect, which underlines our findings.

Table 3.3: Relative Marginal impact of below -2°C Frosts on apple yield, revenue and producer price (subsample 2004 - 2014)

		Log Yield [kg/ha]	**Log Revenue [CHF/ha]**	**Log Price [CHF/kg]**
<-2°C Frost [days]	β_1	**-0.16****	**-0.28*****	**-0.17*****
Chilling [hours]	$\beta_{chilling}$	0.00	0.00	0.00
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.00	-0.02***
Orchard age [years]	$\beta_{orchard\ age}$	0.04***	-0.68	-1.00***
Orchard Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		No	Yes	Yes
Adj. R^2		0.54	0.77	0.80

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

Table 3.4: Relative Marginal impact of below -2°C Frosts on apple yield, revenue and producer price (subsample 1997 - 2003)

		Log Yield [kg/ha]	**Log Revenue [CHF/ha]**	**Log Price [CHF/kg]**
<-2°C Frost [days]	β_1	**-0.03***	**-0.11*****	**-0.10*****
Chilling [hours]	$\beta_{chilling}$	0.003*	0.009*	0.002
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.01*	0.00
Orchard age [years]	$\beta_{orchard\ age}$	0.05***	-0.01	-0.09***
Orchard Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		No	Yes	Yes
Adj. R^2		0.64	0.45	0.46

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

In addition, tables 3.5 and 3.6 show split sample results with respect to early (before April 24th – Table 5) and late (after April 24th – Table 3.6) flowering observations across all years. Compared to our main results, the impact of frosts on yields, revenues and prices within the subsample of observation with early flowering dates (i.e. before April 24th as displayed in table 3.5) is alike. In contrast, when only using observations with late flowering (i.e. after April 24th as displayed in table 3.6) frost no longer impacts neither yields, revenues nor prices. This is intuitive as the later the flowering, the less likely it is that frost events impact flowering. This underlines the validity of our matching procedure between orchard information, regional flowering phenology and daily temperature grid data as we hardly observe frost events in the latter half of the sample. In the appendix, we further include an estimation of the effect of lagged frost events in the past years which translate into current year losses through alternate bearing property of apple trees (Krasniqi et al., 2013).

Table 3.5: Relative Marginal impact of below -2°C Frosts on apple yield, revenue and producer price (subsample flowering before April 24th)

		Log Yield [kg/ha]	Log Revenue [CHF/ha]	Log Price [CHF/kg]
<-2°C Frost [days]	β_1	**-0.06*** **	**-0.15*** **	**-0.13*** **
Chilling [hours]	$\beta_{chilling}$	0.002	0.004	-0.001
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.00	0.00
Orchard age [years]	$\beta_{orchard\ age}$	0.05***	-0.06***	-0.12***
Orchard Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		No	Yes	Yes
Adj. R^2		0.62	0.64	0.69

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

Table 6: Relative Marginal impact of below -2°C Frosts on apple yield, revenue and producer price (subsample flowering after April 24th)

		Log Yield [kg/ha]	Log Revenue [CHF/ha]	Log Price [CHF/kg]
<-2°C Frost [days]	β_1	**-0.14**	**-0.113**	**0.11**
Chilling [hours]	$\beta_{chilling}$	0.000	-0.004	-0.001
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.00	0.00
Orchard age [years]	$\beta_{orchard\ age}$	0.06***	-0.00	-0.05**
Orchard Fixed Effects		Yes	Yes	Yes
Year Fixed Effects		No	Yes	Yes
Adj. R^2		0.62	0.64	0.69

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

3.4 Discussion and Conclusion

Our results regarding the impact of spring frost on apple yields are consistent with the literature and are commonly observed in many regions (Rodrigo, 2000; Menapace et al., 2013). However, our findings on significant reductions of farm gate prices due to frost that result in substantial revenue losses add a new perspective on how spring frost impact apple production. These idiosyncratic weather events, i.e. events that only affect single farms, constitute a major downside risk for individual farmers' income, especially when multiple frost days occur in the same year. Beyond frost induced damages, other effects of climate variability and climate change on apples such as loss of fruit firmness, hail damage and sunburn have been documented (Sugiura et al., 2013; Houston et al., 2017). Moreover, Kawasaki & Uchida (2016) find that economic impacts of weather on rice quality can outweigh those on quantity of yields. However, the monetary consequences of quality losses on the farm level remain unexplored so far. Hence, we extend earlier literature by adding a farm-level perspective on the economic impact of weather on single farmers' revenues.

Our sensitivity analysis on changing the fixed effects specification within our model shows further that major frost events are spatially correlated, impacting a production region as a whole (Gu et al., 2008). In contrast, the effect of frosts on revenues and prices do not change when excluding the year fixed effect from equations 3.2.1 and 3.3.1. Thus, the impact of frosts on quality is idiosyncratic, i.e. impacts only single orchards. Moreover, we clearly acknowledge that we estimate a reduced form model that estimates the impact of frosts on prices. We conclude that this price reduction is due to drops in quality. We are however unable to derive whether these are due to optical/ morphological damages such as frost rings or due to pests that are supported by the frost events that might manifest in rotten fruits. From the economic perspective, both are relevant and constitute frost induced quality damages.

Climate change substantially impacts global crop production (Iglesias et al., 2011) and many studies deal with predicting farmers' response to such changes (e.g. Troost & Berger, 2015). When modelling these adaptations (e.g. crop choice) it is crucial to consider all climate change induced alterations in risk exposure and its monetary consequences to avoid biased predictions (Seo & Mendelsohn, 2008). Regarding apple trees, climate change is expected to cause increases in winter temperatures leading to changes in fulfillment of cooling (chilling) and heat requirements (forcing) that induce the end of the apple trees' winter dormancy (Luedeling et al., 2009a; Luedeling et al. 2009b; Luedeling et al., 2013; Menzel et al.; 2006; Chmielewski et al., 2004; Legave et al. 2013; Vitasse et al., 2018). Thus, apple blooming is more likely to be affected by spring frost events across temperature regimes analyzed here, constituting an increase in the downside risk exposure of apple producers (Blanke & Kunz, 2010; Eccel et al., 2009, Blanke & Kunz, 2009; Stöckle et al. 2010; Fuhrer et al., 2014). When adapting to a changing climate, knowledge of how climate influences production and income is required, to predict but also support farmers' adaptation process. Our results show that quality and quantity effects of frost across different temperature regimes have to be disentangled to avoid biased inference. More specifically, effects of a higher frequency of frost events are underestimated if focusing on quantity effects only.

In order to cope with increasing frost risk, adaptation measures are needed. If irrigation infrastructure is established, frost irrigation through sprinklers can be an efficient way of managing the impact of frost (Foudi & Erdlenbruch, 2011). However, resource efficient water use is on the policy agenda of many countries, leading to limited opportunities to apply those sprinklers (Finger & Lehmann, 2012). Other solutions, such as heating or wind machines are characterized by a high energy use (Snyder & Melo-Abreu, 2005). Thus, more sustainable strategies to adapt to increasing spring frost risks need to be developed. To this end, agricultural insurances might be designed to help farmers to overcome frost related periods of illiquidity. These have shown to be highly idiosyncratic as observed by the absence of natural hedging effects in our case study. In this context, providing indemnity payments based on on-farm damage assessment of frost caused quality drops might be inappropriate and not viable. An alternative tool that covers weather related losses within specific phases of plant growth are weather index based insurances. Here, payouts are triggered based on an observed weather variable, such as temperature, serving as a proxy for losses rather than on losses itself (Dalhaus & Finger, 2016; Dalhaus et al., 2018).

3.4 Appendix

Figure 3.A1: Histogram of Start (grey) and End (red) Dates of Flowering for deriving Frost Variable

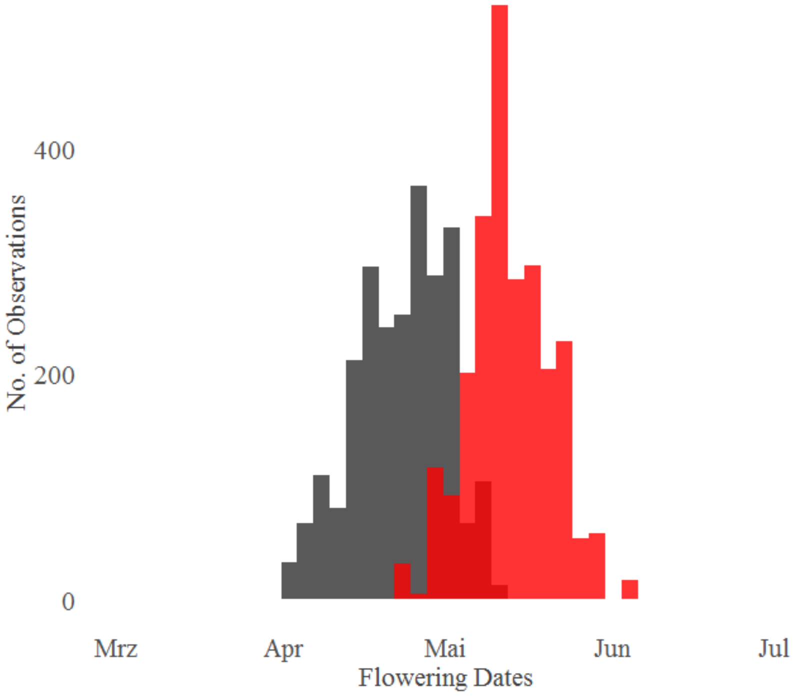
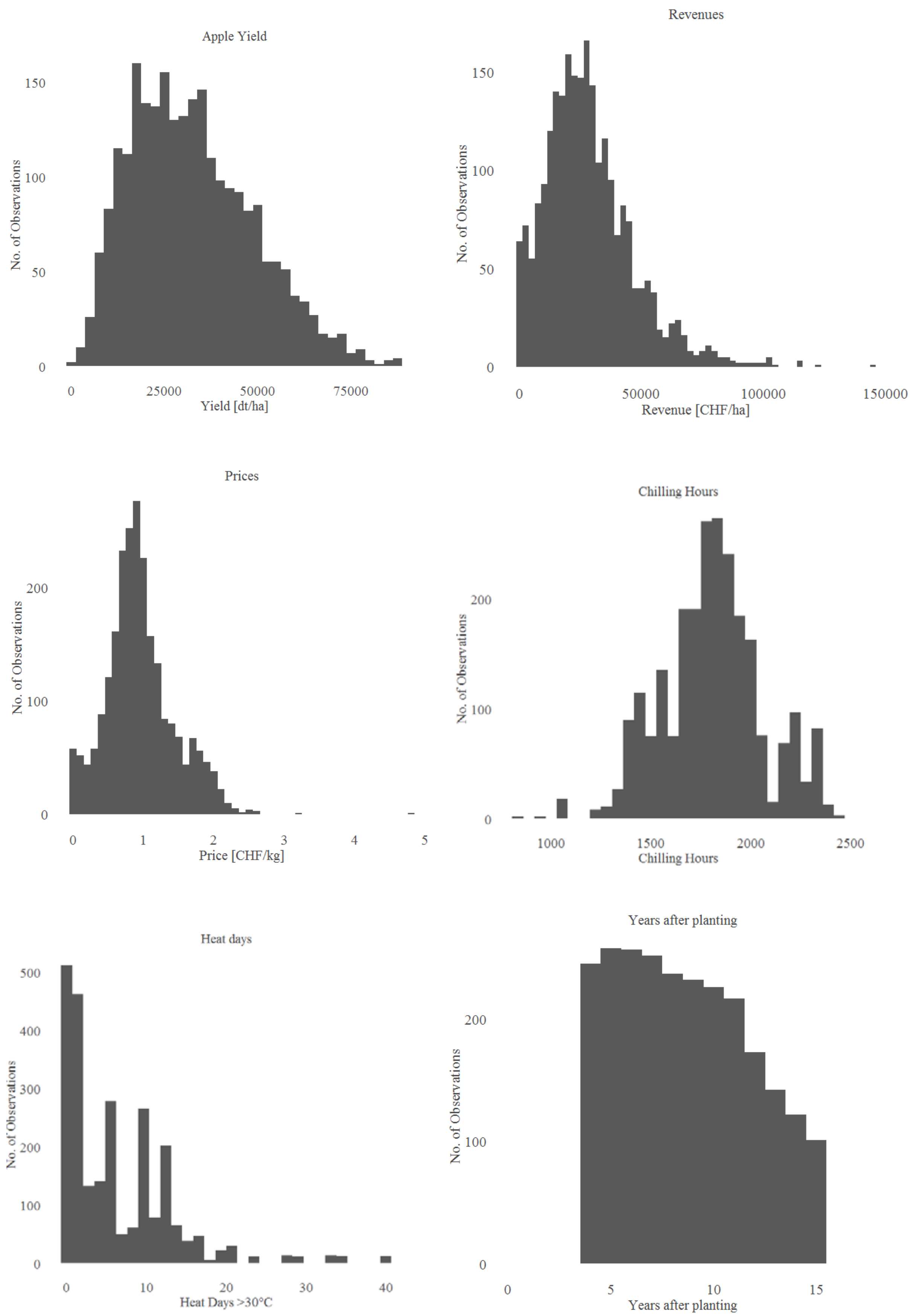


Figure 3.A2: Histograms of Variables under study



3.A1 Frost lags

Caused by the alternate bearing effect observed in apple trees, apple yields are highly dynamic over time (Krasniqi et al., 2013). This implies that, next to reducing apple yield in the year in which the frost occurred, a single frost event is translated into future growing seasons. More specifically, apple trees react to low yield years (e.g. through frost events) with increased yield in the next and decreased yields in the over next season. Common practice in professional apple production is to reduce flowers in the high yield year, which can dampen but not fully stop the effect in the subsequent low yield year. To show that our underlying farm-level records, phenology information and weather data are combined in a reasonable way, we here show that this effect can be clearly observed also within our sample. This estimation is based on only 1419 observations for which we have information on three subsequent years. We estimate equations 3.1.2 to 3.2.2 as we do not expect such an effect in the price model

$$\log(y_{it}) = \beta_{y1}\, frost_{it} + \beta_{y2}\, frost_{it-1} + \beta_{y3}\, frost_{it-2} + \beta_{yX} X_{ti} + \mu_{yi} + \varepsilon_{yit} \qquad (3.1.2)$$

