European Review of Agricultural Economics Vol **48 (2)** (2021) pp. 266–314
doi:10.1093/erae/jbab010
Advance Access Publication 10 February 2021

Insuring crops from space: the potential of satellite-retrieved soil moisture to reduce farmers' drought risk exposure

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Received October 2019; final version accepted January 2021

Abstract

Crop producers face significant and increasing drought risks. We evaluate whether insurances based on globally and freely available satellite-retrieved soil moisture data can reduce farms' financial drought risk exposure. We design farm individual soil moisture index insurances for wheat, maize and rapeseed production using a case study for Eastern Germany. We find that the satellite-retrieved soil moisture index insurances significantly decrease risk exposure for these crops compared to the situation where production is not insured. The satellite-retrieved index also outperforms one based on soil moisture estimates derived from meteorological measurements at ground stations. Important implications for insurers and policy makers are that they could and should develop better suited insurances. Available satellite-retrieved data can be used to increase farmers' resilience in a changing climate.

Keywords: remote sensing, weather index insurance, soil moisture, risk management, agriculture

JEL Code: G22, Q14, Q54

1. Introduction

Droughts put agricultural production and thus farmers' incomes at risk. Systemic drought events are expected to become more frequent and severe in Central Europe due to climate change (e.g. Grillakis, 2019; Kahiluoto *et al.*, 2019; Seneviratne *et al.*, 2010, 2012; Trnka *et al.*, 2014). This is leading to an increasing demand for advanced agricultural drought risk management,

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also through insurance schemes (e.g. Bjerge and Trifkovic, 2018; Finger and El Benni, 2020; Meuwissen, Mey and van Asseldonk, 2018). Index insurances are viable solutions to insure agricultural production, especially for drought risks which can hit an entire region simultaneously and for which there are hardly any insurances in place.

In this paper, we investigate the potential of index insurances based on globally and freely available satellite-retrieved soil moisture data to cope with drought risks. Additionally, we compare index insurances based on satellite-retrieved information with insurance based on spatially interpolated, gridded soil moisture estimates derived from meteorological measurements at ground stations. We quantify the reduction of farmers' financial drought risk exposure in a case study on winter wheat, rapeseed and maize in Eastern Germany.

Systemic droughts affect regions, countries or even larger areas over a long period (Grillakis, 2019) and are a major risk to farmers' income security. With associated yield losses occurring simultaneously, a large amount of loss adjustment-related administration has to be done within a limited assessment window.

The human and economic resources to conduct physical inspections at every farm in a drought-affected region are not available. Therefore, reducing damage assessment time is particularly interesting for systemic risks. Index insurances are cost efficient, reduce the problem of asymmetric information, allow efficient and fast determination of payouts (Barnett and Mahul, 2007) and are thus rapidly being developed in both developing and developed countries (e.g. Jensen, Barrett and Mude, 2015; Leblois and Quirion, 2013; Vroege, Dalhaus and Finger, 2019). We expect that indices based on soil moisture estimates perform well in an insurance setting (Kellner and Musshoff, 2011) because moisture represents the site-specific water deficits resulting from prevalent meteorological conditions, topography and soil properties as well as the crops' physiology (Seneviratne *et al.*, 2010; West, Quinn and Horswell, 2019). Measuring soil moisture *in situ* is however difficult and expensive, and spatial coverage is scarce (Dorigo *et al.*, 2013). Weather-station measurements alone might be an insufficient proxy for soil moisture distant to these stations. Consequently, research interest in the retrieval of soil moisture information by satellites is large (e.g. Albergel *et al.*, 2013; Brocca *et al.*, 2017; de Jeu and Dorigo, 2016; Dorigo and de Jeu, 2016; Dorigo *et al.*, 2017; Hirschi *et al.*, 2014; Martínez-Fernández *et al.*, 2016; Nicolai-Shaw, 2016; Peng and Loew, 2017; Sönegard, 2017). The potential of satellite-retrieved soil moisture measurements in the index design has to our knowledge only been explored without assessing the financial risk-reducing capacity of such insurance schemes at the farm level (Enenkel *et al.*, 2018). Moreover, research and practice on the use of satellite-retrieved data in drought index insurances also considered sensing of the health status of the plant, precipitation and evapotranspiration (see for example Black *et al.* (2016), Bokusheva *et al.* (2016), Enenkel *et al.* (2018), Jensen *et al.* (2019), de Leeuw *et al.* (2014), Roumiguié *et al.* (2017), Vrieling *et al.* (2014) and Vroege, Dalhaus and Finger (2019)).

We extend this literature by quantifying the economic benefits of satellite-retrieved soil moisture measurements in an index insurance scheme for single farms. More specifically, we assess whether a satellite-based index insurance (based on the European Space Agency Climate Change Initiative (ESA CCI) satellite soil moisture product) reduces farmers' financial risk exposure (i.e. farmers risk premium) compared to (i) a situation without insurance and (ii) to an index insurance based on gridded soil moisture estimates derived from meteorological measurements at ground stations (taken from the German Meteorological Service, DWD). We also compare the two insurance options in terms of data availability and quality, spatial resolution and the recognition of individual farming practices (e.g. irrigation). We base our analysis on a case study with unique data from 89 large-scale farms from 1995 to 2015 which produce winter wheat, rapeseed and silage maize in Eastern Germany. This important grain production region is highly susceptible to droughts (Trnka *et al.*, 2014).

We find that both satellite-based and the gridded meteorological station-based soil moisture index insurances can significantly decrease the risk exposure of crop producers. We provide insights to opportunities and challenges of using satellite-retrieved and meteorological station-based soil moisture information. We highlight that the performance of an insurance depends on the location of the farm, the insured crop and the insurance design. Our results allow insurers to develop more efficient drought insurances and thus contribute to a better drought risk management in agriculture.

The remainder of this paper is organized as follows. First, we provide a conceptual framework to condition index insurance payouts to a single farms' risk exposure based on quantile regression and we elaborate on the context of soil moisture as an index variable. Based on this, we develop a testing strategy for the risk-reducing capacity of weather index insurances. After presenting the datasets, we present the results, including the attained risk premium reduction. Finally, we discuss crucial dataset characteristics and draw conclusions for policy makers, insurance practitioners and future research.

2. Background

2.1. Conceptual framework

In index insurance designs, an insurance pays out solely based on an independent index containing one or multiple parameters. This index should correlate with crop yield losses. For an index insurance to be successful, it is important that the index is comprehensive, cannot be influenced by either the insurer or the insured and that data continuity is guaranteed both historically and in the future (Cole *et al.*, 2013; Vrieling *et al.*, 2014). A general advantage of index insurances is that there are no information asymmetries, which means that both the insurance and the crop grower have the same information about the index data. Hence, problems of moral hazard (a shift to riskier practices) and adverse selection (risk exposed farms buying insurances more often) of traditional insurances can be overcome with index insurances

(Turvey, 2001; Vedenov and Barnett, 2004). Moreover, weather index insurances can be fully tailored to farm or even field-individual yield and historical weather records. Index insurances' key drawback is that measurements independent of the yield cannot reflect yield losses perfectly. This problem is known as basis risk (Dalhaus, Musshoff and Finger, 2018; Woodard and Garcia, 2008) and can lead to damages without indemnity payments or vice-versa. An often-named example of basis risk is that a rainfall event may occur at a weather station but not at a distant field, so even a dense network of weather stations might miss this kind of idiosyncratic events. This has important implications for farmers' index insurance uptake (Clarke, 2016) and for the legal basis of index insurances (Vroege, Dalhaus and Finger, 2019).

The goal of the insurances considered here is to reduce financial losses arising from droughts and thus reduce farmers' risk exposure. We focus on insuring changes in production levels while assuming constant price levels.[1] Therefore, farm i pays an annual insurance premium Pr_i. If the severity of a drought in year t undercuts a pre-set threshold (strike level S_i) in terms of soil moisture, farm i receives an insurance payout $PO_{i,t}$:

$$\pi_{i,t} = P * Y_{i,t} - Pr_i + PO_{i,t} \tag{1}$$

where $\pi_{i,t}$ is the insured revenue of crop production, P is the crop price and $Y_{i,t}$ is the crop yield.

We assume a fair premium so that the premium reflects the expected level of payouts made over time (equation (A1) in the appendix). If there is no indicated drought event, the magnitude of the payout is zero. In case of a drought, more specifically when the soil moisture is below the strike level, the magnitude of the payout is determined by the severity of the soil moisture deficiency and the monetary payout per missing index unit (the tick size):

$$PO_{i,t} = \max\{0, S_i - I_{i,t}\} * T_i \tag{2}$$

where $PO_{i,t}$ is the payout, S_i is the individual strike level, T_i the tick size and $I_{i,t}$ the index value (see equation (A2)-(A3)).