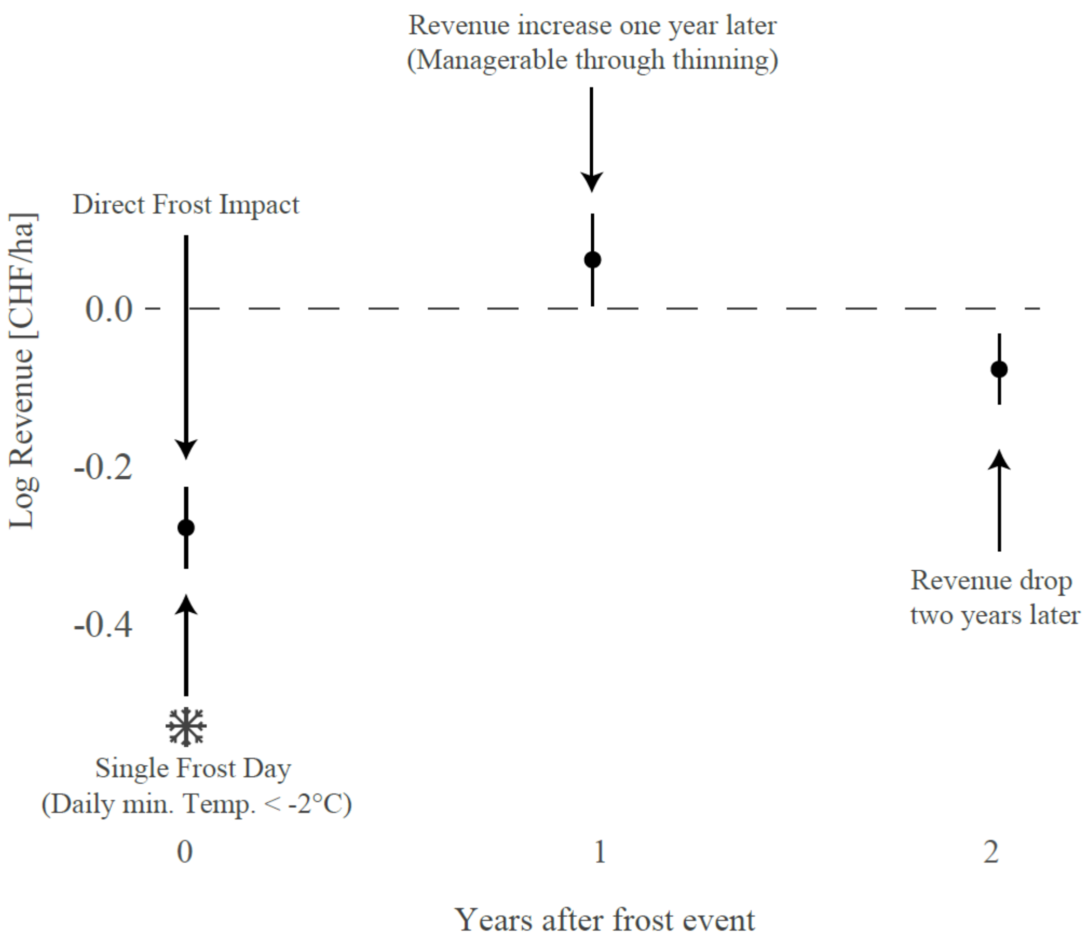
$$\log(r_{it}) = \beta_{r1}\, frost_{it} + \beta_{r2}\, frost_{it-1} + \beta_{r3}\, frost_{it-2} + \beta_{rX} X_{ti} + \mu_{ri} + \upsilon_{rt} + \varepsilon_{rit} \qquad (3.2.2)$$

Table 3.**A1: Relative Marginal impact of below -2°C Frosts in the current and the two preceding years on apple yield, revenue and producer price**

		Log Yield [kg/ha]	**Log Revenue [CHF/ha]**
<-2°C Frost [days]	β_1	**-0.10*** **	**-0.28*** **
One year lag <-2°C Frost [days]	β_2	**0.03**	**0.06***
Two years lag <-2°C Frost [days]	β_3	**-0.04** **	**-0.08*** **
Chilling [hours]	$\beta_{chilling}$	0.001	-0.000
Heat Spells [days]	$\beta_{heat\ spells}$	0.00	0.00
Orchard age [years]	$\beta_{orchard\ age}$	0.03***	-0.34
Orchard Fixed Effects		Yes	Yes
Year Fixed Effects		No	Yes
Adj. R^2		0.62	0.64

*, ** and *** denote levels of statistical significance at the 95%, 99% and 99.9% percent confidence level

Figure 3.A3: Dynamic relative marginal impact of one below -2°C Frost day on revenues in the current and subsequent two years



3.5 References

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Chapter 4

Bayesian quantile regression for weather index insurance design: Insuring idiosyncratic risk under data scarcity

Tobias Dalhaus, Joshua D. Woodard and Robert Finger

Keywords: Quantile Regression, Aggregation Bias, Basis Risk, Weather Insurance

Abstract

Crop insurance plays a key role in managing farmers' financial exposure to weather risks. Recent developments have shown that weather index insurance (WII) can help to overcome problems of asymmetric information in classical indemnity based crop insurance. However, basis risk, i.e. the discrepancy between WII payouts and on-farm losses, presents the largest adoption hurdle for WII. Farm-level yield records are necessary to design and assess the effectiveness of WII contracts, but are more scarcely available than longer and more wide-spread regional level yield data. We explore using Bayesian quantile regression (BQR, Yu & Moyeed, 2001) to estimate WII structures, thus allowing the use of both county-level yield data as informative prior in conjunction with farm-level yields and weather in designing the insurance. We develop an empirical application of insuring drought risk in Eastern German winter wheat production. Our results show that, although BQR helps to design structures to effectively reduce farmers' financial exposure to drought risk, basis risk remains unaffected in this case study context. Further research might expand the use of BQR approach to other perils with higher spatial dependence and regions with longer records of county yields.

4.1 Introduction

Weather index insurance (WII) has a potential role in complementing existing risk management instruments to cope with climatic extremes such as droughts or heat spells. The payout of WII relies on an underlying weather value such as the amount of rainfall, instead of relying on measured crop yield losses at the farm. Thus, WII do not face problems of moral hazard that farm-based insurance covers do, and the adjusting of claims for WII is generally lower than performing on-farm damage assessment. However, the payouts of WII and the losses experienced on the field do not necessarily coincide, a phenomenon that is referred to as basis risk (Woodard and Garcia, 2008a).

Sources of basis risk are threefold. First, design basis risk occurs if, the weather index is generally a poor predictor of losses, e.g. through the choice of the weather variable or the estimation strategy to quantify the impact of weather on yields (Conradt et al. 2015a, Pelka & Musshoff, 2013, Woodard, Shee and Mude, 2016). Second, temporal basis risk occurs, if critical periods of crop growth are not covered within the index, e.g. insurance covers whole year rainfall sum and missing rainfall during single growth phases is the major reason for crop losses (Conradt et al., 2015b, Dalhaus et al. 2018). Third spatial basis risk arises from the spatial distance and the resulting weather difference between the weather station and the farm (e.g. Woodard and Garcia, 2008b, Ritter et al., 2014).

The estimation of relevant WII specifications such as strike level or tick size is usually based on either i) farm-level data or ii) aggregated (e.g. county-level) data. Farm-level data is most informative to account for farm-specific drivers of yield variability. Often, the analyst designing the insurance may have larger datasets on regional level yields, but only limited on-farm yield data. Farm-level yield observations are usually sparse, i.e. either not available at all, only available in short time series or with incomplete records over time, e.g. caused by crop rotation requirements. In contrast, time series of aggregated data are usually available over longer periods and thus also more likely contain yield observations in presence of climatic extreme events. However, the yield variability of aggregated yield data is substantially lower (e.g. Marra and Schurle, 1994, Finger, 2012, Woodard and Garcia, 2008a). Thus, aggregated data is not able to capture idiosyncratic risks and therefore are also less suited to identify the marginal impacts of different weather shocks on crop yields. To overcome these challenges, we explore the use of Bayesian Quantile Regression (BQR, Yu & Moyeed, 2001) to design WII. This allows for combining of data on different levels of aggregation and accounting for spatial and temporal basis risk. Here we propose using aggregated crop yield data to serve as the prior for farm-level estimates in Bayesian regression framework, and the use of quantile regression (QR) to estimate the impact of weather indices on crop yields.

We illustrate the potential benefits utilizing BQR in designing WII using the example of wheat production in a drought-prone region in Germany and a WII that pays out in case of low rainfall events. We explore the following research questions:

RQ1: Do the three insurance options proposed above, i.e. WII designed using i) solely county level yield data, ii) solely farm-level yield data and iii) a combination of county and farm-level yield data using BQR, reduce the financial exposure to drought risk compared to a no insurance scenario?

RQ2: Does the use of county level data as prior information reduce basis risk and thus improve the risk reducing effect of WII?

The remainder of the paper is structured as follows. First, we introduce our conceptual framework including background information of weather index insurance and basis risk, the econometric implementation using quantile regression and Bayesian quantile regression and our hypothesis testing strategy using expected utility as risk measure. Second, we present our data background, namely farm-level winter wheat yields, regional phenology information on the occurrence dates of growth stages of winter wheat and high resolution rainfall grid data. Fourth, we present and discuss our results and conclude.

4.2 Conceptual Framework

Weather index insurance aims at providing payout in case of low yield events that are caused by observed weather perils. Our here proposed basis risk reduction strategy is tested using a case study example of winter wheat production in a drought prone area of Eastern Germany and a WII that aims at providing payout in case of low rainfall events. Therefore, farmers receive a payout once a trigger or strike level of the rainfall sum during a vulnerable phase of plant growth is under cut. The total insurance payout is then determined by the difference between the actual rainfall sum (that serves as weather index) and the strike level multiplied by the estimated yield loss per missing millimeter of rainfall or ticksize. Within this section we first introduce the concept of WII theoretically before deriving possible sources of design basis risk. Afterwards quantile regression and Bayesian quantile regression are suggested as ways of coping with this type of basis risk. Finally, expected utility is explained as a way of testing Bayesian quantile regression's ability to reduce design basis risk.

4.2.1 Weather Index based Insurance

4.2.1.1 Background

We assume crop yield y_{it} of farmer i in year t to be function $g_i(WI_{it})$ of weather WI_{it} (i.e. a weather index) in that given year and at the farms location and other factors, such as inputs, site characteristics or pests, simplified as an error term ε uncorrelated with weather. To reduce farmer's financial exposure to losses in y_{it} caused by weather WI_{it}, WII aims at providing financial compensation that precisely covers those weather induced losses. Hence, the estimated relationship between weather and yield serves as basis for WII payout. More specifically, WII are mostly designed as European put or call options that compensate losses in case a weather variable under- (e.g. rainfall sum during a critical crop growth phase) or over cuts (extreme heat days during a critical crop growth phase) a critical threshold (or strike level S_{lk}). For the former case the payout δ_{ltk} at aggregation level $l \in (c = county, i = farm)$ in year t using regression approach $k \in (QR = quantile\ regression, BQR = Bayesian\ quantile\ regression)$ follows $\delta_{ltk} = T_{lk} * \max\{0,\ S_{lk} - WI_{lt}\}$, where both T_{lk} and S_{lk} are derived from the estimated relationship between yields and weather using either of the regression approaches.

4.2.1.2 Sources of Design Basis Risk

In the hypothetical case of an index insurance perfectly covering all weather related losses, $g(WI)$ would be able to fully capture all effects of weather. In this case design basis risk only arises from shocks that are solely included in ε, such as e.g. pests. In reality however, $g(WI)$ has to be approximated by an estimate $h(WI)$ ($h_c(WI_{it})$ or $h_i(WI_{it})$ depending on data availability), which comes with a second error term ϑ resulting in

$$y_{it} = h_i(WI_{it}) + \vartheta + \varepsilon \qquad (4.1)$$

This second error term ϑ captures basis risk that results from $h(WI_{it})$ not being a perfect predictor for weather induced losses, e.g. through missing weather variables or a biased estimation strategy (e.g. Conradt et al. 2015a/b, Pelka et al., 2012).

In equation 1 we assumed that farm level crop yield data is available to estimate $h_i(WI_{it})$ as expressed in y_{it}.

If this is not the case and if only aggregated average yields y_{ct} of county c in year t are available, $h_i(WI_{it})$ can again only be approximated by the estimate of $h_c(WI_{ct})$ (estimated using county average yields[8] as $h_i(WI_{it}) = h_c(WI_{ct}) + \omega$ adding another error term ω and resulting in

$$y_{ct} = h_c(WI_{it}) + \omega + \vartheta + \varepsilon \tag{4.2}$$

This adds another source of basis risk, namely ω which includes idiosyncratic shocks that cannot be observed in average county yields and which are thus not included in the estimate of $h_c(WI_{it})$[9]. Consequently, $h_i(WI_{it}) \neq h_c(WI_{ct})$ and WII design depends on the data availability at the different aggregation levels. So far, the only strategy to cope with this type of basis risk is to use farm-level yield information.

4.2.2 Econometric Framework

4.2.2.1 Quantile Regression

Our research aims at improving the farm individual estimation of $h_i(WI_{it})$ in case of data scarcity. i.e a very limited number of observations on single farm crop yields. We therefore propose to use the county level estimate $h_c(WI_{ct})$ as prior distribution for estimating the posterior distribution of the single farm impact of weather on yield within a Bayesian quantile regression framework.

To quantify the weather yield relationship econometrically we estimate $h_i(WI_{lt})$ based on the model

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[8] Next to weather index based insurances described here, also area yield index insurances are available (Skees et al., 1997). Here the insurance payout does not depend on weather but directly on the achieved average yield within a specific region. However, drawbacks include basis risk, due to the same reason as presented here, and limited opportunities to reinsure the risk due to data availability.

[9] In fact, the three error terms presented here cannot be perfectly separated as illustratively argued. This does however not impact our later testing strategy as set out in the below subsection on *Expected Utility as Risk Measure*.

$$y_{lt} = \alpha_l + WI'_l\boldsymbol{\beta}_l + \nu_{lt} \tag{4.3}$$

y_{lt} is the crop yield at aggregation level $l \in (c = county, i = farm)$ in year t. Where α_l and β_l are intercept and slope coefficients respectively and ν_{lt} is an error term that includes ω, ϑ and ε from equation 4.2. WI'_l is a vector of weather (in our later empirical example the sum of rainfall during a critical growth stage of winter wheat) at farm i or in county c across years. Standard approaches use the ordinary least squares (OLS) estimator to determine the average marginal impact $\boldsymbol{\beta_l}$ of weather on yields y_{lt} (Pietola et al., 2011). More specifically, this marginal impact gives the average change in yield if rainfall changes by one unit (e.g. mm). However insurances are designed to provide indemnification rather in case of downside yield events than average events. Therefore, not the average effect of weather across all realizations of y_{lt} but the effect of weather if yields are low is of interest. We therefore use QR to model the marginal impact of WI_{it} on y_{lt}, dependent on quantile $\tau \in (0,1)$ of the yield distribution and aggregation level l resulting in $\boldsymbol{\beta_{l\tau QR}}$ (See also figure 4.1 as exemplary presentation of changes in $\boldsymbol{\beta_{l\tau QR}}$ across τ) (Koenker & Basset, 1978, Koenker, 2004, Conradt et al., 2015a).

τ can be specifically chosen to reflect downside yield events, i.e. $\tau < 1/2$. We thus estimate the model

$$y_{lt} = \alpha_i + WI'_{lt}\boldsymbol{\beta_{l\tau QR}} + \nu_{lt} \tag{4.4}$$

QR minimizes the sum of asymmetrically weighted deviations (rather than the sum of squared residuals in the OLS case) to obtain $\boldsymbol{\beta_{i\tau QR}}$ as expressed in

$$\boldsymbol{\beta_{i\tau QR}} = \min_{\boldsymbol{\beta_{i\tau}}} \textstyle\sum_{t=1}^{n} \rho_\tau(y_{lt} - WI'_l\boldsymbol{\beta}_{l\tau QR}) \tag{4.5}$$

where

$$\rho_\tau\left(y_{lt} - WI'_{lt}\boldsymbol{\beta}_{l\tau QR}\right) = \begin{cases} \tau\left|y_{lt} - WI'_{lt}\boldsymbol{\beta}_{l\tau QR}\right| & if\ y_{it} \geq WI'_{lt}\boldsymbol{\beta}_{l\tau QR} \\ (1-\tau)\left|y_{lt} - WI'_{lt}\boldsymbol{\beta}_{l\tau QR}\right| & if\ y_{it} \leq WI'_{lt}\boldsymbol{\beta}_{l\tau QR} \end{cases} \tag{4.6}$$

$\boldsymbol{\beta}_{l\tau}$ is therefore not only focusing on low realizations of y_{lt} but is also more robust to outliers in the data, as the weighted absolute residuals are minimized rather than the average distance between observation and mean in the OLS case, where an extreme outlier affects both jointly. Moreover, the error term ν_{lt} can take any distribution and variance across errors is allowed to vary (heteroscedastic errors).

4.2.2.2 Bayesian Quantile Regression

Drawback of this estimation strategy so far is that $\boldsymbol{\beta}_{l\tau}$ is either estimated on $l = i$ farm level or $l = c$ county level and that there is so far no strategy to jointly consider data from both aggregation levels jointly. Bayesian inference, where any informative information can be used as a prior for the impact estimate, seems an appropriate tool to incorporate information from both aggregation levels. To this end, we use Bayesian quantile regression (BQR) (Yu & Moyeed (2001), Yue & Rue (2011)). Yu & Moyeed (2001) show that BQR enables to model the posterior distribution of the farm level weather impact $\boldsymbol{\beta}_{i\tau BQR}$, $\pi(\boldsymbol{\beta}_{i\tau BQR}|y_{it})$ based on a likelihood function $L(\boldsymbol{\beta}_{i\tau BQR}|y_{it})$ and a prior $\pi(\beta,\sigma)$ on β and standard error σ as expressed in

$$\pi\left(\boldsymbol{\beta}_{i\tau BQR}\middle|y_{it}\right) \propto L(\boldsymbol{\beta}_{i\tau BQR}|y_{it})\pi(\beta,\sigma) \tag{4.7}$$

In contrast to QR, BQR requires distributional assumptions on the likelihood function. Following Koenker et al. (1999) and Yu & Moyeed (2001) the minimization problem of equation 6 can be rewritten as maximizing an asymmetric Laplace likelihood function with density function

$$L\left(\boldsymbol{\beta}_{\boldsymbol{i\tau BQR}}\middle|y_{it}\right) = \frac{\tau(1-\tau)}{\sigma}\exp\{-\rho_{\tau}\left(\frac{x-\mu}{\sigma}\right)\} \tag{4.8}$$

and errors $\mu = WI'_{it}\boldsymbol{\beta}_{\boldsymbol{i\tau BQR}}$. We use county level estimates $\boldsymbol{\beta}_{\boldsymbol{c\tau QR}}$ and bootstrapped standard errors $\sigma_{c\tau}$ as informative priors.

Resulting we have three different approaches of estimating the marginal impact of rainfall on winter wheat yields. First, the county level marginal impact $\boldsymbol{\beta_{c\tau QR}}$ of county level rainfall WI_{ct} on county level yields y_{ct} based on quantile regression. Second, the farm level marginal impact $\boldsymbol{\beta_{i\tau QR}}$ of farm level rainfall WI_{it} on farm level yields y_{it} based on quantile regression. Third, the farm level marginal impact $\boldsymbol{\beta_{i\tau BQR}}$ of farm level rainfall WI_{it} on farm level yields y_{it} based on Bayesian quantile regression using estimate and standard error of $\boldsymbol{\beta_{c\tau QR}}$ as prior. These three scenarios serve as basis for the comparison indicated in above **RQ1**.

We use the statistical software environment R together with the packages 'quantreg' (for single farm and county QR) and 'bayesQR' (for BQR) as proposed by Koenker (2013) and Benoit & van den Poel (2017) respectively.

4.2.3 Index Design & Pricing

Combining the former sections on weather index based insurance and the econometric framework, the Ticksize T_{lk} is the estimated slope coefficient $\boldsymbol{\beta}_{l\tau k}$ (whereas strike level S_{lk} is derived by setting in the average yield $\bar{y}_l$ into equation 4.4 and solving for the associated realization of WI ($S_l = h_{lk}{}^{-1}(\bar{y}_l)$)[10]. The fair insurance premium can then be estimated by approximating $E(\delta_{ltk})$, for which various methods exist (see Odening et al. 2007 for an overview). We here use the nonparametric burn rate pricing by bootstrapping 10.000 times from the historically realized payouts δ_{ltk}. The average over those bootstrapped values is then the fair insurance premium φ_{lk}.

For WI we follow Dalhaus et al. (2018) and use the sum of rainfall from stem elongation to milk ripening, which constitute the most drought sensitive growth stages in winter wheat.

[10] Please note that in many other WII applications the insurance aims at below average rainfall levels (e.g. Heimfarth et al., 2012) here we aim at providing indemnification rather below the rainfall level that triggers average yields.

Therefore, the weather index follows $WI_{li} = \sum_{d=start}^{end} R_d^{lt}$, where WI_{lt} is the weather index at location *l* (either farm *i* or county *c*) and R_d^{lt} is the rainfall sum from *d* = 'start date' to *d* = 'end date' determined using phenology observations. More specifically, we use regional observations on plant growth stages to specifically account for shifts in growth phases over space and time. Moreover we use high resolution rainfall grid data to specifically derive rainfall for the single farm and county locations (Dalhaus & Finger, 2016). Our WII therefore comes with a minimum of spatial and temporal basis risk. Please see section *4.3 Data* for more information on the underlying datasets used.

4.2.4 Expected Utility as Risk Measure & Hypothesis Testing

We assume that a farmer choses an insurance contract that maximizes her expected utility arising from terminal wealth W_{ltk} to solve the maximization problem $\max E[U(\,W_{ltk})]$, where W_{ltk} is the terminal wealth being defined as $W_{ltk} = by_{it} + \delta_{ltk} - \varphi_{lk} + W_0$. W_{ltk} includes stochastic yields y_{it} and b which is the market price for yields y. Moreover, W_0 is the initial (beginning of period) wealth. $U(.)$ is the von Neumann-Morgenstern representation of decision makers' preferences towards risk. If farmers are risk averse, a specification of WII that reduces the variance and/or skewness of terminal wealth and has a fair premium would increase the expected utility. Thus WII would be chosen, $W_{uninsured} \prec W_{insured}$ if $E[U(W_{uninsured})] < E[U(W_{insured})]$. This implies that losses in yields y_{it} can be compensated through insurance payouts δ_{ltk}. Any discrepancies between these two variables arise from the error terms ω, ϑ and ε, i.e. basis risk. Holding everything else constant we are thus able to test i) whether an insurance is reducing the farmers financial exposure towards risk compared to the uninsured case (**RQ1**) and ii) to compare different WII designs with respect to their risk reducing properties, i.e. with respect to their ability to reduce design basis risk (**RQ2**). According to above econometric framework, we compare and test the following null hypotheses with respect to the research questions derived in the introduction:

Regarding **RQ1**:

H1: H_0: $E[U(W_{cQR})] \leq E[U(W_{no\ insurance})]$

H2: H_0: $E[U(W_{iQR})] \leq E[U(W_{no\ insurance})]$

H3: H_0: $E[U(W_{iBQR})] \leq E[U(W_{no\ insurance})]$

Regarding **RQ2**:

H4: H_0: $E[U(W_{iBQR})] \leq E[U(W_{cQR})]$

H5: H_0: $E[U(W_{iBQR})] \leq E[U(W_{iQR})]$

To consistently account for downside risk aversion in $U(W)$ we use a power utility function to reflect farmers' preferences:

$$\mathrm{U}_{ltk}(W_{ltk}) = \begin{cases} \dfrac{W_{ltk}^{1-\alpha}}{1-\alpha} & if\ \alpha \neq 1 \\ \ln(W_{ltk}) & if\ \alpha = 1 \end{cases}$$

where α is the Arrow Pratt coefficient of relative risk aversion (Di Falco & Chavas, 2009). We test for scenarios $\alpha \in (0, 0.2, 0.4, 0.6, 0.8, 1)$ ranging from lower to higher risk aversion (for elicited preferences of German farmers see Maart-Noelck & Musshoff, 2014 or Meraner & Finger, 2017). To account for the ordinal nature of expected utility values we use one sided paired Wilcoxon test to test Hypotheses 1 to 5.

4.3 Data

This study employs farm and county level winter wheat yields, as well as precipitation data to evaluate the efficacy of using BQR in WII design.

4.3.1 Winter Wheat Yield

Winter wheat yield data for the period 1995 to 2014 for 73 counties in a drought prone area of Eastern Germany are obtained from the German Statistical office[11] (N = 1255 observations). We include counties located in the Federal States Mecklenburg-Western Pomerania, Brandenburg, Saxony-Anhalt, Saxony and Thuringia. This Region is characterized by considerable drought risk. The farms in this region are primarily commercial scale operations. Farm-level yield data are obtained from 84 winter wheat producing farms in this region for the same period (N= 1252 observations). Both datasets are unbalanced. The 84 farms are located in 44 different counties (N=804 remaining county yield observations). Controlling for technological change, both county and farm level yield was detrended using an M-estimator as proposed by Finger (2013). The trend is based on national average winter wheat yields (FAO, 2018). We use the average level of direct payments (i.e. 280 €/ha following Dalhaus & Finger (2016)) as proxy for initial wealth W_0.

[11] Please note also that these federal states lie within the area of the former German Democratic Republic, therefore average county yields are available earliest from 1992 on.

Table 4.1: Summary statistics of detrended winter wheat yields in decitons per hectare

	County-Level	**Farm-Level**
Mean	65.28	65.14
Median	66.44	65.51
Min	23.12	10.75
Max	92.38	109.90
Standard Deviation	11.23	14.52
Coefficient of Variation	0.17	0.22

4.3.2 Precipitation

Rainfall grid data was obtained from the German Meteorological Office (Deutscher Wetterdienst) as suggested by Dalhaus & Finger (2016). The rainfall data are daily and have a spatial resolution of 1 square kilometer. For the county level data, we use the grid cell in which the respective county's centroid is located. For the farm level, we use the grid cell in which the farm is located. All rainfall grid data can be accessed via ftp://ftp-cdc.dwd.de/pub/CDC/

Table 4.2: Summary statistics of cumulative rainfall [l/m^2] from stem elongation to milk ripening in liter per squaremeter

	County-Level	Farm-Level
Mean	139.6	139.20
Median	130.3	132.80
Min	17.4	9.30
Max	372.2	402.70
Standard Deviation	61.3	59.22
Coefficient of Variation	0.44	0.43

4.3.3 Phenology

As proposed by Dalhaus & Finger (2016) and Dalhaus et al. (2017) we use regional observations on the occurrence dates of plant growth stages to find the drought sensitive growth stage of anthesis and to capture shifts of this phase across time and space. Those phenological observations are provided by the German Meteorologial Office and can be freely accessed at ftp://ftp-cdc.dwd.de/pub/CDC/. For the county level we minimize the spatial distance between the center of the county and the phenology reporting station taking into account that both must lie within the same natural region. Natural regions are defined by having homogenous plant growth conditions (Dalhaus et al. 2018). We use start dates of the growth stage stem elongation and end dates of milk ripeness and sum up daily rainfall during this period. This rainfall sum index constitutes the insured weather index.

4.4 Results

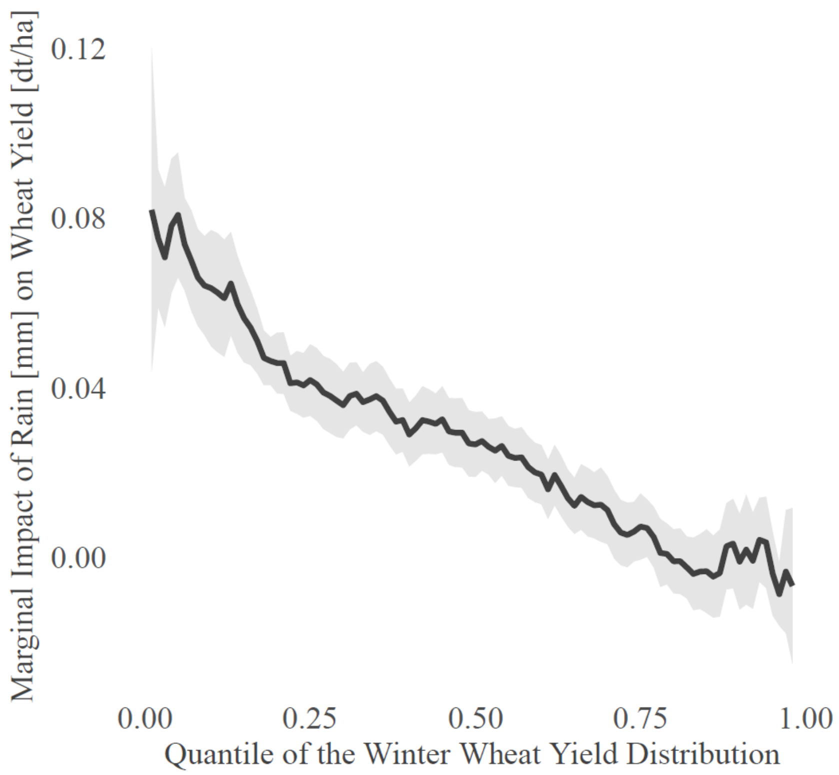

Figure 4.1: Marginal Impact of the Rainfall Sum [l/m^2] during the Anthesis Stage of Winter Wheat on Winter Wheat Yields

Note: This exemplary figure is based on estimating equation (4) systematically shifting τ (Quantile of the Winter Wheat Yield Distribution) between zero and one. Moreover all farm-level observations are pooled together (N=1252). Shaded areas constitute bootstrapped standard errors.