To evaluate insurance options and to compare the satellite-retrieved and meteorological station-based index insurances, we assess the reduction of the farm-individual risk premium (RP) in an expected utility maximization framework. This framework allows us to compare and evaluate different insurance options in terms of their ability to reduce basis risk. More specifically, the risk premium reflects the loss of utility a producer experiences through the presence of risk. The risk premium depends on the risk exposure, which

1 Droughts might also indirectly affect the risk exposure of farmers via price mechanisms, however it remains unclear in which direction. On one hand, crop prices could increase during a drought due to negative price-yield correlations (Finger, 2012). On the other hand, the use of forward contracts increases the need for insurance mechanisms to cope with production risks because production targets are contractually fixed. The use of forward contracts is typical in the case study region (Anastassiadis *et al.*, 2014).

consists of the variably of revenues and risk preferences. The risk premium can be approximated as in equation (3) (see for example Chavas, 2004):

$$RP \approx -\sum_{q=2}^{k} \left[\frac{1}{q!}\right] (U^q/U^1) M_q \tag{3}$$

where derivatives of the utility function are $U^q = \partial^q U / \partial x^q$; and moments M_q of the revenue distribution are represented as follows:

$$M_q = E[\pi_{i,t} - E(\pi_{i,t})]^q. \tag{4}$$

We test the superiority of having insurance over having no insurance[2] (as well as differences across insurance solutions) by comparing the respective risk premiums. More specifically, any improvement in the ability to reduce the financial exposure to drought risk, for example by using an insurance or substituting different data sources in the insurance design, would *ceteris paribus* result in a reduced risk premium. Under the assumption of fair premiums, this results in a higher expected utility for the farmer.

2.2. Soil moisture as the index variable

To represent droughts, we chose soil moisture as the index variable. Agricultural droughts are typically defined as the combined effect of shortage in precipitation and enhanced evapotranspiration (induced by enhanced radiation, wind speed, or a vapour pressure deficit), leading to a critical drop in soil moisture that negatively affects crop yields (Panu and Sharma, 2002). Soil moisture is the water content of the unsaturated part of the soil and typically expressed as m^3 water per m^3 of soil (volumetric soil moisture content). Depending on soil type, absolute levels and dynamic ranges of volumetric soil moisture differ between locations, even at shorter distances (Mittelbach and Seneviratne, 2012). Alternatively, soil moisture can also be defined in relation to the porosity of the soil as percentage (or degree) of saturation, indicating the fraction of pore volume that is filled with water (Seneviratne *et al.*, 2010). This relative measure reduces the impact of static soil properties and can be derived by rescaling the volumetric soil moisture time series (Brocca *et al.*, 2014). Soil moisture is crucial for agricultural production and is of key importance for various climate processes as it impacts the partitioning of the available energy at the earth surface into sensible and latent heat fluxes as well as the generation of runoff and groundwater recharge (Seneviratne *et al.*, 2010). We favour soil moisture as our index variable because it integrates both effects from water in—and outflows and it allows to account for temporal autocorrelation, as it accounts for water in—and outflows from previous periods.

2 The scenario in which farmers do not have drought insurance is a realistic scenario in our case study region (see also Section 4.1). In regions, where other insurance solutions such as area-yield insurances (Glauber, 2013) or farm income insurances (El Benni, Finger and Meuwissen, 2016; Turvey, 2012) are in place, other reference scenarios might be of further interest.

Measuring soil moisture on ground is difficult and costly and, accordingly, coverage with *in situ* soil moisture data is scarce (Dorigo *et al.*, 2013; Panu and Sharma, 2002; Seneviratne *et al.*, 2010). As a consequence, scientific interest in the retrieval of global soil moisture estimates from satellite sensors has grown in recent years (de Jeu and Dorigo, 2016; Dorigo and de Jeu, 2016). Multiple satellite sensors are available that can be used to retrieve soil moisture data globally (de Jeu and Dorigo, 2016). Soil moisture remote sensing is mostly based on micro-wave techniques which can provide information on moisture conditions in the upper few centimetres of the soil. Due to the large contrast between the dielectric properties of dry soil and water, the microwave radiance emitted or reflected by the surface soil volume is almost linearly dependent on the soil–water mixing ratio (Ulaby, Moore and Fung, 1982). Both active and passive microwave instruments can be used to retrieve soil moisture information. Active instruments emit microwave radiation themselves and measure variations in the reflected backscatter. Passive instruments measure the natural emissions from reflected (sun)light. Both options can provide observations under nearly any weather conditions and independent of daylight (Dorigo *et al.*, 2017). Retrievals are however impossible under snow and ice or when the soil is frozen, and complex topography, surface water, and urban structures have negative impacts on the retrieval quality. In addition, dense vegetation attenuates the microwave emission and backscatter from the soil surface and may mask the soil moisture signal. Altogether, these limitations may result in spatio-temporal data gaps of remote-sensing based soil moisture estimates.

In addition, global and regional soil moisture estimates can be derived by means of modelling (e.g. with a land surface or agrometeorological model (AMBAV)) using observed meteorological variables as input (e.g. Seneviratne *et al.*, 2010). The meteorological forcing therefore can be either based on gridded measurements from meteorological stations (e.g. Balsamo *et al.*, 2015; Orth and Seneviratne, 2015) or directly based on meteorological measurements at the stations with a subsequent gridding of the calculated soil moisture data (e.g. Deutscher Wetterdienst, 2018, further described in Section 4.3 DWD station-based soil moisture product). In both cases, the resulting soil moisture estimates are dependent on the quality of the applied physical model as well as the quality of the meteorological input data and gridding procedures.

Droughts affect crops differently. This can be due to differences in physiology, their root architecture (Walter, Silk and Schurr, 2009), and due to temporal differences of their phenological phases (Estrella, Sparks and Menzel, 2007) across crops. For insurance purposes, it is meaningful to focus on drought occurrence during crops' generative (and vegetative) phase, in which crops are most vulnerable to drought (Dalhaus, Musshoff and Finger, 2018). A drought during the generative phase leads for example to a reduced number of grains (wheat), reduced filling of the pods (rapeseed) or concurrence during the female and male reproductive organs (silage maize). Droughts during the vegetative phase of crops lead to less developed rooting systems and reduced leaf areas, numbers and lifetime. However, when still in the vegetative phase, crops can recover relatively well when water is again available and yield reductions are often lower (e.g. Daryanto, Wang and Jacinthe, 2017; Farooq, Hussain and Siddique, 2014; Hlavinka *et al.*, 2009; Qaderi, Kurepin and Reid, 2006).

3. Empirical implementation

We compare the risk-reducing capacity of index insurances based on different index specifications to each other and to scenarios without insurance. Following Dalhaus, Musshoff and Finger (2018), we focus on the critical phenological phases of each crop and restrict the index measurement to this time frame. The indices are the median[3] of farm-individual satellite-retrieved soil moisture estimates (I_{sat}) and the median of the meteorological station-based soil moisture estimates ($I_{station}$) at the farm-level within different critical phenological phases. More specifically, we use two definitions of the critical phenological phase per crop to avoid biased inference due to potential imprecisions in the phenology reporting. We use a 'short phase', which includes the crop's generative phase. Moreover, we consider an extended phase, which additionally includes a preceding (wheat and maize) or a subsequent (rapeseed) phase. In total, we test 12 different insurances based on two methods, in two phenological phases for three crops and six scenarios without insurance (two phenological phases for three crops).

We detrend the yield data to account for technological progress. More specifically, we use Germany-wide yield data provided by the German statistical office Destatis (Statistisches Bundesamt (Destatis), 2019) to find a common linear time trend for all farms using the robust, i.e. outlier resistant, M-estimator following Finger (2013).[4]

We first estimate the impact of the respective index variable I on farm-specific yields[5] using quantile regression. Then, we use these estimates to design the insurance contract parameters, i.e. strike levels and tick sizes, and simulate historical insurance payouts and derive respective insurance premiums. From this, we obtain simulated revenue observations per farm, per crop, per year and per index specification. Eventually, we test for differences in the risk premiums between these different scenarios.

To find individual impacts of soil moisture deficits on yield losses, we use a regression framework to estimate equation (5):

$$Y_{i,t} = \beta_{0_{i,v}} + \beta_{1_{i,v}} * I_{i,t,v} + \varepsilon_{i,t,v} \tag{5}$$

3 We use the median soil moisture of all estimates within the insured timeframe to get a more robust estimate (compared to the mean) of the soil moisture average.

4 To transform yields into monetary units, we use the following crop prices: 15.1 €/dt for wheat, 35.9 €/dt for maize and 41 €/dt for rapeseed (Kuratorium für Technik und Bauwesen in der Landwirtschaft, 2019).