Figure 4.1 shows the marginal impact of the rainfall sum during the growth stages from stem elongation to milk ripening on winter wheat yields. Thus, the impact is highly nonlinear across the yield distribution, which generally motivates to use a quantile regression approach. Moreover, the impact of rainfall is positive for large parts of the distribution and insignificant for the upper part, i.e. when yields are high. Thus, drought events during this growth stage substantially drop winter wheat yields.

Table 4.3: Summary Statistics of Contract Parameters

	County-Level Data	Farm-Level Data	Bayes
Strike level [median in millimeter]	160.2	174.5	170.8
Ticksize [median €/millimeter]	0.34	0.55	0.41
Premium [median in €/ha]	69.05	93.79	84.10

Note: Displayed values constitute medians across county, farm-level and combined contracts using Bayesian quantile regression.

Summary statistics of WII contracts shown in table 4.3 show that drought risk on the county level is substantially lower compared to the farm-level as indicated by a lower strike level, ticksize and resulting also the premium per hectare. Vice versa, farm-level WII already pays out at higher levels of rainfall (on average 174.5 compared to 160.2 at county level), the impact of one missing millimeter of rainfall is here on average 60% higher (0.55 compared to 0.34 on county level) and resulting the premium of farm-level based WII is 35% higher compared to county-level WII. Consequently, when combining both insurances using our BQR approach, the average drought risk and the average contract parameters lie in between.

Table 4.4 shows the results of hypotheses tests 1 to 3. For risk neutral decision makers, i.e. coefficient of relative risk aversion equals zero, no difference exists between insured and uninsured expected utility. As expected, unsubsidized WII does not increase utility of risk neutral decision makers. We find that WII based on county level data is not effectively risk reducing under all scenarios of risk aversion. In contrast, if WII is specified using farm-level data, it increases the EU of a risk averse farmer. More specifically, in the second column comparative results of farm-level based WII compared to a no insurance scenario show that WII conditioned based on farm-level yield data is able to reduce the financial exposure to drought risk across all levels of risk aversion tested. In the third column, it can be seen that this also holds for WII designed using both aggregation levels of winter wheat yields and Bayesian quantile regression.

Table 4.4 Results RQ1: Tests for risk reducing properties of different WII compared to 'no insurance' reference scenario

	County-Level Data	Farm-Level Data	Bayes
Coefficient of relative risk aversion α	H1:H_0: $E[U(W_{cQR})] \leq E[U(W_{no\ insurance})]$	H2:H_0:$E[U(W_{iQR})] \leq E[U(W_{no\ insurance})]$	H2:H_0: $E[U(W_{iBQR})] \leq E[U(W_{no\ insurance})]$
	p- value		
0 (risk neutral)	0.96	0.69	0.85
0.2	0.63	$6.56 \cdot 10^{-2}$	0.13
0.4	0.55	$1.94 \cdot 10^{-2}$	$2.09 \cdot 10^{-2}$
0.6	0.38	$6.76 \cdot 10^{-3}$	$1.13 \cdot 10^{-2}$
0.8	0.32	$6.06 \cdot 10^{-3}$	$9.75 \cdot 10^{-3}$
1 (extremely risk averse)	0.24	$4.75 \cdot 10^{-3}$	$7.52 \cdot 10^{-3}$

Note: Tests are based on comparing vectors of expected utility values per farm. Pairwise testing between vectors (one per insurance scenario) was done using non parametric Wilcoxon rank sum tests.

Table 4.5 shows results of hypotheses tests 4 to 6. Here WII using BQR, i.e. including farm- and county-level data, outperforms WII designed solely using county-level yield data.

Table 4.5 Results RQ2: Comparison tests for risk reducing properties between different WII

	Bayesian Quantile vs. County-Level	Bayesian Quantile vs. Farm-Level
Coefficient of relative risk aversion α	H4: H_0:$E[U(W_{iBQR})] \leq E[U(W_{cQR})]$	H5:H_0:$E[U(W_{iBQR})] \leq E[U(W_{iQR})]$
	p- value	
0 (risk neutral)	0.23	0.45
0.2	0.14	0.59
0.4	0.09	0.56
0.6	0.05	0.58
0.8	0.05	0.60
1 (extremely risk averse)	0.04	0.65

Note: Tests are based on comparing vectors of expected utility values per farm. Pairwise testing between vectors (one per insurance scenario) was done using non parametric Wilcoxon rank sum tests.

All results in tables 4.4 & 4.5[12] underline the necessity of sufficiently long farm-level yield time series. Vice versa, county-level winter wheat yields do not constitute a valuable basis for designing risk reducing WII neither in the classical nor in the Bayesian quantile regression framework.

4.5 Discussion & Conclusion

We find that WII based on farm-level data is able to reduce the drought risk exposure of wheat producing farms in Eastern Germany. However, this only holds if farm-level yield data is sufficiently available for a long time period. In contrast, our results indicate that WII designed using county average yields instead of farm-level yields, are unable to reduce farmers' financial exposure to drought risk. This is in line with literature on aggregation bias (e.g. Marra and Schurle, 1994, Finger, 2012). This implies that in aggregated winter wheat yields, e.g. county average yields, single spikes in yield observations that are observable in farm-level yield observations, can be averaged out when occurring idiosyncratically, i.e. on single farms only. For drought risk, i.e. lack of rainfall, in our cases study region eastern Germany, this idiosyncratic component seems to be the driver of single farm yield losses, as WII conditioned based on county average yields does not provide any potential to reduce farmers financial exposure to drought risk. This finding is in line with Heimfarth et al. (2012). This underlines that for insuring drought risk in eastern German winter wheat production, time series of single farm yields are indispensable.

Although the Bayesian quantile regression framework presented here did not improve the risk reducing properties of WII, Bayesian inference has been proven to be supportive in crop insurance pricing (Shen et al. (2015)). These findings and results presented by März et al.

[12] See also table A1 & A2 of the appendix for simulated data scarcity.

(2016), who found Bayesian quantile regression to be superior in estimating farmland rental rates, might encourage future research to extend the findings presented here to other weather perils. In case of threats that occur more systemically, e.g. temperature or joint indices of temperature and rainfall, the BQR framework might present more promising results. Moreover, BQR needs to be tested in a framework where larger differences exist between farm-level and county-level data availability. In our case study, reliable county-level yields were available from 1992 onwards only, due to the end of the German Democratic Republic. In case of longer time series on county yield records, more extreme events and systemically occurring shocks might be available serving as better priors for estimating farm-level risk.

Next to extending our findings to other perils, future research might also apply the BQR framework to other more drought exposed regions such as Africa. Here single farm yield data is hardly available and WII are mostly designed based on panel data estimation, i.e. similar contracts for multiple farmers (Woodard et al. 2016).

4.5 Appendix

Analogously to tables 4.2 & 4.3 in the main body of the paper, tables 4.A1 and 4.A2 show results of RQ1 and RQ2 when farm-level yield data is scarce, but county level data is available for the entire period. More specifically the full farm-level yield dataset described above mainly includes farms that provided time series of yield data longer than 12 years. For results in tables 4.A1 and 4.A2 we simulated yield data scarcity by randomly sampling 5 years per farm and using yield and rainfall information to design WII using the three presented approaches. For testing the performance of the resulting WIIs we then again used the full time series of data.

Results in table 4.A1 show that under farm-level yield data scarcity none of the three insurance designs tested is able to reduce the financial exposure to drought risk in our case study. Moreover, table 4.A2 shows accordingly that no differences exist between the WIIs in terms of risk reduction when farm level yield data is scarce.

Table 4.A1 Results RQ1: Tests for risk reducing properties of different WII compared to 'no insurance' reference scenario under farm-level yield data scarcity

	County Data	Farm-Level Data	Bayes
Coefficient of relative risk aversion α	H1:H_0: $E[U(W_{cQR})] \leq E[U(W_{no\ insurance})]$	H2:H_0:$E[U(W_{iQR})] \leq E[U(W_{no\ insurance})]$	H2:H_0: $E[U(W_{iBQR})] \leq E[U(W_{no\ insurance})]$
	p- value		
0 (risk neutral)	0.59	0.69	0.51
0.2	0.57	0.34	0.46
0.4	0.54	0.33	0.41
0.6	0.51	0.29	0.38
0.8	0.47	0.27	0.33
1 (extremely risk averse)	0.43	0.25	0.30

Note: Tests are based on comparing vectors of expected utility values per farm. Pairwise testing between vectors (one per insurance scenario) was done using non parametric Wilcoxon rank sum tests.

Table 4.A2 Results RQ2: Comparison tests for risk reducing properties between different WII under farm level yield data scarcity

Coefficient of relative risk aversion α	Bayesian Quantile vs. County-Level	Bayesian Quantile vs. Farm-Level
	H4: H_0:$E[U(W_{iBQR})] \leq E[U(W_{cQR})]$	H5:H_0:$E[U(W_{iBQR})] \leq E[U(W_{iQR})]$
	p- value	
0 (risk neutral)	0.27	0.77
0.2	0.25	0.76
0.4	0.23	0.75
0.6	0.22	0.70
0.8	0.22	0.71
1 (extremely risk averse)	0.22	0.69

Note: Tests are based on comparing vectors of expected utility values per farm. Pairwise testing between vectors (one per insurance scenario) was done using non parametric Wilcoxon rank sum tests.

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Chapter 5

Behavioral weather insurance: Applying cumulative prospect theory to agricultural insurance design under narrow framing

Tobias Dalhaus, Barry J. Barnett and Robert Finger

Keywords: Behavioral Insurance, Cumulative Prospect Theory, Drought, Risk Management, Weather Insurance

Abstract

Experience across many countries has shown that, without large premium subsidies, crop insurance uptake rates are generally quite low. In this article, we propose to use cumulative prospect theory in designing weather insurance products, for situations in which farmers narrowly frame insurance as stand-alone investment. To this end, we adjust insurance contract parameters to better tailor farmers' preferences by introducing what we call behavioral weather insurance. We find that a stochastic multiyear premium increases the prospect value of weather insurances depending on farmers' preferences, while a zero deductible design does not. We suggest that insurance contracts be tailored to optimally serve farmers' needs, which offers potential benefits for both insurer and insured.

5.1 Introduction

Climate risks threaten agricultural crop production and are expected to become even more pronounced due to climate change (Schlenker & Roberts, 2009). Crop insurance could be one of the key risk management tools that can help address increased weather variability due to climate change (IPCC 2014, Di Falco et al., 2014). Crop insurance products can be classified into two groups: i) those that indemnify farmers for realized losses (indemnity-based insurance); and, ii) those that make payments based on some objective measure that is assumed to be highly correlated with realized losses (index-based insurance). Standard examples of the latter include area yield insurance (AYI) (Skees, Black, & Barnett, 1997) and weather insurance (WI) (Martin, Barnett, & Coble, 2001; Vedenov & Barnett, 2004; Odening, Musshoff, & Xu, 2007).

In many countries, farmers' participation in crop insurance schemes is facilitated with massive subsidization, so that high levels of crop insurance uptake have required premium subsidies to the point that insurance purchasing often has a positive expected value (Glauber, 2004; Coble & Barnett, 2013; Du, Feng & Hennessy, 2017). In contrast, the uptake of unsubsidized crop insurance is often low.[13] Assuming a standard expected utility (EU) framework, this observation is not consistent with the optimal behaviour of risk averse farmers. A potential explanation for this anomaly is that a share of farmers does not assign insurance premiums and payouts to fluctuations in crop income, but rather narrowly frames insurance as a stand-alone investment (Babcock, 2015). Recent evidence also suggests that cumulative prospect theory (CPT) (Tversky & Kahneman, 1992) may be a better predictor of farmers' insurance decision-making than EU theory (Du, Feng & Hennessy, 2017; Babcock, 2015). CPT extends EU theory

[13] A small number of countries with functioning non-subsidized crop insurance markets, such as Switzerland (e.g. Finger and Lehmann, 2012), represent exceptions and do not preclude this general tendency.

in three dimensions that are relevant for insurance uptake. First, it distinguishes outcomes into gains and losses with respect to a certain reference point. Second, the slope of the value function is steeper in the loss domain compared to the gain domain indicating loss aversion. Third, individual outcomes receive weights according to a function accounting for decision makers' subjective distortions of probability values.

Since actual crop insurance purchasing behavior deviates so significantly and so consistently from what standard EU theory would predict, it seems appropriate to reconsider conventional behavioral assumptions. As one path, we follow Babcock (2015) and assume that some farmers frame insurance purchase decisions as a stand-alone investment rather than a risk management tool. Therefore, we adjust insurance parameters to better fit such framing. We propose to modify the traditional weather insurance (TWI) design and introduce what we call behavioral weather insurance (BWI). To this end, we propose a two-step design of WI products. First, the BWI should be effective in reducing farmers risk exposure and basis risk should be as small as possible. Second, the design of this BWI should be adjusted in line with insights derived from CPT, extending the narrower EU framework.