5 To address potential overfitting issues, we also use other approaches: one in which we use pooled yields of all other farms but exclude the farm's own yields and one in which we use farm-specific yields but exclude the year in which we specify insurance payouts. See also the discussion section as well as Tables A15 and A16.

where $Y_{i,t}$ reflects the individual yield at farm i in year t, $\beta_{0_{i,v}}$ and $\beta_{1_{i,v}}$ farm individual regression coefficients (intercept and slope) for each index specification v (i.e. soil moisture from satellite observations or derived from meteorological measurements at ground stations), $I_{i,t,v}$ is the soil moisture index value at farm i in year t for the index specification v and the error term $\varepsilon_{\mathrm{i,t,}v}$ reflects the farm, year and index-specific basis risk, i.e. the potential mismatch between the index value $I_{i,t,v}$ and the crop yield $Y_{i,t}$ (e.g. Woodard and Garcia, 2008). With this farm-specific regression framework, we assess the relationship between soil moisture and lower yields for each farm individually. These farm-fixed effects allow for control of farm-specific, time-invariant factors such as soil types.[6] Because we are particularly interested in the impact $\beta_{1_{i,v}}$ of $I_{i,t,v}$ for low levels of yield $Y_{i,t}$, we follow Conradt, Finger and Bokusheva (2015) and use quantile regressions (equation (6)) to find the regression coefficients $\beta_{0_{i,v}}$ and $\beta_{1_{i,v}}$, which we use to set individual strike levels $S_{i,v}$ and tick sizes $T_{i,v}$. Quantile regression allows us to focus on the impact of the weather index $I_{i,t,v}$ in the lowest 30 per cent ($\tau = 0.3$) of yield observations. More specifically, quantile regression minimizes the absolute distance sum between fitted values $x^T_{i,t,v} * \beta_{1_{i,v}}$ and observed values $Y_{i,t}$ while weighting downside yield events by $(1-\tau)$ and upward residuals by

$$\widehat{\beta_{1_{i,v}}}(\tau) = argmin\left(\tau * \sum_{Y_{i,t} \geq x^T_{iv}\beta_{1_{i,v}}} \left|Y_{i,t} - x^T_{i,t,v} * \beta_{1_{i,v}}\right| + (1-\tau) * \right.$$

$$\left. \sum_{Y_{i,t} < x^T_{i,t,v}\beta_{1\,i,v}} \left|Y_{i,t} - x^T_{i,t,v} * \beta_{1_{i,v}}\right|\right). \tag{6}$$

Quantile regression is therefore more robust against outliers compared to Ordinary Least Squares (OLS) regression and allows us to condition the insurance to downside yield events.

We design insurance contracts when the impact $\beta_{1_{i,v}}$ of the index variable $I_{i,t,v}$ on the yield $Y_{i,t}$ is positive following quantile regression. In other words, when we find a positive relation between the index and yields, while focussing on the lower tail of the yield distribution, we assume that farms voluntarily buy the index insurance contract in all years for which we know their yields.[7] Based on the positive quantile regression estimates, we simulate payouts $PO_{i,t,v}$ of farm i in year t and for index specification v. As in Dalhaus, Musshoff and Finger (2018), we expand the individual payout distributions

6 If farm-level data are not available and regional-level yields are used to design the insurance, the inclusion of additional information such as information on soil types has been shown to improve the insurance design (Du *et al.*, 2017; Woodard and Verteramo-Chiu, 2017).

7 Note that when this relationship is negative, drought is not a major weather risk for the farm (quantile regression suggests that drier conditions imply higher yields). It is thus not possible to design a drought index insurance with fair premiums.

using a bootstrapping procedure with 1000 draws and take the average of these as farm individual premium $Pr_{i,v}$ and derive insured revenues $R_{i,t,v}$ according to equation (1). Note that for the scenarios without insurance ($v =$ uninsured production), the insurance payouts and premiums in equation (1) are zero, i.e. the revenues of farm i are uninsured and thus solely depend on yields and prices.

To compare the satellite-retrieved and meteorological station-based index insurances and compare them to scenario's where farmers do not have insurance, we assess the reduction of the farm-individual risk premium $RP_{i,v}$ in an expected utility framework. We follow Di Falco and Chavas (2006) and define the risk premium $RP_{i,v}$ (see equation (3)–(5)) of farm i for each index specification v with respect to moments $\sigma^2_{\pi_{i,v}}$ (variance) and $\sigma^3_{\pi_{i,v}}$ (skewness)[8] (equation (A4)-(A5)) of the revenue distribution as follows:

$$RP_{i,v} = -\frac{1}{2} * U''/U * \sigma^2_{\pi_{i,v}} - \frac{1}{6} * U'''/U' * \sigma^3_{\pi_{i,v}}, \tag{7}$$

where $-U''/U'$ represents the Arrow–Pratt coefficient of risk aversion and $-U'''/U'$ reflects the aversion against downside risks (e.g. Chavas, 2004). We follow Leblois *et al.* (2014) and base the analysis on the power utility function:

$$U = \frac{1}{1-\alpha}\pi^{(1-\alpha)}. \tag{8}$$

To test for differences in a farm's risk exposure across insurance options, we compare different vectors of individual risk premiums RP_v with paired difference tests, i.e. the Wilcoxon−signed-rank test comparing the relative rank (Dalhaus, Musshoff and Finger, 2018). Because farmers' level of risk aversion α is highly diverse (Iyer *et al.*, 2020), we compare the risk-reducing capacities of insurances for different levels of risk aversion $\alpha \in [0.5, 2, 3,4]$. The chosen levels of risk aversion reflect recently elicited risk preferences of German farmers (see Iyer *et al.*, 2020 for an overview).

4. Data

4.1. Yield and phenology data

We use unique crop yield data from 1995 to 2015 on 89 farms in Eastern Germany (Figure A1 and Table A1), collected by a local agricultural insurance agency. These data are from large-scale farms (i.e. farms representative for Eastern Germany, where farms are on average about 400 ha (Bokusheva and Kimura, 2016; Hartvigsen, 2014; Huettel *et al.*, 2013)) and yield records

8 Higher moments of the revenue distribution such as Kurtosis and decision maker's preference with respect to these higher moments may also influence farmers' decisions. Yet, previous research has shown little relevance of these higher moments in empirical research (e.g. Chavas, 2004; Groom *et al.*, 2008). Indeed, including kurtosis (and higher moments) in our analysis did not change our results.

for different crops are available at the farm level. Of these farms, 85 farms provide winter wheat yield records, 82 rapeseed and 43 maize yield records. Most yield records are not complete for all years, with the majority of missing values before 1997 and after 2013. The average record length is 14.5 years. Until 2015, there were no drought insurance options available to farmers in this region. Recently, a German insurance company (Vereinigte Hagel) started offering a double trigger drought index insurance. This insurance pays out when both regional soil moisture estimates from the German meteorological service (DWD) and regional yield levels are below a certain threshold (Vereingte Hagel, 2019). Also the payout size is determined based on the regional level yield losses. Due to the double trigger and because also the size of the payout is determined based on the regional yield level, this product suffers from a considerable amount of basis risk. Also, governmental ad hoc disaster aid payments are still paid to the most drought affected farms, for example in 2018 (Bundesministerium für Ernährung und Landwirtschaft, 2018), setting incentives for more risky production practices. As a result, there is currently still a low drought insurance uptake.

To define the insurance period, we follow Dalhaus and Finger (2016) and Dalhaus, Musshoff and Finger (2018) and chose the insurance start and end date based on phenology observations. We extend the approach of Dalhaus, Musshoff and Finger (2018) by using site- and crop-specific phenology estimations of plant growth stages taken from the phase model (Gerstmann *et al.*, 2016). This interpolation model is developed specifically to interpolate a German phenology point database that is provided by the German Weather Service and based on real phenology reports of voluntary observers from over 1200 active stations (Deutscher Wetterdienst, 2019a; Gerstmann *et al.*, 2016). The model uses daily mean temperatures as well as a free elevation data product to interpolate the phenological observations (Gerstmann *et al.*, 2016) to 1 km $\times$ 1 km gridded phenology estimates for crops in Germany. This model thus provides Germany-wide gridded data on 'day of the year' (DOY) of the start of crop-specific growth phases. In the case of wheat, the generative phase (here: 'short' phase) lasts from heading until milk ripeness and the extended time frame starts with the earlier stem elongation (see Table 1). The generative phase of rapeseed goes from bud formation until flowering and as extension, we used a timeframe lasting until full ripeness of the rapeseed. For maize, we use the generative phase going from the visibility of the tip of the tassel until flowering. We also consider an 'extended' phase in which the insured timeframe already starts with the vegetative growth in height. See Table 1 for an overview and Figures A2-A4 for more details. The definition of the phases is based on the manual on the phenology data (Deutscher Wetterdienst, 2014).

4.2. ESA CCI satellite-retrieved soil moisture product

The ESA CCI data (version 04.4) offer a global harmonized surface soil moisture product based on satellite-retrieved information covering more than 40 years (Dorigo *et al.*, 2017; Gruber *et al.*, 2017). Three products are

Table 1. Description of the phenological start and end of the critical growth phases per crop

Crop	Phase	Start	End
Wheat	Extended	Stem elongation	Milk ripeness
Wheat	Short	Heading	Milk ripeness
Rapeseed	Extended	Bud formation	Full ripeness
Rapeseed	Short	Bud formation	Flowering
Maize	Extended	Growth in height	Flowering
Maize	Short	Tip of tassel visible	Flowering

available: one from active and one from passive microwave sensors, as well as a product based on a combination of both data sources based on their error characteristics (Liu *et al.*, 2012, 2011). The data are available at a resolution of 0.25° (∼28 km × 18 km in Eastern Germany) at a daily basis and regularly updated with a latency of about 1 year at the ESA CCI website. Recently, the ESA CCI soil moisture data (version 03.3) have been integrated in the Copernicus Climate Data Store data and are now made available with an update frequency of 10 days (Copernicus Climate Change Service, 2019).

Soil moisture content is given in unit of m^3m^{-3} for the passive and combined (active and passive) product and in degree [per cent] of saturation for the active product. We use version v04.4 of the combined product, which has increased coverage due to the optimal combination of both retrieval techniques. In the production process, the ESA CCI soil moisture product is validated with *in situ* measurements from the International Soil Moisture Network (Dorigo *et al.*, 2013). The ESA CCI product provides information on moisture conditions in the upper few centimetres of the soil. This layer is highly correlated with soil moisture of deeper soil layers, except under very dry conditions when the surface layer may dry out completely and thus exhibit a reduction in temporal variation (Hirschi *et al.*, 2014). For our study region however, such behaviour is less relevant as complete dryness is not encountered.