Thus, we also adopt a two-step empirical procedure to design BWI. First, we test whether both TWI and BWI can effectively reduce the insured's financial exposure to production risk, which we underline by testing for increases in EU across various scenarios of risk aversion. Second, we evaluate potential changes in insurance demand through BWI compared to TWI by testing for prospect value changes under various real world CPT specifications and the assumption of the above stand-alone investment framing. As a descriptive analogy, in a first step, we produce a food product and test for healthiness. Subsequently, in a second step, we design a nice packaging that fits observed purchase behavior to increase demand for the product. Analogously, farmers buy a risk reducing insurance not only because of its risk reducing properties but also because of factors like the number of payouts or the timing of premium payments. It remains unexplored in the existing literature if adjusting those parameters can lead to an increase in insurance demand across risk averse decision makers and thus a more resilient farming system.

We proceed as follows. First, the theoretical framework of EU and CPT is used to propose modifications to the design of TWI contracts yielding BWI. Second, we posit hypotheses about preferences for BWI designs relative to TWI assuming first an EU value function and then a CPT value function, according to the above two-step procedure. Third, we test these hypotheses using data from a drought-prone wheat production region in eastern Germany.

5.2 Methodology

This section gives an overview about decision making criteria under risk, specifications used, the underlying testing procedure and the insurance design.

5.2.1 Decision-making under risk

In the subsequent section we introduce the underlying methodology to address our two step approach for designing BWI. We first present an overview of the EU framework used in step one. We then describe how cumulative prospect theory is used to assess insurance from a narrowly framed stand-alone investment perspective in step two. Afterwards we combine both frameworks within one decision making model. Based on that, we are able to propose adjustments to the insurance contract that potentially increase both expected utility and the prospect value and thus market demand of two parts of the farmers' population.

5.2.1.1 Expected Utility Theory (Step 1)

In the EU framework, terminal wealth W_{ti} for farm *i* in year *t* is transformed into a utility value using a utility function $U(W_{ti})$. The occurrence probability weighted average of these results is the expected utility $E[U(W_{ti})]$ (EU). For clarity of our analysis, we assume farmers produce wheat only, resulting in terminal wealth W_{ti} to follow $W_{ti} = \delta y_{it} + \pi_{ti} - \Gamma_i + W_0$. Here, δ denotes the wheat price[14], $y_{it}$the yield of farm *i* in year *t*, π_{ti} the insurance payout, Γ_i the insurance premium and W_0 the initial wealth. The standard assumption is that farmers chose their insurance plans according to the expected utility maximization problem, i.e. $\max E[U(W_{ti})]$. In case of farmers being downside risk averse, insurance payouts π_{ti} shall cover downward movements of stochastic yields y_{it}. Furthermore, insurance premium Γ_i shall not exceed farmers individual risk premium which constitutes the maximum amount a farmer is willing to pay to get rid of the risk arising from y_{it} and which is dependent on her risk preferences. Thus, everything else being equal, changes in $E[U(W_{ti})]$ while changing insurance plans serve as proxy for changes in welfare and consequently, in case of insurance premium Γ_i being fair, as changes in the respective insurance's ability to reduce the financial exposure to risks.

For this analysis we use a power utility function to reflect farmers' preferences (Di Falco & Chavas, 2006, 2009).

$$\mathrm{U}_{ti\varphi}(W_{ti}) = \begin{cases} \frac{W_{ti}^{1-\varphi}}{1-\varphi} & if\ \varphi \neq 1 \\ \ln(W_{ti}) & if\ \varphi = 1 \end{cases} \tag{5.1}$$

[14] The insurance does not protect against stochastic prices and we do not expect a natural hedge at the farm-level. Thus, for the analysis presented here, price is included just as a scaler that translates stochastic yield events into monetary units.

where φ is the measure of relative risk aversion. As a result, we obtain vectors $eu_{\kappa\varphi i}$ containing EU values for each of the *i* farms for the two insurance designs κ ($\kappa = TWI$ or BWI) and levels of risk aversion φ.

5.2.1.2 Cumulative Prospect Theory (Step 2)

As farmers tend to deviate from expected utility maximizing insurance choice, Babcock (2015) suggests that farmers might narrowly frame insurance as stand-alone investment and evaluate this investment violating expected utility theory. In fact, previous studies suggest that people frequently make decisions that violate EU determined preference rankings (see Stamer, 2000 for an overview). Consequently, a number of alternative theories to explain and predict human behavior have been proposed, such as CPT or rank-dependent expected utility (e.g. Quiggin, 1991). Especially CPT has received considerable attention in recent agricultural economics literature (e.g. Liu, 2013, Holden & Quiggin, 2017).

CPT extends EU by distinguishing gains and losses as deviations from a certain reference point, resulting in two (potentially) different ‘utility’ functions combined into a value function $\mathrm{v}(\sigma)$, which implies risk aversion over gains and risk seeking behavior over losses:

$$\mathrm{v}_{ti\alpha\lambda}(\sigma_{ti}) = \begin{cases} \sigma_{ti}^{\alpha} & if\ \sigma_{ti} > 0 \\ 0 & if\ \sigma_{ti} = 0 \\ -\lambda(-\sigma_{ti})^{\alpha} & if\ \sigma_{ti} < 0 \end{cases} \tag{5.2}$$

Instead of terminal wealth realizations, CPT transforms single prospect outcomes σ into prospect values v, which depend on the level of risk aversion α and loss aversion λ.[15] $\mathrm{v}(\sigma)$ is strikly increasing and $|\mathrm{v}(\sigma)| < |\mathrm{v}(-\sigma)|$ implying loss aversion. Moreover, $\partial^2\mathrm{v}(\sigma)/\sigma^2 \leq 0$ for

[15] Note that α is an anti-index for risk aversion. $0 < \alpha < 1$ implies risk aversion, $\alpha = 1$ risk neutrality, and $\alpha > 1$ risk seeking.

σ > 0 (implying risk aversion in gains) and $\partial^2 \mathrm{v}(\sigma)/\sigma^2 \geq 0$ for σ < 0 (implying risk seeking in losses) jointly implying diminishing sensitivity towards changes in σ with increasing distance from the reference point for both gains and losses (Barberis, 2013).

For the second step CPT framework, we follow Babcock (2015) and frame the EU increasing weather insurance from the first step as a stand-alone investment, thus gains are felt, when payouts exceed premiums and losses are felt in the opposite case (see also Barberis, Huang & Thaler, 2006 for further details on narrow framing). Babcock (2015) finds that farmers tend to use the premium paid Γ_i as reference point R_i so that the difference between payouts and premiums for farm *i* in year t is indicated by the prospect outcome $\sigma_{ti} = \pi_{ti} - R_i = \pi_{ti} - \Gamma_i$. For each σ_{ti} there is a corresponding probability of occurrence p_{ti}. These probabilities are translated into decision weights, considering the observed tendency for decision-makers to overweight small probabilities and underweight large ones (Quiggin, 1991; Tversky & Kahneman, 1992), i.e. by using a function $\omega(p)$. Assuming ordered outcomes σ_i with probabilities p_i of farm *i* over the years *t* from largest loss year *m* to largest gain year *n* the decision weight of a gain in year *t* is defined as

$$\vartheta_{ti}^{+} = \omega(p_t + \cdots + p_n) \\ - \omega(p_{t+1} + \cdots + p_n)$$

And of a loss in *t* as

$$\vartheta_{ti}^{-} = \omega(p_m + \cdots + p_i) \\ - \omega(p_m + \cdots + p_{i-1})$$

The final prospect value $pv_{i\alpha}$ is evaluated by summing up the weighted single year values:

$$pv_{i\alpha\lambda\gamma} = \sum_{t=1}^{n} \vartheta_{ti} \mathrm{v}_{ti\alpha}(\sigma_{ti}) \quad (5.3)$$

Thus, in case of narrowly framing insurance as a stand-alone investment, the maximization problem is $max\ pv_{i\alpha\lambda\gamma}$. Hence, based on CPT we are able to add a second performance measure to assess insurance next to the risk reducing properties provided by the EU framework. This is in line with Jäntti et al. (2014) who suggest the use of welfare measures according to the subject's underlying decision making process. More specifically, we use prospect value to measure welfare in the case of the subject being prospect value maximizing.

5.2.1.3 Coexistence of decision making processes and contract adjustments

By following Harrison & Rutström (2009) we assume that "several behavioral processes […] coexists" within the farmers population. Hence, any number of (unobservable) decision rules could be assumed and our framework allows one to test for various decision rules. However, we will focus on the two that have been addressed most prominently in the literature. Thus $\max E[U(W_{ti})]$ and $max\ pv_{i\alpha\lambda\gamma}$ are two representations of the potentially existing decision making processes. Our here presented framework allows further processes to be included if experimental evidence suggests their existence. Assuming that a share of farmers maximizes $pv_{i\alpha\lambda\gamma}$, we state that insurance design should take this into account. By assuming that BWI should increase both, EU and pv according to our two step-procedure we aim at increasing the welfare for both groups of individuals, i.e. EU and CPT maximization (Jäntti et al., 2014), while holding EU related risk reducing properties constant. Therefore, we test two adjustments for their ability to increase both the expected utility $E[U(W_{ti})]$ and the prospect value $pv_{i\alpha\lambda\gamma}$ of weather insurance.

ADJUSTMENT 1: Insure also small losses (no deductible).

The diminishing sensitivity property of $\mathrm{v}(\sigma)$ in the gain domain, i.e. $\partial^2\mathrm{v}(\sigma)/\sigma^2 \leq 0$ for $\sigma > 0$, implies that decision makers particularly positively value small gains that occur close to their reference point. This property is consistent with the decreasing marginal utility property of $U(W)$. However, in CPT this sensitivity is shifted and appears close to the reference point. Moreover, the concavity of $\mathrm{v}(\sigma)$ in the gain domain implies risk aversion in gains. Therefore, individuals prefer multiple small gains relative to, or in addition to, infrequent large gains (Thaler, 1985, Thaler & Johnson, 1990, Tversky & Kahneman, 1991). Applying this to weather insurance, farmers would prefer contracts that provide larger payouts in the case of catastrophic losses but also small payouts with higher frequencies (Vargas Hill, Robles & Ceballos, 2016, Cole, Stein & Tobacman, 2014, Enjolras & Sentis 2011; Platteau, De Bock & Gelade 2017). Increasing the number of payouts comes at the cost of higher premiums, which are, in our narrow framing example, experienced as losses. Hence, changes in pv through ADJUSTMENT 1 are dependent on how decision makers value less risk in the gain domain in comparison to additional losses. More specifically, the success of ADJUSTMENT 1 is expected to be a function of α and λ, i.e. risk aversion and loss aversion. Our focus on an index insurance product allows us to enable high frequency payouts (no deductibles) because of low administrative costs as payouts are automatically triggered based on the performance of the index rather than by farm damage assessments. Moreover, in the index insurance framework one is less concerned about moral hazard which reduces the need for a deductible.

ADJUSTMENT 2: Conclude a multi-year contract and pay premiums only in years of no crop losses or, if there are no years with no losses, at the end of the contract period.

The convexity of the value function in the loss domain, $\partial^2 \mathrm{v}(\sigma)/\sigma^2 \geq 0$ for $\sigma < 0$, implies risk-seeking behavior in losses, i.e. $\mathrm{v}(-x) + \mathrm{v}(-y) < \mathrm{v}(-(x+y))$ (Thaler, 1985). Translated into the weather insurance context, this implies that farmers prefer volatile premium payments in contrast to stable premium payments. Paying premiums only every nth year makes the amount of the premium payment depend on how many yearly payments are summed together. Thus, we propose to change the deterministic annual premium into a stochastic multi-year premium, which considers risk seeking behavior and diminishing sensitivity in losses. This requires extending the insurance contract period over several years. Multi-year contracts have additional benefits compared to annual contracts because administrative costs and premium loadings can be reduced (Osipenko, Chen & Odening, 2015, Chen & Goodwin, 2015). This part of ADJUSTMENT 2 acknowledges CPT's principle of 'integrating losses' (Thaler, 1985).

Moreover, in case of mixed gain/loss events, i.e. occurrence of outcome (x,-y) with x < y, it is not intuitive whether $\mathrm{v}(x) + \mathrm{v}(-y) \gtrless \mathrm{v}(x-y))$. The general tendency is that the smaller x is in relation to y, the more segregation of x and $-y$ is preferred as $\mathrm{v}(x) + \mathrm{v}(-y) > \mathrm{v}(x-y))$ tends to hold. Related to weather insurance, farmers should be able to postpone their premium payment in case of a small insurance payout (coming from ADJUSTMENT 1) to be able to experience $\mathrm{v}(payout)$ as a gain. This part of ADJUSTMENT 2 acknowledges CPT's principle of 'segregation of silver linings'.

5.2.1.4 Specification of EU & CPT

For the empirical analysis, we conduct sensitivity analysis using different EU and CPT specifications. For EU we vary the measure of risk aversion φ across $[0, 0.2, 0.4, 0.6, 0.8, 1.0]$. This range is in accordance with experimentally elicited preferences of farmers in Germany, e.g. Meraner & Finger (2017) or Musshoff et al. (2013).

Regarding CPT, we expect our results to be dependent on α, λ and $\gamma/\,\delta$. More specifically, we use specifications from the only two peer reviewed empirical studies that elicited CPT preferences in European agriculture (Bocquého, Jacquet. and Reynaud, 2014, Bougherara et al., 2017). Bocquého, Jacquet. and Reynaud (2014) deliver three sets of CPT parameters based on different estimation techniques (abbreviated as *Boc.1- 3* hereafter). In addition, Bougherara et al. (2014) provide a fourth set of CPT elicited parameters (abbreviated as *Bou* hereafter). Extending real-world elicited preferences, we use CPT specifications employed by Babcock (2015), which were taken from the original cumulative prospect theory paper of Tversky & Kahneman (1992) (abbreviated as *Bab* hereafter). Table 5.1 and figure 5.1 summarize and visualize the different specifications applied in the above papers. Here, *Boc.1* is characterized by a low α-coefficient indicating relatively high risk aversion over gains and risk seeking over losses. The loss aversion coefficient λ indicates the losses are weighted almost twice as much as gains. Similarly, *Boc.2* implies slightly lower risk aversion in gains (and lower risk seeking in losses) and similar loss aversion compared to *Boc.1*. *Boc.3* has still lower risk aversion over gains and risk seeking over losses compared to *Boc.1* and *Boc.2* but with higher loss aversion. *Bou*, as compared to the former three scenarios, has lower risk aversion over gains (and risk seeking over losses) together with considerably lower loss aversion. The *Bab* specification has relatively lower risk aversion over gains and risk seeking over losses together with a loss aversion specification that is similar to *Boc.1* and *Boc.2*.

Table 5.1. CPT Specifications of recent Studies

	Abbreviation	α – coefficient (risk aversion)[a]	λ – coefficient (loss aversion)	γ/ δ – coefficient (probability distortion)
Bocquého, Jacquet. and Reynaud (2014)	*Boc.1*	0.280	2.275	0.655
	Boc.2	0.325	2.110	0.679
	Boc.3	0.512	3.756	0.647
Bougherara et al. (2017)	*Bou*	0.614	1.374	0.785 / 0.844
Babcock (2015)	*Bab*	0.880	2.250	0.610 / 0.690[b]

a Note that smaller numbers imply higher risk aversion.

b According to equations 5.1 and 5.2 different weighting functions are used for gains and losses respectively

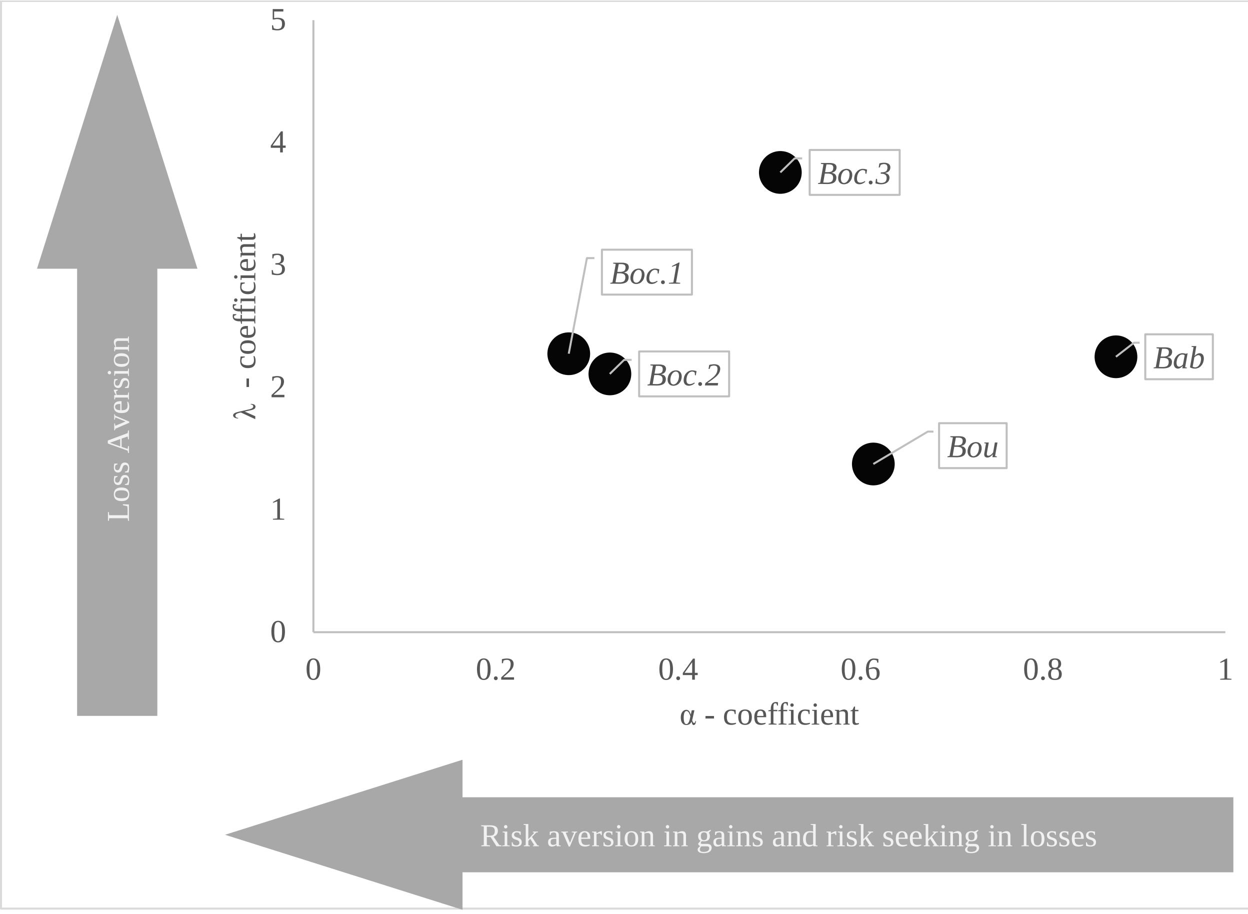

Figure 5.1. Visual Classification of CPT Specifications of recent Studies. Flags indicate Abbreviations according to Table 1.

With respect to probability weighting, all CPT specifications imply overweighting of small and underweighting of high probability values with almost similar magnitudes. The employed specifications also differ with respect to the functional forms of $\omega(p)$. Equations 5.4 to 5.5.2 show the specifications of $\omega(p)$ as proposed by i) Bocquého, Jacquet. and Reynaud (2014) (ω_1) and ii) Bougherara et al. (2017) and Babcock (2015) (ω_2^+ and ω_2^- for gain and loss probabilities respectively):

$$\omega_1(p) = \exp[-(-\ln(p))^\gamma] \tag{5.4}$$

$$\omega_3^+(p) = \frac{p^\gamma}{(p^\gamma+(1-q)^\gamma)^{\frac{1}{\gamma}}} \qquad \omega_3^-(p) = \frac{p^\delta}{(p^\delta+(1-q)^\delta)^{\frac{1}{\delta}}} \qquad (5.5.1/\ 5.5.2)$$

We thus obtain vectors $pv_{\kappa\alpha\lambda\gamma}$ for the two insurance designs κ and the five CPT specifications. These vectors contain insurance prospect values for each farm. Altogether, the five above specifications allow us to implement a realistic range of preference scenarios that support our empirical analysis.

5.2.2 Testing

We investigate the proposed BWI by conducting statistical tests in three different dimensions. First, we test the risk reducing properties of an actuarially fair TWI scheme against the actuarially fair BWI by comparing $eu_{\kappa\varphi}$ vectors of insured terminal wealth. More specifically, we test the following null hypotheses based on observations across various farms and across different levels of risk aversion φ :

H1: H_0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$
H2: H_0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$
H3: H_0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$

Second, we test whether the BWI scheme is better suited to farmers' preferences (in terms of prospect value) than a TWI scheme and thus would be likely to increase insurance demand. Furthermore, we explore the stability of the expected performance of the BWI scheme using different CPT value function parameters. We then compare the performance of BWI and TWI across the different CPT specifications (See Table 5.1).

H4: H_0: $pv_{behavioral\ boc.1} \geq pv_{traditional\ boc.1}$

H5: H_0: $pv_{behavioral\ boc.2} \geq pv_{traditional\ boc.2}$

H6: H_0: $pv_{behavioral\ boc.3} \geq pv_{traditional\ boc.3}$

H7: H_0: $pv_{behavioral\ bou} \geq pv_{traditional\ bou}$

H8: H_0: $pv_{behavioral\ bab} \geq pv_{traditional\ bab}$

Third, we disentangle how some of the individual adjustments that inform our approach contribute to an increase in the prospect value of the insurance. More specifically, we present results for the statistical tests of H4 – H8 when BWI ADJUSTMENT 1 ("Insure also small losses --no deductible") has been turned off and when ADJUSTMENT 2: ("Conclude a multi-year contract and pay premiums only in years of no crop losses or, if there are no years with no losses, at the end of the contract period") has been turned off.

For all the above hypotheses, we use nonparametric paired Wilcoxon rank sum tests to compare vectors $eu_{\kappa\varphi}$ (to test for expected utility changes across levels of risk aversion) and $pv_{\kappa\alpha\lambda\gamma}$ (to test for prospect value changes across levels of risk and loss aversion as well as probability weighting functions). The Wilcoxon rank sum test makes a pairwise comparison of whether the differences between the vectors stated in the above hypotheses are positive. We thus obtain a p-value for each tested scenario.

5.2.3 Index design

Both the TWI and the BWI aim at providing indemnification in case of a drought event during sensitive stages of plant growth. We consider a TWI design with a standard linear payout function, a 10% deductible, and premium payment every year. We contrast TWI with a BWI design that includes the two adjustments described earlier. The multi-year contract length was fixed to three years (following Chen & Goodwin, 2015).[16] In any year during the three year period, if a payout is not made, the cumulative premium due must be paid. If the insurance makes payouts in each of the three years, the cumulative premium due must be paid at the end of the contract period. Figure 2 displays an example case of yields together with premiums and payouts for both TWI and BWI across a 12 year period[17].

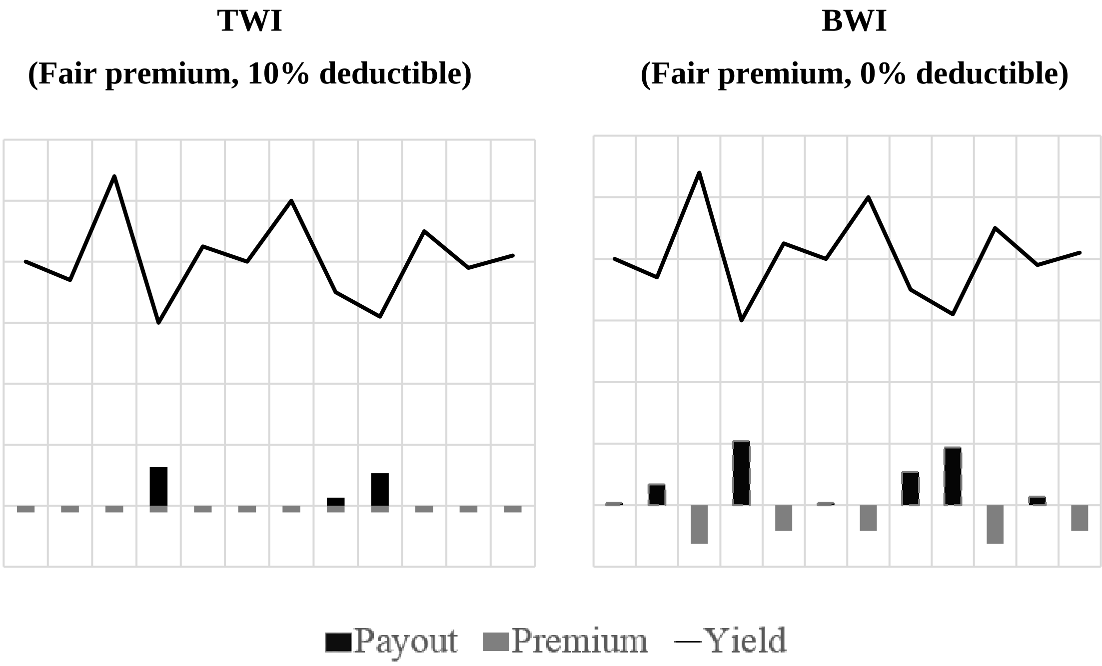

Figure 5.2. Exemplary visualization of TWI and BWI (no basis risk)

Following Conradt et al. (2015), we select the characteristics of the weather insurance contracts for each farm to minimize basis risk and maximize risk reducing properties. Focusing on the coverage of winter wheat yield losses due to a lack of rainfall during vulnerable growth stages,

16 Our results were robust against changes in the contract length. See the Appendix for results using two and four year contracts.

17 Our results were qualitatively robust against the consideration of discounting. We discounted all payouts and premium payments of BWI back to the year of contract closure (interest rate = 2%). As this procedure results in premiums being no longer fair, we continued without assuming an interest charge.

we match farm level yield records with historical cumulative rainfall data during vulnerable stages of plant growth that are exogenous to our analysis.[18] We use high resolution grid data to remove spatial basis risk (Dalhaus & Finger 2016). Thus, the rainfall index value r_{ti}^{R} for farm *i* in year *t* is calculated as the sum of rainfall R_{d}^{ti} from day *d* = 'start date' to day *d* = 'end date':

$$r_{ti}^{R} = \sum_{d=start}^{end} R_{d}^{ti} \tag{5.6}$$

Start and end dates of critical plant growth stages (i.e. from stem elongation to milk ripening) are determined using regional crop growth monitoring network data for each year as proposed by Dalhaus, Musshoff & Finger (2018). Thus, the farm individual insurance period is flexible in both, space and time according to individual occurrence dates of winter wheat growth stages, which vary across reporting stations and years.

We estimate the relationship between r_{ti}^{R} and farm yields y_{ti} using quantile regression (QR) that puts a special emphasis on explaining low yield outcomes (Conradt et al. 2015). More specifically, we expect y_{ti} to be a function $g(r_{ti}^{R})$ including r_{ti}^{R} and other factors that are summarized within an error term ε that are uncorrelated with weather. To quantify the relation between weather and yield econometrically, we estimate the model

$$y_i = \alpha_i + r_i^{R\prime}\boldsymbol{\beta}_i + \varepsilon_i \tag{5.7}$$

where $\boldsymbol{\beta_i}$ marks the change in yields when changing the rainfall index value r_{ti}^{R} by one unit (millimeter). As we expect this change to be nonlinear across yield levels (i.e., the impact of missing rainfall is more severe when yields are low), we use QR as proposed by Conradt et al.

[18] Please see section '5.3 Data' for a detailed explanation of both, the yield dataset and the high resolution rainfall grid used to design the rainfall index. The latter allows an individual matching between farm yield and historical rainfall.

(2015). First, QR minimizes the absolute sum of residuals rather than the squares and second it allows to focus on different quantiles of the yield distribution dependent on $\tau \in (0,1)$. The minimization problem of QR is

$$\boldsymbol{\beta}_{\boldsymbol{i\tau}} = \min_{\boldsymbol{\beta}_{\boldsymbol{i\tau}}} \sum_{t=1}^{n} \rho_\tau (y_{it} - r_{ti}^{R\prime} \boldsymbol{\beta}_{i\tau}) \quad (5.8)$$

where

$$\rho_\tau (y_{it} - r_{ti}^{R\prime} \boldsymbol{\beta}_{i\tau}) = \begin{cases} \tau \left| y_{it} - r_{ti}^{R\prime} \boldsymbol{\beta}_{i\tau} \right| & if\ y_{it} \geq r_{ti}^{R\prime} \boldsymbol{\beta}_{i\tau} \\ (1-\tau) \left| y_{it} - r_{ti}^{R\prime} \boldsymbol{\beta}_{i\tau} \right| & if\ y_{it} \leq r_{ti}^{R\prime} \boldsymbol{\beta}_{i\tau} \end{cases} \quad (5.9)$$

We follow Conradt et al. (2015) and use $\tau = 0.3$ to put a special emphasis on low yield outcomes.