We rescale the volumetric soil moisture content (in m^3m^{-3}) to percentage (or degree) of saturation following Brocca *et al.* (2014) to correct the soil moisture index for spatially varying soil porosities. The rescaling is done relative to the observed minimum and maximum soil moisture values within the analysed 1995 to 2015 time period (Table 2, Table A2 and Figure A5).

The spatio-temporal coverage of the ESA CCI product increases over time due to the increasing number of available satellites, reaching 80 per cent to full temporal coverage for recent years in most parts of the case study region (Dorigo *et al.*, 2017). Nevertheless, full coverage cannot be achieved for specific grid cells and due to the limitations outlined in Section 2.2.

4.3. DWD station-based soil moisture product

We compare the index insurance based on satellite-retrieved soil moisture to a gridded meteorological station-based soil moisture product

Table 2. Overview of two soil moisture products

	ESA CCI satellite product v04.4	DWD station-based product
Spatial resolution	0.25°	1 km × 1 km
Temporal resolution	Daily	Daily
Record length	40 years	27 years
Unit	m^3m^{-3} rescaled to per cent of saturation	per cent plant available water capacity under grass and for sandy loam soil
Lag until data available	∼1 year[a]	∼1 month

[a] A predecessor version of this product with an update frequency of 10 days is made available within the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/).

(Deutscher Wetterdienst, 2019b).[9] The DWD calculates soil moisture values at 280 weather stations throughout Germany for sandy loam soils covered with grassland. The values represent soil moisture of the top 60 cm soil column and are calculated with an AMBAV (Löpmeier, 1994) using meteorological measurements as inputs. The soil moisture unit is in percentage of plant available water capacity assuming a wilting point of 13 volume per cent and a field capacity of 37 volume per cent. Subsequently, the DWD interpolates the calculated soil moisture values into a publicly available gridded dataset with a spatial resolution of 1 km × 1 km by using regionalised multiple linear regression and triangulation with respect to orographic parameters (Table 2, Table A3 and Figure A6) (Deutscher Wetterdienst, 2018). The interpolation does not adjust the soil moisture values to soil and vegetation type and thus uncertainties arise from model design, parameterization and interpolation (Gerstmann *et al.*, 2016). Publication of the latest data is done at the end of the penultimate month, which allows an indemnification in near time. Summary statistics of the yield, index values and phenology observations are provided in Table 3.

5. Results and discussion

By assessing the individual risk premium change for all farms, we find that both the satellite-based and the meteorological station-based soil moisture index insurance products significantly decrease farmers' risk exposure. More specifically, they reduce the sample average risk premium of crop production for each crop and timeframe (Table 4). Regarding the meteorological station-based insurances, these findings are in line with previous findings of Kellner and Musshoff (2011). We find some differences in the performance of the two insurance options for different crops and timeframes, but there is no clear best insurance option regarding the soil moisture estimation method. The satellite product significantly outperforms the meteorological station-based product in the extended insured time frame of maize and the meteorological station-based product performs better in the shorter insured time frame of rapeseed

9 The non-gridded version of this data set has been tested in an index insurance setting by Kellner and Musshoff (2011).

Table 3. Summary statistics

	Variable	Mean	Std.	Min	Max
Wheat	Yield (dt/ha)	74.53	14.44	21.72	117.39
	$I_{station}$, extended[a]	0.68	0.09	0.47	0.98
	$I_{satellite}$, extended	0.43	0.09	0.13	0.68
	$I_{station}$, short[b]	0.64	0.10	0.42	0.99
	$I_{satellite}$, short	0.45	0.10	0.01	0.87
	First day (DOY) of extended critical crop growth phase	117	7	95	136
	First day of short critical crop growth phase	152	7	133	173
	Last day of both critical crop growth phases	182	8	160	206
Rapeseed	Yield (dt/ha)	41.82	8.19	10.75	63.22
	$I_{station}$, extended	0.68	0.09	0.48	0.93
	$I_{satellite}$, extended	0.45	0.09	0.18	0.69
	$I_{station}$, short	0.83	0.10	0.56	1.07
	$I_{satellite}$, short	0.47	0.11	0.07	0.82
	First day of both critical crop growth phases	102	9	80	123
	Last day of short critical crop growth phase	118	8	89	143
	Last day of extended critical crop growth phase	194	7	174	226
Maize	Yield (dt/ha)	421.88	120.18	85.00	809.73
	$I_{station}$, extended	0.62	0.10	0.43	0.95
	$I_{satellite}$, extended	0.46	0.08	0.23	0.79
	$I_{station}$, short	0.63	0.13	0.40	1.07
	$I_{satellite}$, short	0.46	0.10	0.14	0.79
	First day of extended critical crop growth phase	158	6	143	172
	First day of short critical crop growth phase	196	7	179	217
	Last day of both critical crop growth phases	203	7	187	228

[a] Extended critical crop growth phase.
[b] Short critical crop growth phase.

Table 4. Simulated changes in risk premiums due to insurance availability

Crop	Phase	Index	Compared to no insurance			Compared to station-based insurance		
			Ø Relative RP change[a]	Confidence interval (95%)	p-value[b]	Ø Relative RP change	Confidence interval (95%)	p-value[b]
WHEAT	Extended	Station	−4.88	(−6.8, −3)	0.00			
		Satellite	−6.59	(−9.4, −3.8)	0.00	−1.75	(−4.2, 0.7)	0.30
	Short	Station	−3.90	(−5.4, −2.4)	0.00			
		Satellite	−5.27	(−8.1, −2.5)	0.00	−1.37	(−4.1, 1.3)	0.15
RAPESEED	Extended	Station	−8.34	(−10.8, −5.9)	0.00			
		Satellite	−5.84	(−9, −2.6)	0.00	4.17	(−0.4, 8.7)	0.87
	Short	Station	−3.28	(−5.2, −1.3)	0.00			
		Satellite	−0.17	(−2.1, 1.8)	0.06	4.06	(1, 7.1)	0.98
MAIZE	Extended	Station	−1.72	(−3.8, 0.3)	0.03			
		Satellite	−5.44	(−9.4, −1.5)	0.00	−3.41	(−7.9, 1.1)	0.04
	Short	Station	−7.75	(−11.4, −4.1)	0.00			
		Satellite	−5.63	(−10.7, −0.5)	0.03	2.74	(−2.1, 7.6)	0.95

[a] $Ø\ Relative\ RP\ Change = Ø\ ((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i})$

[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

and maize (see also Table A4). The duration of the short phase of rapeseed (16 days) and maize (7 days) is short compared to the short phase of wheat (on average 30 days). A reason for this could be that the satellite-retrieved data appears to have larger gaps in the first years of our sample (Dorigo *et al.*, 2017). Therefore, the satellite-retrieved soil moisture averages in shorter time-frames that are only based on a small number of observations, which might be a reason for the better performance of the meteorological station-estimated soil moisture insurances with the shorter insurance timeframes. This effect might be amplified because the temporal auto-correlation of the satellite-retrieved soil moisture appears lower than the one of the meteorological station-based data, likely due to the applied normalization step in the production of latter (see Figure A7).

We identify that a drought risk can be identified at between 63 per cent (extended phase, meteorological station-based insurance for rapeseed) and 86 per cent (short phase, meteorological station-based insurance for maize) of the farms in our sample (Table A5). For two of the farms we were not able to retrieve reliable satellite-derived soil moisture information (and thus not able to create a satellite-retrieved index insurance) due to their location close to the Baltic Sea. To avoid potential bias in our results, we did not design any insurance contract for these two farms. By assuming fair insurance premiums, overall revenues are equal for the uninsured and the insured scenarios. The index insurance premium costs, depending on the index, on average around 2–4 per cent of the average revenues (Table A6). Note that we assess the risk premium change for all farms, i.e. including both those with and without insurance (so the change is zero for the latter). For detailed results, see Table A4–A11. Moreover, we here also use a quantile approach to select the strike level (see equation (A3)). Earlier research mostly used yield averages to define the strike level of the insurance (e.g. Conradt, Finger and Bokusheva, 2015; Dalhaus and Finger, 2016) and Table A12 shows that we find larger differences between the insurance designs with that approach. Furthermore, when we select the insured time frame for each crop based on the largest individual risk reduction potential, we achieve a larger on average risk reduction (Table A13). Additionally, we have also used a split sample with observations only from 2005 onwards to assess the influence of missing satellite data in earlier years. We find that including less observations in general decreases the performance of the insurances, which highlights the importance of long historical records, even when data gaps appear (Table A14).

Important advantages of both soil moisture data sets in the design of index insurances are the length of the consistent data record, which are needed to design meaningful insurances (Vrieling *et al.*, 2014). This, as well as the consistency and the short data latency (10 days for version 3.03), makes the ESA CCI a unique satellite-based soil moisture product. Compared to the DWD soil moisture data, an important advantage of the satellite-retrieved data set is the data validation process. Moreover, its global data availability can reduce transaction costs for multinational insurance companies because the information is not restricted to national borders, as is the case for data from national weather services. Another important advantage of the satellite-retrieved data is that the retrieved soil moisture value is informative for the area of the sampled pixel. More specifically, while the nominal spatial resolution of the meteorological station-based data is much higher, it relies on a spatial interpolation of a limited number of stations. Therefore, soil moisture anomalies in between the weather stations could be missed or averaged out. In contrast, the satellite measured soil moisture is representative for the pixel area, resulting in spatially more distinct and localized information (Figures A2 and A3). Furthermore, soil type and vegetation affect absolute soil moisture availability. The consideration of relative soil moisture estimates (i.e. per cent of plant water capacity and per cent of saturation) reduces the impact of spatially varying soil properties and vegetation type (Mittelbach and Seneviratne, 2012). The meteorological station-based approach directly provides relative soil moisture estimates based on an AMBAV. These, however, are only estimated for sandy loam soils covered with grasslands. Therefore, these soil moisture estimates might not well reflect droughts where soil types and vegetation are different. In contrast, the satellite information initially provided as absolute values is rescaled to relative soil moisture estimates based on the pixel-specific minima and maxima, which corrects for the impact of location-specific soil and vegetation characteristics (Brocca *et al.*, 2014).

Generally, the systemic nature of drought risk reduces the importance of data with high spatial resolution, which might be another reason why the low-resolution satellite product works comparably well. This fits to our case study region, as Eastern Germany is characterized by large farms (on average about 400 ha) (Bokusheva and Kimura, 2016; Hartvigsen, 2014; Huettel *et al.*, 2013). Here, idiosyncratic risks often affect only a small share of the overall production, which can be either averaged out or managed by savings. Large-scale systemic risks, however, can threaten the complete farming system of the region. This makes the availability of insurance against systemic risks particularly important in this area. Thus, the approach we take here is particularly viable for farming systems with large-scale farms. However, the newer Sentinel satellites have since 2015 been collecting data at much higher resolutions. A soil moisture product with a resolution of 1 km $\times$ 1 km is already freely available for Europe (Bauer-Marschallinger *et al.*, 2019). Thus, opportunities to use similar approaches also for smaller scale farming are emerging. Future research could evaluate an insurance scheme, where the historical record is specified based on the ESA CCI (and possibly also on the newer data product), while the payout could be determined with the newer product (Setiyono *et al.*, 2018; Vroege, Dalhaus and Finger, 2019). Yet, at this moment, the quality of the ESA CCI product is better validated.

Satellite information from the drought summer of 2003 misses systematically in some areas, particularly in the Northern area of our case study region (close to the Baltic Sea). This is due to spatial gaps in the retrieval from the passive sensor (mostly due to vegetation cover) used as replacement for the temporary failure of the active sensor in this specific time period (Dorigo *et al.*, 2017). Because it is crucial in insurance practice to have a continuous information flow, the possibility of sensor failure might be perceived a disadvantage for satellite-based insurances (while the probability for an extensive failure of the meteorological station measurements is likely lower). Yet, this problem has been reduced substantially in recent years, strengthening the reliability of satellite-retrieved soil moisture index insurance. Moreover, this problem can be greatly reduced by relying on data from multiple active and passive sensors, as is nowadays the case for the ESA CCI product (Dorigo *et al.*, 2017).

Moreover, an important difference between the two products is that farming practices like irrigation and tillage and its effects on soil moisture is not observed with the meteorological station-based soil moisture estimation (Ding, Schoengold and Tadesse, 2009), since it is calculated from meteorological observations. In contrast, satellite measurements are able to capture these effects, most importantly reflect the signal of large-scale irrigation (Qiu *et al.*, 2016). Yet, this is not an important constraint of our case study because irrigation is not widespread (e.g. Siebert *et al.*, 2015). Nevertheless, this is more general an important consideration to make in the design of satellite index insurances in the future, because farmers might have an incentive to change the riskiness of the production and face problems of moral hazard. Yet, this is limited as farm practices at a single farm only have a restricted impact on the estimated soil moisture in the coarse-scale pixel of the applied low-resolution product.

By comparing the performance of satellite-retrieved and meteorological station-based soil moisture estimates, this research puts the usefulness of earth observation approaches for insurance applications into a perspective. Still, other drought indicators can be observed from space and associated global data sets are available (AghaKouchak *et al.*, 2015; West, Quinn and Horswell, 2019). Satellite-retrieved spectral vegetation indices as well as precipitation and evapotranspiration estimates also deliver information that can well be used in index insurance designs (e.g. Black *et al.*, 2016; Enenkel *et al.*, 2018; Jensen *et al.*, 2019). Nicolai-Shaw *et al.* (2017) show that the drought indicators (soil moisture, precipitation, evapotranspiration and vegetation activity) co-vary but that temporal delays occur. For example, missing rainfall, which is a key element of drought development, precedes soil moisture droughts in most regions and increased evapotranspiration is often followed by a response in vegetation activity (Nicolai-Shaw *et al.*, 2017; West, Quinn and Horswell, 2019). Which (satellite-retrieved) drought indicator performs best to insure farmers against drought risks is an empirical question and the answer may differ for each individual farm (Bucheli, Dalhaus and Finger, 2020), for different insurance timeframe settings and for different crops. Nevertheless, soil moisture is in general more informative to agricultural droughts than precipitation or evapotranspiration anomalies alone (Seneviratne *et al.*, 2010; West, Quinn and Horswell, 2019). Vegetation spectral reflectance indices, such as the Normalized Difference Vegetation Index, which reflect the impact of a drought on the vegetation, could relate even more directly to farmer's yield losses. Yet, management practices and other risks, such as pests and diseases as well as heat and frost, have similar impacts on yields (e.g. Webber *et al.*, 2020) and the vegetation's spectral reflection as droughts. Therefore, identifying if a drought was the cause of the yield loss may be a challenge with spectral indices (AghaKouchak *et al.*, 2015).

In the future, further data integration could improve both investigated products. For the meteorological station-based product, integrating localized data on soil type and vegetation activity into the AMBAV could improve the product. For the satellite product, integrating sub-daily information could increase the product accuracy (Dorigo *et al.*, 2017). Moreover, satellite microwave remote sensing may deliver drought indicators that combine soil moisture and vegetation water content assessments (AghaKouchak *et al.*, 2015). In addition to these developments of gridded products, *in-situ* soil moisture sensors can deliver point-scale information on drought status. However, installation of large-scale *in situ* soil moisture networks is difficult and expensive, and spatial coverage of *in situ* soil moisture observations will barely reach the extent of the current meteorological station networks or the available satellite-based soil moisture products. Nevertheless, the expansion of *in situ* soil moisture networks is beneficial to validate gridded soil moisture products as used in this study and to reduce associated uncertainties.

In this study, we focus on insuring production risks in an expected utility framework. While we here compare the ability of different insurances to reduce basis risk, this might not fully explain farmers' actual insurance choice. To understand which insurance contract farmers might purchase also other factors play a role. These are captured in other decision making frameworks such as Cumulative Prospect Theory and especially state-dependent reference levels therein might be better able to explain farmers' insurance choice (Babcock, 2015; Bocquého, Jacquet and Reynaud, 2014; Du, Feng and Hennessy, 2016; Feng, Du and Hennessy, 2019). More specifically, Dalhaus, Barnett and Finger (2020) take up the current knowledge on behavioural factors in crop insurance decisions and propose a behavioural weather insurance that is particularly designed to better fit farmers' behavioural preferences.

Moreover, we are unable to come up with a single farm in-sample training out-of-sample testing procedure (as for example in Conradt, Finger and Bokusheva, 2015), which would require longer records of yield data at a single farm. We address potential overfitting issues by using pooled approaches as robustness checks (Tables A14 and Table A15). Differences in results displayed in Table 4, Tables A15 and A16 arise not solely from potential overfitting but also because the insurance contracts are no longer tailored to the specific drought risk at the insured farm. More specifically, while our farm-specific tailoring procedure (Table 4) captures farm-specific time-invariant characteristics in the tick size and strike level, the pooled procedure (Tables A15 and Table A16) does not. The digitalization of agriculture will increase the availability of long-term and site-specific yield data (Walter *et al.*, 2017), which can contribute to design better insurance solutions.

6. Conclusion

In this paper, we evaluate whether soil moisture insurance solutions can reduce farms' financial drought risk exposure using a case study for wheat, maize and rapeseed production in Eastern Germany. We find that soil moisture index insurances, both from gridded meteorological station-based and satellite-retrieved soil moisture, can reduce the financial exposure to drought risk-related yield losses and thus enlarge farmers' possibilities to cope with climate change. We show how both approaches can be used to reduce farmers' risk premium and argue that considerations for the design of satellite index insurances should include data availability, product quality and validation as well as location-specific farming practices.

Our findings have clear industry and policy implications. Insurance companies should use more, farm-specific information when offering insurance to farms. Moreover, we find performance differences between the satellite-retrieved soil moisture insurance and the meteorological station-based soil moisture insurance depending on the insured crop and growth stage. This heterogeneity calls for tailored, farm- and crop-specific, index insurance solutions.