Aiming at paying out in drought cases, our insurance is designed as a European put option, i.e. insurance payout $\pi_{tik} = \delta \cdot [T_{ik} \cdot \max\{(S_{ik} - r_{tik}^{R}), 0\}]$. The optimal Ticksize and strike are determined from quantile regression results. More specifically, the strike level S_{ik} of rainfall under which a payout is triggered is estimated as the rainfall value that corresponds to the mean yield $\overline{y_i}$ in the case of BWI, i.e. $S_{iBWI} = g^{-1}(\overline{y_i})$, and to 90% of the mean yield in the case of TWI, i.e. $S_{ik} = g^{-1}(0.9\overline{y_i})$. We thus follow Conradt et al. (2015) and indemnify not for below average rainfall but rather for rainfall levels that would imply below average yields. Ticksize T_{ik} is the estimated slope coefficient $\boldsymbol{\beta}_{\boldsymbol{i\tau}}$.

Actuarially fair premiums for the TWI and BWI contracts are calculated using the burn rate method (e.g. Odening, Musshoff & Xu, 2007).[19] The actuarially fair insurance premium is

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[19] Qualitatively, our results were robust to changes in the premium rate loading factor. Results assuming a premium rate load of 20% are in the online appendix.

determined based on the average payout over 10,000 bootstrapped payout realizations from the estimated rainfall distribution.

5.3 Data

In the following section we introduce the underlying farm level yield, crop phenology and weather datasets used.

5.3.1 Yield data

Our case study region is located in a drought prone area of eastern Germany (see figure 3). More specifically, the farms lie in the German Federal states of Mecklenburg-Western Pomerania, Brandenburg, Saxony-Anhalt, Thuringia and Saxony. Here, crop yield variability is much larger compared to other regions in Germany (Lüttger & Feike 2017). Our farm-level yield dataset originally consisted of a panel of 90 farms for the years 1995 to 2015 obtained from a local insurance provider. Each farm has a minimum size of 1,500 hectares, which is considerably higher than the German average (of only 60 hectares) but representative for the eastern part of Germany. The farms are highly specialized with crop production being the main source of farm income. As a result, they have a significant interest in managing their exposure to weather risk. In order to obtain an individual weather risk assessment from the insurance provider, farmers provided their historical yield records for multiple crops, of which we use winter wheat as an example for this study. Based on the findings of the weather risk assessments, private non-subsidized and individually-tailored weather insurance contracts were offered to the farmers. To our knowledge this unsubsidized weather index insurance market is a unique case in a developed country context, which underlines the importance of further improving weather insurance to help farmers insure their weather risks (for further details see www.die-wetterversicherung.de).

Concentrating our analysis on a single weather risk, we reduced the dataset to 38 farms that provided at least 15 years of wheat yield data and where a considerable vulnerability against a lack of precipitation was indicated.[20] Farms that are more vulnerable to a lack of precipitation are also more likely to be interested in a rainfall insurance. We consider a fixed wheat price of 15.3 €/deciton to transform wheat yield units into monetary terms and use per hectare direct payments of 280 € as a proxy for initial wealth in the expected utility calculations. Considering technological trends, the yield data were detrended using the M-Estimator as suggested by Finger (2013b) (R Core Team, 2016)[21].

Table 5.2: Summary statistics of detrended winter wheat yields in decitons per hectare

Mean	66.39
Median	66.55
Min	17.42
Max	109.88
Standard Deviation	13.90
Coefficient of Variation	0.21

[20] Heterogeneous soil conditions across the region lead to a lack of precipitation being an insufficient trigger for drought losses for 17 farms.

[21] We used the rlm function included in the ‘MASS’ package in the statistical software environment R.

Figure 5.3. Location of Case Study Farms within German Federal States

5.3.2 Phenology and Weather Data

Table 5.3: Summary statistics of cumulative rainfall from stem elongation to milk ripening in liter per squaremeter

Mean	133.73
Median	127.1
Min	9.1
Max	402.7
Standard Deviation	56.14
Coefficient of Variation	0.42

To define critical farm-level growth phases, in which wheat is especially reactive to drought stress, we make use of a rich phenology observation network provided by the Deutscher Wetterdienst (DWD; engl. German meteorological office) (Dalhaus & Finger, 2016). As proposed by Dalhaus & Finger (2016) and Dalhaus et al. (2018), droughts during both periods from stem elongation to ear emergence and from ear emergence to milk ripening can cause large damages to final yields. Insurance contracts include the sum of rainfall across both stages as insured weather index.

Rainfall grid data is used to generate records of farm-level rainfall levels for the period 1997 to 2014. More specifically, we follow Dalhaus & Finger (2016) and use the RegNie weather rainfall grid, which is also provided by the DWD (available under ftp://ftp-cdc.dwd.de/). We used the read.regnie function provided within the ‘esmisc’ package of the statistical software environment R to derive this weather information (Szöcs, 2017).

5.4 Results

Table 5.4 Summary Statistics of Contract Parameters

		TWI	BWI
Strike level [millimeter]			
Median	Across all farms	127.70	206.20
Min		1.47	1.33
Max		5935.00	25850.00
Ticksize [€/millimeter]			
Mean	Across all farms	1.06	
Min		0.00	
Max		3.34	
Premium rate [in %]			
Mean	Across all farms	2.71	8.85
Min		0.00	2.54
Max		13.40	22.25
Years with payout [in %]			
Mean	Across all farms	24.6	78.0
Min		5.8	35.0
Max		60.0	100
Years with premium [in %]			
Mean	Across all farms	100	33.3
Min		100	38.44
Max		100	66.67

Table 5.4 gives summary statistics of the WI contract parameters. The median rainfall strike level was 206.20 mm for BWI and 127.70 mm for TWI respectively. The average Ticksize was 1.06 €/mm (here displayed in monetary terms, i.e. 0.07 deciton/ millimeter rainfall [yield terms] * 15.3 €/ deciton [wheat price]). The average premium rate for the TWI was 2.71% whereas it was 8.85% for the BWI. BWI was comparably more expensive because it did not include a deductible. Hence the percentage of years for which a payout was made was also considerably higher in the BWI case, 78% compared to 24.6% for TWI on average.

5.4.1 Risk reducing Properties of TWI and BWI according to EUT (Step 1)

Referring to our two step procedure described above, tables 5.5, 5.6 and 5.7 show Wilcox test results for step 1 (H1, H2 and H3). Test results for H1 and H2 in table 5.5 reveal, that while TWI significantly increases farmers' expected utility relative to a no insurance scenario, BWI with both ADJUSTMENTS in place does not. Thus, assuming a fair premium and EU preferences, only TWI products reduce weather risk and are thus beneficial for risk averse farmers. Accordingly, results for H3 indicate no statistically significant expected utility increase through BWI compared to TWI, which is unsurprising as BWI was proposed to better fit CPT preferences. The inability of BWI to increase EU compared to the no insurance scenario (H2) is due to the fact that the summed up premium payment at the end of the contract period is especially high in this context due to the non-existence of a deductible. If this end of contract payment occurs jointly with a yield loss event, the payment exacerbates the already bad financial situation of the farm. Thus, for BWI with both ADJUSTMENTS being fulfilled, farmers can be worse off in case of yield losses making this insurance design unattractive for risk averse EU decision makers, which exacerbates the consequences of basis risk. Results regarding hypotheses H1-H3 are robust across all levels of risk aversion tested. For risk neutral decision makers, no differences between the scenarios occur, indicating that the charged premium is actuarially fair.

Table 5.5. Wilcox Test Results for Changes in Expected Utility (H1, H2 and H3)

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.32	0.52
0.2	$3.72 \cdot 10^{-2}$	0.99	0.99
0.4	$4.58 \cdot 10^{-3}$	0.99	0.99
0.6	$1.61 \cdot 10^{-3}$	0.99	0.99
0.8	$1.00 \cdot 10^{-3}$	0.99	0.99
1.0	$7.20 \cdot 10^{-3}$	0.99	0.99

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

In addition to table 5.5, where both ADJUSTMENTS of BWI are fulfilled, table 5.6 shows tests for expected utility changes when ADJUSTMENT 1 is switched off. Here, BWI only differs from TWI with respect to the stochastic multiyear premium (ADJUSTMENT 2), i.e. small losses are uninsured. Accordingly, results for H1 do not differ from those displayed in table 5.5. In contrast, results for H2 show that expected utility of BWI is significantly greater compared to a no insurance scenario. Hence assuming a fair premium, BWI without ADJUSTMENT 1 is able to significantly reduce farmers' financial exposure to weather risk. For the sake of completeness, again H3 reveals that no differences exist between TWI and BWI with respect to expected utility changes, which was to be expected as the ADJUSTMENTS made were specifically suited to CPT decision makers.

Table 5.6. Wilcox Test Results for Changes in Expected Utility when switching off ADJUSTMENT 1 (insure also small losses) (H1, H2 and H3)

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.42	0.29
0.2	$3.72 \cdot 10^{-2}$	$2.48 \cdot 10^{-2}$	0.23
0.4	$4.58 \cdot 10^{-3}$	$2.72 \cdot 10^{-3}$	0.14
0.6	$1.61 \cdot 10^{-3}$	$2.04 \cdot 10^{-3}$	0.10
0.8	$1.00 \cdot 10^{-3}$	$2.96 \cdot 10^{-3}$	0.10
1.0	$7.20 \cdot 10^{-3}$	$3.70 \cdot 10^{-3}$	0.08

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

Table 5.7 shows test results for H1-H3 when switching ADJUSTMENT 1 back on and ADJUSTMENT 2 off. Here, small losses are insured and premiums are due every year. Results for H1 are in accordance to those of tables 5.5 and 5.6. Moreover, results for H2 show, that BWI insuring small losses is able to significantly increase expected utility and thus reduce farmers' financial exposure to weather risk. Thus BWI is EU increasing for each of the ADJUSTMENTS separately and only the combination of both (as indicated in table 5.5) seems to make BWI not EU increasing.

According to above results and unsurprisingly, H3 shows that no differences exist between expected utility of BWI and TWI insured farmers.

Table 5.7. Wilcox Test Results for Changes in Expected Utility when switching off Adjustment 2 (Conclude a multi-year contract and pay premiums only in years of no crop losses or, if there are no years with no losses, at the end of the contract period) (H1, H2 and H3)

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H_0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.32	0.52
0.2	$3.72 \cdot 10^{-2}$	$5.36 \cdot 10^{-2}$	0.30
0.4	$4.58 \cdot 10^{-3}$	$1.49 \cdot 10^{-3}$	0.14
0.6	$1.61 \cdot 10^{-3}$	$3.80 \cdot 10^{-4}$	0.18
0.8	$1.00 \cdot 10^{-3}$	$1.02 \cdot 10^{-4}$	0.10
1.0	$7.20 \cdot 10^{-3}$	$8.00 \cdot 10^{-5}$	0.04

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

5.4.2 Prospect Value Changes of TWI and BWI according to CPT (step 2)

The previous section focused on comparing TWI and BWI assuming farmers' preferences are characterized by standard EU assumptions. This section makes the same comparison but assuming that farmers' preferences are instead characterized by CPT. Regarding step 2 of our analysis, i.e. investigating the performance of the different insurance schemes across CPT specifications, table 5.4 shows significance levels of Wilcoxon test results of hypotheses H4 to H8, with respect to three different BWI designs, i.e. all ADJUSTMENTS fulfilled, ADJUSTMENT 1 switched off, ADJUSTMENT 2 switched off.

The second column of table 5.8 and the upper left graph of figure 5.4 present BWI results with all adjustments described above being fulfilled (According to table 5.5 of section 5.4.1). In this case, BWI provided no significant improvement with respect to prospect value compared to TWI for all CPT specifications, i.e. Bocquého, Jacquet. and Reynaud (2014) (*Boc.1*, *Boc.2* and *Boc.*3), Bougherara et al. (2017) (*Bou*) and Babcock (2015) (*Bab*).

The third column of table 5.8 displays results for BWI excluding ADJUSTMENT 1 (“insure also small losses”). Contrary to the first specification, BWI outperformed (in terms of prospect value) TWI for specifications *Boc.1*, *Boc.2* and *Boc.*3. Compared to the former column, this BWI design introduces more uncertainty in the gain domain, while overall losses are smaller, due to lower premiums caused by the now implemented deductible. Thus, the effect of saved premium payments outweighs the effect of covering small losses for these specifications. Said differently, loss aversion (the premium payments would be small losses for the insured) clearly dominates risk aversion in these cases.

The fourth column of table 5.8 shows results for BWI excluding ADJUSTMENT 2 (“Conclude a multi-year contract and pay premiums only in years of no crop losses or, if there are no years with no losses, at the end of the contract period”). Here, BWI does not outperform TWI (in terms of prospect value) across all specifications. In this scenario, premium payments (small losses from the perspective of the insured) come every year and the overall amount of losses is experienced more intensively as single year premium payments appear close to the reference point.