For policy makers our results indicate that the resilience of the farming sector could be enlarged by improving data availability and accessibility for insurers. For example, our analysis highlights the value of high-quality satellite imagery, weather station, phenology and crop yield data that is freely available for the development of better insurance solutions. Better insurance solutions contribute to the resilience of agricultural systems by maintaining stable incomes and the economic viability of farms (Finger and El Benni, 2020). This helps to avoid costly collective drought-related governmental disaster payments (Meuwissen *et al.*, 2019). Supporting the development of satellite data products that enable the development of better agricultural insurances could thus complement with and substitute for other forms of governmental support of agricultural insurances such as premium subsidies. Insurance solutions based on soil moisture retrieved from satellite imagery have clear advantages as these are cheap, efficient and applicable for various crops globally. Moreover, satellite based index insurance can ensure immediate compensation for a high number of farmers at the same time. In contrast, traditional insurances could not ensure cost-efficient on-farm damage assessments within a narrow timeframe of many farms within a short-time period. Here, satellite based index insurance can bring relief.

Future research should consider how other than drought events that can be measured from space could be integrated into index insurance design. Increasing the number of options to insure, will likely reduce basis risk and stimulate adoption of index insurance. Further considerations about farmers' preferences, beliefs and experiences with insurance based on satellite-retrieved weather data is needed as this can influence insurance uptake and thus performance of the insurance.

Acknowledgements

This research was undertaken within the SURE-Farm (Towards SUstainable and REsilient EU FARMing systems) project, funded by the European Union (EU)'s Horizon 2020 research and innovation programme under Grant Agreement No 727520 (http://surefarmproject.eu). MH acknowledges funding from ESA's Climate Change Initiative for Soil Moisture (Contract No. 4000126684/19/I-NB). The content of this article does not reflect the official opinion of the European Union. Responsibility for the information and views expressed therein lies entirely with the authors. We thank 'gvf Versicherungsmakler', especially S. Mahler, for providing the yield data.

Conflict of Interest

The authors declare that they have no conflict of Interest.

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Appendix

$$Pr_{i,v} = \frac{1}{N_{i,t}} \sum_{t=1}^{N_{i,t}} PO_{i,t,v} \tag{A1}$$

where $Pr_{i,v}$ is the farm-specific insurance premium based on the index specification v and $PO_{i,t,v}$ is the insurance payout to farm i in year t based on index specification v. $N_{i,t}$ is the total number of years from which we know farm i's yield.

$$T_{i,v} = \beta_{1_{i,v}} * P \tag{A2}$$

where $T_{i,v}$ is the tick size in farm i's insurance contract that equals the slope of the quantile regression $\beta_{1_{i,v}}$ (relation between farm i's yield and index values at the lower part of the yield distribution) multiplied by a constant price P to make this a monetary unit.

$$S_{i,v} = \frac{q_{0.3}(Y_i) - \beta_{0_{i,v}}}{\beta_{1_{i,v}}} \tag{A3}$$

where $S_{i,v}$ is the strike level of the index insurance specified at farm i with index specification v. Y_i are the yields at farm i. $q_{0.3}(Y_i)$ reflects that we focus on the 30 per cent percentile of the empirical yield distribution Y_i. $\beta_{0_{i,v}}$ and $\beta_{1_{i,v}}$ are farm individual regression coefficients (intercept and slope) for each index specification v (i.e. soil moisture data from satellite observations or derived from meteorological measurements at ground stations).

$$\sigma^2_{\pi_{i,v}} = E(E(\pi_{i,v}) - \pi_{i,v})^2) \tag{A4}$$

$\sigma^2_{\pi_{i,v}}$ is the second moment (the variance) of the revenue distribution $\pi_{i,v}$ at farm i under index specification v.

$$\sigma^3_{\pi_{i,v}} = E\left(\frac{(E(\pi_{i,v}) - \pi_{i,v})^3}{\sigma^3_{i,v}}\right) \tag{A5}$$

$\sigma^3_{\pi_{i,v}}$ is the third moment (the skewness) of the revenue distribution $\pi_{i,v}$ at farm i under index specification v.

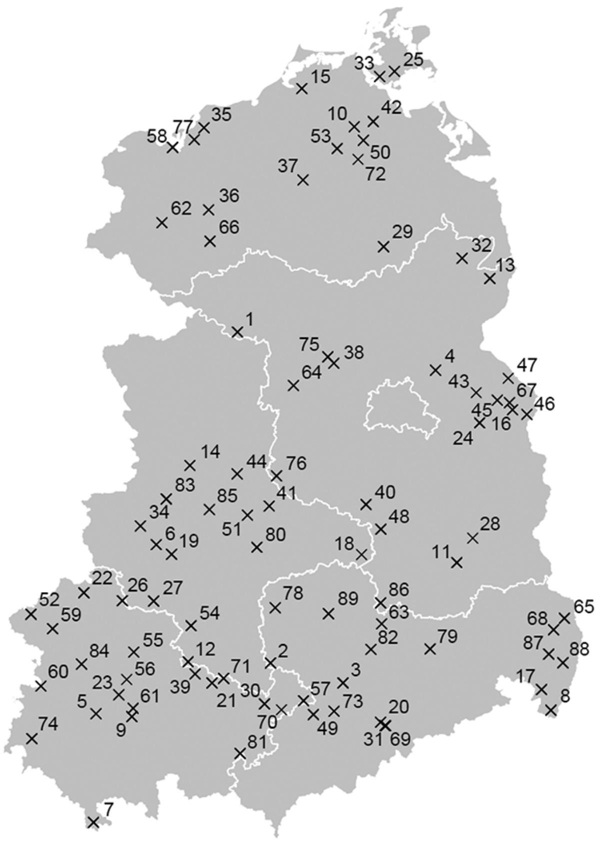

Figure A1. Farm locations in Eastern Germany.

Table A1. Summary statistics of the detrended annual yield data

	Wheat yield [dt/ha]					Rapeseed yield [dt/ha]					Maize yield [dt/ha]				
Year	Mean	Std.	Min.	Max.	n	Mean	Std.	Min.	Max.	n	Mean	Std.	Min.	Max.	n
1995	81	-	81	81	1	44	-	44	44	1	-	-	-	-	0
1996	80	-	80	80	1	36	-	36	36	1	-	-	-	-	0
1997	94	-	94	94	1	49	-	49	49	1	-	-	-	-	0
1998	88	1	87	89	2	51	4	48	54	2	-	-	-	-	0
1999	82	11	42	102	62	46	8	15	61	62	463	130	210	598	15
2000	77	13	43	106	69	45	9	14	63	66	458	106	200	642	23
2001	82	11	54	117	71	47	6	36	59	68	456	107	188	727	25
2002	71	12	22	98	79	38	6	23	48	75	441	97	209	689	28
2003	62	15	28	100	80	37	9	18	54	75	355	98	185	575	28
2004	86	11	54	112	80	50	6	36	59	77	425	111	195	734	31
2005	75	12	50	105	80	44	6	27	54	78	430	113	204	810	31
2006	68	14	41	102	82	42	7	21	52	80	387	118	138	588	37
2007	70	12	29	93	83	38	6	25	48	80	467	103	192	641	38
2008	78	15	41	109	83	42	7	22	52	81	403	103	89	598	42
2009	77	13	36	104	84	47	6	34	61	82	436	122	182	748	40
2010	70	11	43	90	85	42	5	28	51	81	381	109	135	598	42
2011	65	15	30	92	85	32	9	11	50	82	457	142	135	805	42
2012	70	16	23	97	85	38	9	13	52	82	447	123	152	774	39
2013	78	11	56	101	84	41	5	25	50	82	357	127	122	743	41
2014	88	11	69	117	55	47	5	34	55	53	464	109	163	598	24
2015	77	11	61	98	25	38	6	30	47	25	367	150	85	564	12

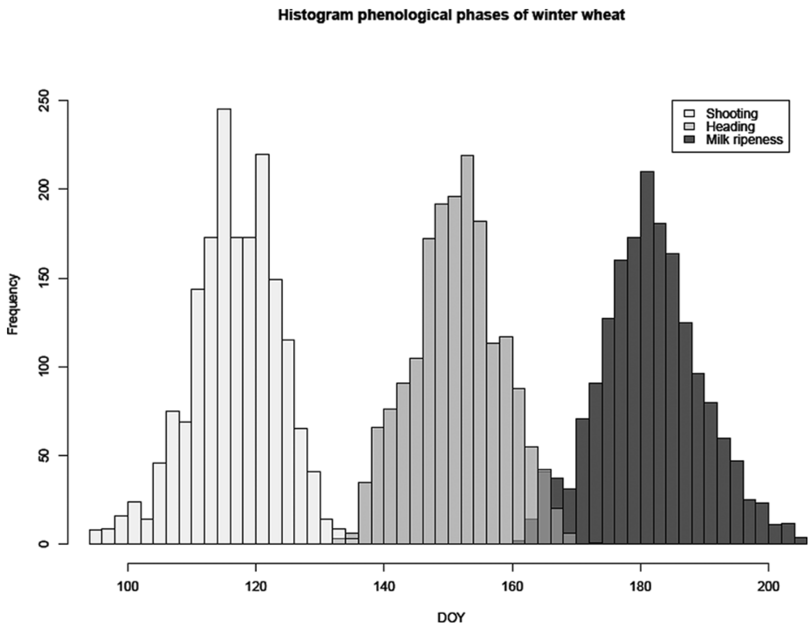

Figure A2. Phenological phases of wheat, all farms and years included.