Table 5.8. Wilcox Test Results for Differences in the Prospect Value using CPT Specifications *Boc.1*, *Boc.2* *Boc.3* and *Bab* (H4 – H8)

	BWI with all adjustments fulfilled	BWI excluding adjustment ii) (Small losses not insured)	BWI excluding adjustment iv) (Payment every year)
Specifications	**p-value**[a,b] H0: $pv_{behavioral} \leq pv_{traditional}$ H1: $pv_{behavioral} > pv_{traditional}$		
H4: Boc.1	0.99	$5.29 \cdot 10^{-5}$	0.25
H5: Boc.2	0.99	$2.63 \cdot 10^{-4}$	0.87
H6: Boc.3	1	0.03	1
H7: Bou	1	0.15	0.99
H8: Bab	0.99	0.65	0.99

a Low p-values imply a rejection of the null hypotheses stated in H4-H8

b Bonferroni corrected p-values

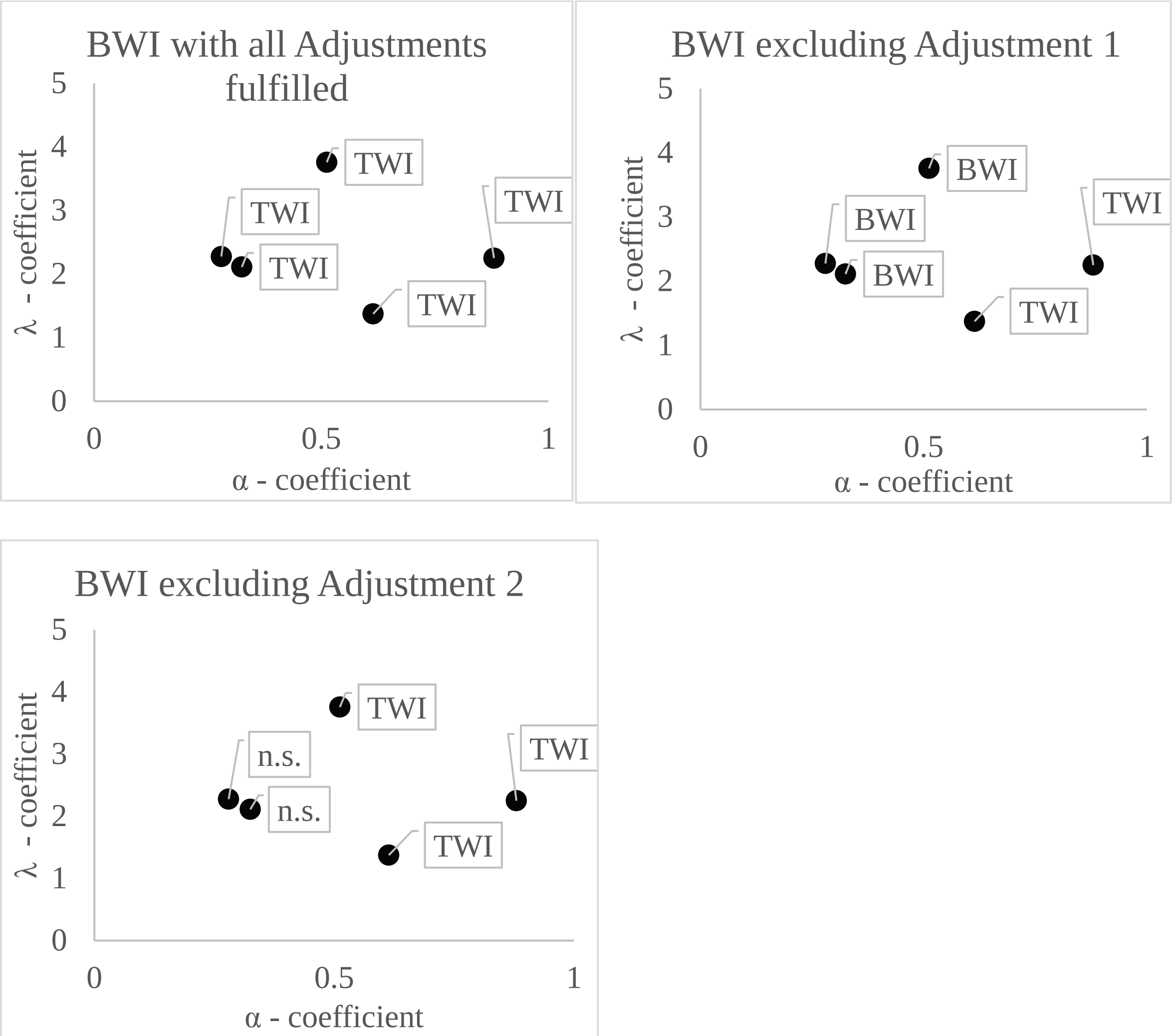

Figure 5.4 Performance of Weather Insurance schemes under different CPT Specifications.

n.s. = not significant. Neither of the both insurances outperformed the other.

Note: Flags indicate the outperforming insurance scenario according to test results displayed in table four. The underlying literature sources of CPT preferences can be derived from figure 1.

5.5 Discussion

Babcock (2015) shows that loss aversion can lead to a reduction of optimal crop insurance coverage levels and thus to less protection against potential income losses. The BWI proposed here aims to counteract this tendency by accounting for CPT properties of farmers' preferences. This includes transforming single year premiums into multiyear premiums (ADJUSTMENT 1). With BWI a farmer can also experience frequent small gains (insurance payouts) as a result of having no deductible (ADJUSTMENT 2). We introduce a two-step procedure to test the ADJUSTMENTS with respect to changes in the risk reducing properties (Step 1: Expected Utility Theory) and changes in the prospect value (Step 2: Cumulative Prospect Theory) under various real world preference scenarios.

Regarding step 1, we find that the actuarially fair BWI objectively reduces weather risk exposure as each of the ADJUSTMENTS separately increases EU while the combination of both ADJUSTMENTS does not. In the case of both ADJUSTMENTS being fulfilled, BWI is not able to increase EU as it can exacerbate adverse financial situations. Regarding this, Clarke (2016) finds that weather insurance becomes unattractive for risk averse decision makers if it worsens bad financial situations Thus, combining both ADJUSTMENT would increase the possibility of basis risk, i.e. the discrepancy between insurance payout and financial losses on the farm, through relatively high multiyear payments.

Regarding step 2, we find that the BWI with both ADJUSTMENTS implemented jointly, is also unable to increase the prospect value as compared to TWI. However, when switching off ADJUSTMENT 1, BWI increases the prospect value compared to TWI for CPT specifications in *Boc.1, Boc.2* and *Boc.3*. More specifically, higher risk aversion over gains and risk seeking over losses, such as observed in these specifications increases preferences for BWI compared to TWI. This is due to the fact that BWI with only ADJUSTMENT 1 implemented enables stochastic multi-year premiums rather than deterministic yearly premiums as is the case with TWI, satisfying the risk seeking behaviour over losses. Hence, stochastic multiyear premiums potentially increase the insurance demand of prospect value maximizing farmers. It needs to be noted that postponing premium payments also enables the possibility of strategic default possibly requiring actions to avoid this behavior (Elabed et al., 2013).

In contrast, a zero deductible design (ADJUSTMENT 1) does not benefit farmers in terms of prospect value as it increases the total amount of premium payments which are framed as losses in the CPT setting. This holds in the situation when both ADJUSTMENTS are fulfilled and when only ADJUSTMENT 1 is implemented. This result is in line with Babcock (2015) who shows that prospect value maximizing farmers with relatively low risk aversion and average loss aversion prefer insurance with higher deductibles. Consequently, a stochastic multiyear premium, although being itself prospect value increasing, is not able to counteract the overweighting of premium payments framed as losses. Thus the ‘segregation of silver linings’ is unable to counterbalance loss aversion in our case study. Regarding this, Du, Feng & Hennessy (2017) show that farmers are reluctant to buy actuarially fair insurance as out of pocket premium payments increase. This further underlines that farmers avoid higher premium payments even if these objectively reflect their risk profile in case of a fair premium.

It should be noted that our test results rely on the framing of insurance as stand-alone investment and thus the choice of the reference point. As indicated, we expect that more decision making behaviors might exist across farmers and that especially differences in the reference point can require further ADJUSTMENTS being necessary. We therefore see our analysis as first step into the direction of insurance being specifically designed according to farmers’ decision making behavior. Especially, findings of Köszegi & Rabin (2006) offer various entry points of adjusting the reference point to include also basis risk and frame this as a loss. Future research should take this into account and include experimental findings of farmers' behavior in insurance design. Regarding further behavioral economic insights and entry points for further research, Elabed & Carter (2015) deliver insights on how compound risk aversion influences index insurance demand under basis risk.

As our results rely on simulations, they have to be proven in the field before offering a market ready BWI. Furthermore, it is important to note that the analysis presented is based on data from large farms in eastern Germany. Due to differences in institutional structures, and possibly differences in risk preferences, future research could examine how generalizable these findings are to developing country contexts where many efforts to develop weather insurance markets are currently ongoing.

5.6 Conclusion

In summary, our approach proposes at two-step procedure to first set-up an insurance product that has risk reducing properties under EU and second evaluate insurances' prospect value under CPT. Recalling the analogy raised at the beginning of the article we compare our strategy to first design a healthy food product and second a packaging that fits observed purchase behavior. For both theories we propose to test for various preference scenarios. Our strategy includes a temporal redistribution of money flows to frame crop insurance in a way that we believe may be more attractive to farmers.

We find that for farmers with EU preferences, BWI is not preferred to TWI, which was to be expected. In fact, some BWI designs (both ADJUSTMENTS implemented) are not even preferred to a no-insurance scenario. However, when switching off either of the two ADJUSTMENTS BWI is able to reduce the financial exposure to weather risk and is preferred by farmers with EU preferences (is a healthy food product that should be consumed by risk averse farmers). Moreover and most importantly, for farmers with CPT preferences BWI may be preferred to

TWI depending on the assumed CPT preference specifications if only the stochastic multiyear premium is implemented (ADJUSTMENT 2). BWI might thus lead to an increase of insurance demand (as the packaging fits to observed purchase behavior).

Important conclusions can be drawn. First, to our knowledge this is the first study explicitly designing crop insurance in general and weather insurance in particular, according to farmers CPT preferences. By doing so, we point out, how integrated premium payments together with a multi-year contract, can lead to an increase in insurance demand. Second, we show that the relative benefits of the BWI depend strongly on assumed CPT value function characteristics such as the degree of risk aversion and loss aversion. In this respect, farmers' characteristics should be considered when designing individual crop insurance contracts to increase attractiveness of the contracts and thus insurance purchases. Hence, offering multiple types of contracts should be considered. Third, with BWI potentially more farmers are insured against downside risks compared to the initial state, which makes the farming system as a whole more resilient against climate shocks. Finally, recalling the contract parameters displayed in table 5.4 and weather summary statistics in table 5.3, we tested across a wide range of risk scenarios (as displayed through the very heterogeneous premium rates), we thus conclude that our findings are upscalable also to other perils and regions.

5.7 Appendix

Table 5.A1. Wilcox Test Results for Changes in Expected Utility (H1, H2 and H3) – Sensitivity Analysis two year contract

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.32	0.52
0.2	$3.72 \cdot 10^{-2}$	0.93	0.99
0.4	$4.58 \cdot 10^{-3}$	0.96	0.99
0.6	$1.61 \cdot 10^{-3}$	0.97	0.99
0.8	$1.00 \cdot 10^{-3}$	0.97	0.99
1.0	$7.20 \cdot 10^{-3}$	0.97	0.99

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

Table 5.A2. Wilcox Test Results for Changes in Expected Utility (H1, H2 and H3) – Sensitivity Analysis four year contract

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H_0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.32	0.52
0.2	$3.72 \cdot 10^{-2}$	0.99	0.99
0.4	$4.58 \cdot 10^{-3}$	0.99	0.99
0.6	$1.61 \cdot 10^{-3}$	0.99	0.99
0.8	$1.00 \cdot 10^{-3}$	0.99	0.99
1.0	$7.20 \cdot 10^{-3}$	0.99	0.99

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

Table 5.A3. Wilcox Test Results for Changes in Expected Utility when switching off ADJUSTMENT 1 (insure also small losses) (H1, H2 and H3) – Sensitivity Analysis two year contract

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H_0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.42	0.29
0.2	$3.72 \cdot 10^{-2}$	$3.32 \cdot 10^{-2}$	0.47
0.4	$4.58 \cdot 10^{-3}$	$1.63 \cdot 10^{-2}$	0.64
0.6	$1.61 \cdot 10^{-3}$	$1.27 \cdot 10^{-2}$	0.71
0.8	$1.00 \cdot 10^{-3}$	$1.84 \cdot 10^{-2}$	0.67
1.0	$7.20 \cdot 10^{-3}$	$1.63 \cdot 10^{-2}$	0.65

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

Table 5.A4. Wilcox Test Results for Changes in Expected Utility when switching off ADJUSTMENT 1 (insure also small losses) (H1, H2 and H3) – Sensitivity Analysis four year contract

	p-value[a/b]		
	H1	H2	H3
Coefficient of relative risk aversion φ	H_0: $eu_{traditional\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{traditional\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{no\ insurance\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{no\ insurance\ \varphi}$	H_0: $eu_{behavioral\ \varphi} \leq eu_{traditional\ \varphi}$ H_1: $eu_{behavioral\ \varphi} > eu_{traditional\ \varphi}$
0	0.56	0.42	0.29
0.2	$3.72 \cdot 10^{-2}$	0.44	0.80
0.4	$4.58 \cdot 10^{-3}$	0.21	0.90
0.6	$1.61 \cdot 10^{-3}$	0.13	0.84
0.8	$1.00 \cdot 10^{-3}$	0.11	0.91
1.0	$7.20 \cdot 10^{-3}$	0.10	0.92

a Low p-values imply a rejection of the null hypotheses stated in H1-H3.

b Bonferroni corrected p-values

Table 5.A5. Wilcox Test Results for Differences in the Prospect Value using CPT Specifications *Boc.1*, *Boc.2 Boc.3* and *Bab* (H4 – H8) – Sensitivity Analysis two year contract

Specifications	BWI with all adjustments fulfilled	BWI exluding adjustment ii) (Small losses not insured)
	p-value[a,b] $H_0: pv_{behavioral} \leq pv_{traditional}$ $H_1: pv_{behavioral} > pv_{traditional}$	
H4: Boc.1	1	$4.73 \cdot 10^{-4}$
H5: Boc.2	1	$4.73 \cdot 10^{-3}$
H6: Boc.3	1	$9.66 \cdot 10^{-4}$
H7: Bou	1	$2.90 \cdot 10^{-3}$
H8: Bab	0.99	$3.79 \cdot 10^{-2}$

a Low p-values imply a rejection of the null hypotheses stated in H4-H8

b Bonferroni corrected p-values

Table 5.A6. Wilcox Test Results for Differences in the Prospect Value using CPT Specifications *Boc.1*, *Boc.2* *Boc.3* and *Bab* (H4 – H8) - Sensitivity Analysis 20 % Loading

Specifications	BWI with all adjustments fulfilled	BWI exluding adjustment ii) (Small losses not insured)	BWI excluding adjustment iv) (Payment every year)
		p-value[a,b] H0: $pv_{behavioral} \leq pv_{traditional}$ H1: $pv_{behavioral} > pv_{traditional}$	
H4: Boc.1	0.99	$1.35 \cdot 10^{-5}$	1
H5: Boc.2	0.99	$5.48 \cdot 10^{-5}$	1
H6: Boc.3	1	0.03	1
H7: Bou	1	0.13	1
H8: Bab	0.99	0.58	1

a Low p-values imply a rejection of the null hypotheses stated in H4-H8

b Bonferroni corrected p-values

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