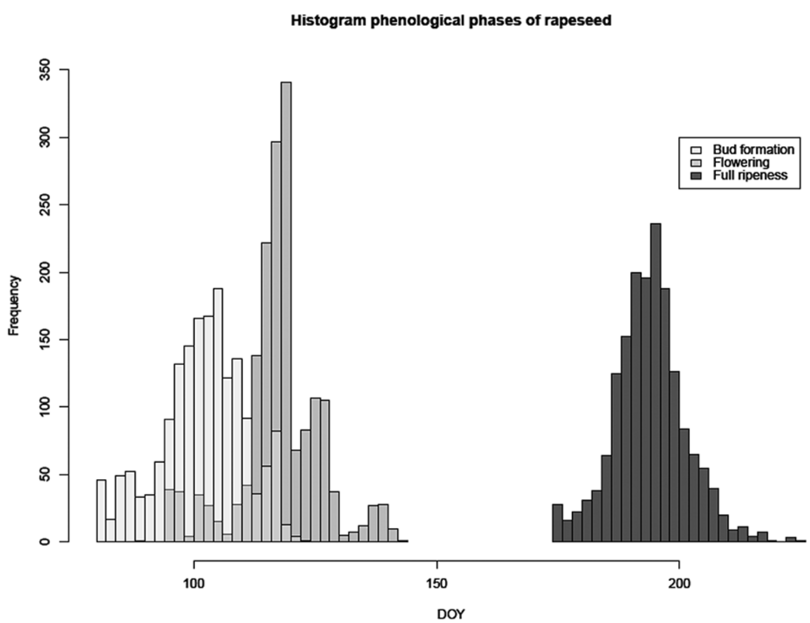

Figure A3. Phenological phases of rapeseed, all farms and years included.

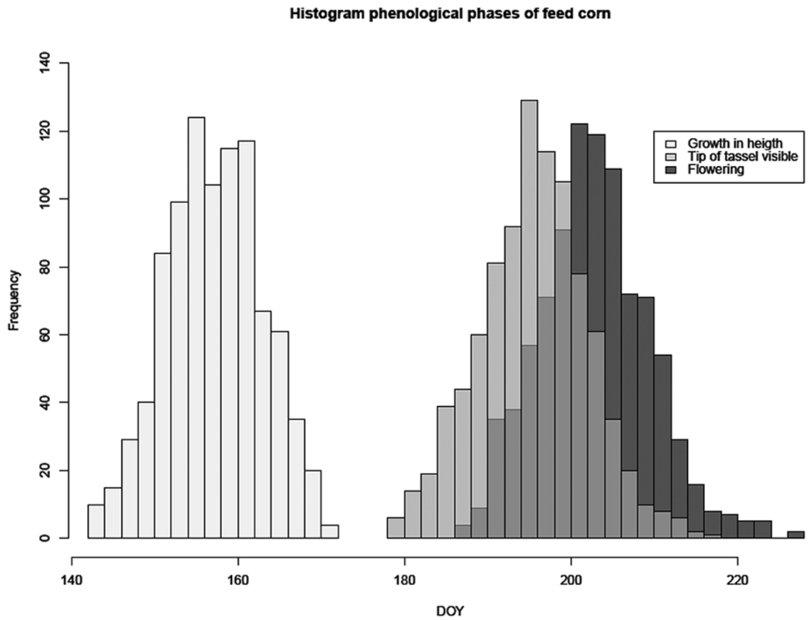

Figure A4. Phenological phases of maize, all farms and years included.

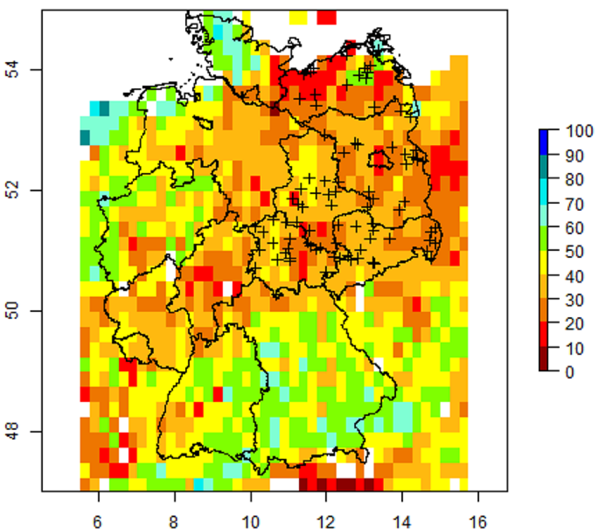

Figure A5. Illustration of the satellite-retrieved soil moisture data (ESA CCI) in per cent saturation on day 150 of the year 2015.

Table A2. Soil moisture statistics based on satellite estimations at the farm level

Year	Winter wheat extended				Rapeseed extended				Maize extended			
	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
1995	0.40	0.07	0.25	0.60	0.41	0.08	0.25	0.62	0.49	0.08	0.32	0.68
1996	0.47	0.08	0.25	0.62	0.46	0.08	0.25	0.63	0.41	0.07	0.23	0.59
1997	0.40	0.08	0.13	0.68	0.40	0.08	0.24	0.57	0.45	0.07	0.34	0.64
1998	0.41	0.07	0.25	0.62	0.43	0.07	0.26	0.65	0.44	0.06	0.35	0.65
1999	0.48	0.09	0.26	0.68	0.50	0.09	0.29	0.68	0.45	0.08	0.29	0.63
2000	0.38	0.08	0.25	0.59	0.41	0.08	0.25	0.63	0.36	0.08	0.24	0.56
2001	0.46	0.10	0.21	0.66	0.49	0.08	0.29	0.66	0.52	0.09	0.39	0.79
2002	0.44	0.09	0.26	0.66	0.45	0.09	0.26	0.66	0.44	0.08	0.28	0.69
2003	0.38	0.08	0.23	0.53	0.39	0.08	0.25	0.55	0.39	0.07	0.25	0.50
2004	0.50	0.08	0.31	0.62	0.51	0.08	0.31	0.63	0.52	0.08	0.36	0.69
2005	0.48	0.07	0.30	0.67	0.49	0.08	0.30	0.68	0.46	0.07	0.32	0.67
2006	0.44	0.07	0.25	0.60	0.46	0.08	0.26	0.64	0.42	0.09	0.25	0.67
2007	0.43	0.09	0.24	0.64	0.46	0.09	0.25	0.66	0.49	0.07	0.32	0.72
2008	0.40	0.09	0.21	0.63	0.45	0.10	0.23	0.68	0.44	0.08	0.33	0.67
2009	0.46	0.09	0.25	0.68	0.48	0.09	0.26	0.69	0.51	0.07	0.39	0.70
2010	0.48	0.08	0.28	0.66	0.49	0.09	0.27	0.67	0.44	0.07	0.32	0.68
2011	0.41	0.09	0.25	0.60	0.45	0.09	0.28	0.65	0.49	0.08	0.32	0.68
2012	0.40	0.08	0.18	0.58	0.46	0.08	0.24	0.62	0.50	0.07	0.37	0.63
2013	0.49	0.09	0.30	0.63	0.49	0.08	0.31	0.65	0.50	0.06	0.39	0.63
2014	0.44	0.08	0.25	0.63	0.46	0.07	0.29	0.64	0.48	0.07	0.34	0.69
2015	0.36	0.08	0.15	0.61	0.39	0.09	0.18	0.61	0.46	0.07	0.35	0.65

Table A3. Soil moisture statistics based on gridded data from meteorological stations

	Winter wheat extended				Rapeseed extended				Maize extended			
Year	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
1995	0.82	0.06	0.73	0.98	0.82	0.05	0.75	0.93	0.74	0.06	0.61	0.86
1996	0.74	0.06	0.64	0.90	0.73	0.06	0.65	0.90	0.68	0.07	0.56	0.87
1997	0.64	0.06	0.54	0.78	0.67	0.07	0.54	0.79	0.60	0.07	0.48	0.74
1998	0.66	0.05	0.57	0.76	0.68	0.06	0.59	0.81	0.65	0.06	0.55	0.78
1999	0.71	0.06	0.62	0.85	0.73	0.06	0.64	0.86	0.67	0.09	0.53	0.83
2000	0.61	0.02	0.58	0.67	0.62	0.02	0.58	0.68	0.57	0.03	0.52	0.66
2001	0.68	0.06	0.57	0.83	0.68	0.06	0.58	0.85	0.65	0.07	0.52	0.79
2002	0.80	0.05	0.70	0.89	0.81	0.05	0.72	0.89	0.68	0.06	0.57	0.81
2003	0.57	0.04	0.51	0.65	0.58	0.04	0.52	0.65	0.51	0.02	0.47	0.56
2004	0.68	0.07	0.52	0.85	0.68	0.07	0.54	0.85	0.63	0.06	0.53	0.75
2005	0.68	0.05	0.59	0.78	0.69	0.05	0.61	0.79	0.59	0.06	0.51	0.76
2006	0.68	0.05	0.55	0.75	0.67	0.05	0.55	0.75	0.55	0.05	0.47	0.64
2007	0.68	0.04	0.64	0.81	0.72	0.04	0.65	0.83	0.79	0.12	0.54	0.95
2008	0.64	0.02	0.61	0.68	0.65	0.02	0.62	0.69	0.57	0.02	0.54	0.61
2009	0.69	0.06	0.61	0.86	0.69	0.07	0.60	0.86	0.68	0.10	0.55	0.93
2010	0.80	0.03	0.73	0.90	0.78	0.03	0.74	0.86	0.61	0.04	0.56	0.70
2011	0.56	0.03	0.52	0.65	0.57	0.03	0.53	0.69	0.56	0.05	0.49	0.67
2012	0.58	0.04	0.53	0.69	0.61	0.04	0.55	0.72	0.60	0.06	0.51	0.81
2013	0.79	0.05	0.70	0.90	0.79	0.04	0.71	0.88	0.72	0.06	0.64	0.83
2014	0.63	0.04	0.57	0.73	0.63	0.05	0.56	0.74	0.55	0.04	0.48	0.66
2015	0.56	0.05	0.47	0.67	0.56	0.04	0.48	0.66	0.49	0.03	0.43	0.56

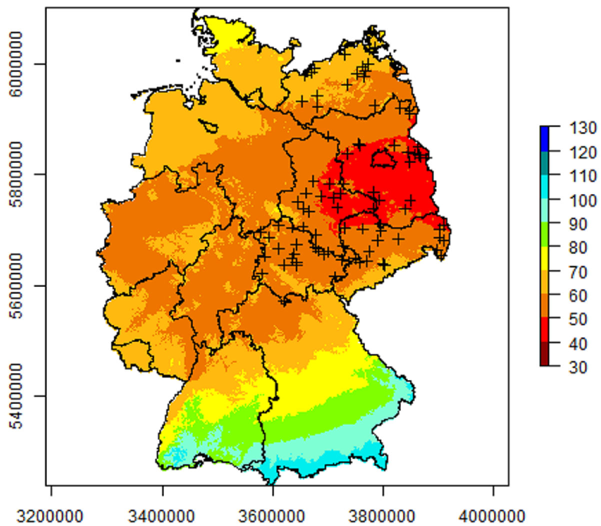

Figure A6. Illustration of the gridded soil moisture data based on estimates at meteorological stations (DWD) in per cent plant available water capacity under grass and for sandy loam soil on day 150 of the year 2015.

Figure A7. Soil moisture development in three selected years at two randomly selected farms during the extended phenological phase. The smoother line shows the gridded soil moisture data from the meteorological stations and is always complete. The noisier line shows the soil moisture data retrieved with satellites and shows many data gaps in 1995, some in 2005 and almost no data gaps in 2015.

Table A4. Average relative risk premium reduction of the insurances based on meteorological station soil moisture estimates compared to risk premium reduction with insurances based on satellite-retrieved soil moisture estimates

Crop	Phase	Index	Compared to satellite-retrieved insurance		
			Ø Relative RP Change[a]	Confidence Interval (95%)	p-value[b]
WHEAT	Extended	Station Satellite	3.48	(0.2, 6.8)	0.69
	Short	Station Satellite	3.17	(0, 6.4)	0.85
RAPESEED	Extended	Station Satellite	−0.25	(−4.7, 4.2)	0.14
	Short	Station Satellite	−2.59	(−4.8, −0.3)	0.02
MAIZE	Extended	Station Satellite	6.15	(0.3, 12)	0.96
	Short	Station Satellite	−0.26	(−5.4, 4.9)	0.05

[a] $\text{Ø } \textit{Relative RP Change} = \text{Ø}\left((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i}\right)$

[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

Table A5. Payout summary statistics (of payouts > 0)

Crop	Phase	Method	Mean	Std.	Max	Min	Insured farms	Share insured farms
Wheat	Extended	Station	58.41	63.34	357.78	0.00	58	0.68
		Satellite	61.31	70.61	382.53	0.00	61	0.72
	Short	Station	48.28	46.54	271.80	0.00	56	0.66
		Satellite	66.70	74.27	464.34	0.00	66	0.78
Rapeseed	Extended	Station	90.49	95.07	712.70	0.00	55	0.67
		Satellite	109.16	126.09	839.43	0.00	64	0.78
	Short	Station	82.61	77.67	518.63	0.00	60	0.73
		Satellite	87.47	85.33	518.63	0.00	47	0.57
Maize	Extended	Station	90.14	76.32	359.47	0.00	27	0.63
		Satellite	88.88	92.59	600.93	0.00	34	0.79
	Short	Station	98.80	101.15	566.86	0.00	37	0.86
		Satellite	105.68	145.03	1073.96	0.00	33	0.77

Only farms with a positive correlation between yield and soil moisture (i.e. a positive beta in the quantile regression) are considered. For other farms we do not identify drought risks.

Table A6. Revenues and insurance premiums

		Revenues				Insurance premium			
		Station		Satellite		Station		Satellite	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Wheat	Extended	1125	214.8	1125	213.6	29.5	39.0	30.3	28.2
	Short	1125	215.5	1125	214.3	24.5	29.3	35.3	33.3
Rapeseed	Extended	1501	285.7	1501	286.9	48.2	59.4	57.2	52.4
	Short	1501	291.0	1501	293.7	44.2	42.2	45.7	49.7
Maize	Extended	1730	491.4	1730	487.5	50.2	46.6	43.9	36.8
	Short	1730	486.2	1730	489.9	53.2	48.4	59.5	62.1

Note that farm revenues are largely the same in different scenario's (including the uninsured scenario) but slight difference may occur from the bootstrapping procedure.

Table A7. Mean and standard deviation of the quantile regression coefficients

Crops	Phase	Station				Satellite			
		Intercept		Beta		Intercept		Beta	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Wheat	Extended	56.9	35.2	18.1	43.9	49.0	41.5	47.2	85.8
	Short	60.2	32.4	14.9	41.2	43.3	42.2	57.1	91.9
Rapeseed	Extended	28.4	22.0	15.5	27.2	15.6	36.3	53.9	74.7
	Short	28.7	19.1	11.8	21.3	34.9	18.1	8.0	34.0
Maize	Extended	346.3	287.4	54.6	456.0	234.7	279.3	338.2	607.9
	Short	237.0	188.6	251.0	275.8	246.2	227.3	304.4	435.2

Table A8. Average and standard deviation of the strike level and tick size

		Strike level				Tick size			
		Station		Satellite		Station		Satellite	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Wheat	Extended	0.67	0.08	0.44	0.09	578.6	520.2	1262.6	1001.2
	Short	0.63	0.08	0.47	0.09	557.5	434	1280.6	1121.5
Rapeseed	Extended	0.69	0.08	0.46	0.08	1043.3	742.8	2744.6	2343.2
	Short	0.85	0.09	0.49	0.11	768.3	431.6	1081.8	707.7
Maize	Extended	0.65	0.07	0.47	0.07	776.2	926	1796.5	1787.5
	Short	0.64	0.10	0.45	0.09	1115.3	1024.2	1435.5	1595.3

Only farms with a positive correlation between yield and soil moisture (i.e. a positive beta in the quantile regression) are considered. Other farms are assumed not to be experience drought risks.

Table A9. Average absolute risk premiums in €/ha for different levels of risk aversion α.

Crops	Phase	Index	Absolute risk premium in €/ha per coefficient of risk aversion			
			0.5	2	3	4
Wheat	None	Uninsured	5.9	23.7	35.5	47.3
	Extended	Station	5.5	22.2	33.3	44.4
		Satellite	5.4	21.7	32.5	43.4
	Short	Station	5.6	22.4	33.7	44.9
		Satellite	5.5	21.9	32.8	43.7
Rapeseed	None	Uninsured	9.9	39.4	59.2	78.9
	Extended	Station	8.9	35.5	53.2	71.0
		Satellite	9.0	36.1	54.2	72.3
	Short	Station	9.5	38.1	57.2	76.2
		Satellite	9.8	39.3	58.9	78.5
Maize	None	Uninsured	11.5	46.1	69.1	92.2
	Extended	Station	11.3	45.2	67.8	90.4
		Satellite	10.9	43.5	65.2	86.9
	Short	Station	10.6	42.5	63.7	85.0
		Satellite	11.2	44.6	66.9	89.2

Table A10. Overview on premiums of each farm per crop and insurance

	Wheat				Rapeseed				Maize			
	Extended		Short		Extended		Short		Extended		Short	
ID	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat
1	0.0	9.9	0.0	59.1	107.3	236.8	176.9	261.0	50.8	22.8	47.2	42.9
2	–	–	–	–	–	0.5	14.4	1.7	–	–	106.4	–
3	9.8	13.1	12.9	10.0	–	6.9	0.3	–	51.8	2.9	74.7	–
4	1.1	7.9	18.5	14.6	0.0	2.0	0.0	0.0				
5	–	5.7	–	7.7	63.0	71.1	52.6	57.3				
6	36.0	34.7	–	26.9	7.2	–	4.9	14.2				
7	19.4	40.2	17.4	12.8	87.6	57.9	69.7	–	17.5	–	7.3	247.2
8	–	–	–	–	–	–	69.9	–	–	–	–	–
9	5.4	8.7	0.0	12.8	115.2	78.3	119.5	91.0	19.7	103.2	46.5	–
10	82.7	97.1	–	107.3	–	–	2.2	–				
11	4.0	1.0	8.5	56.3	12.4	1.5	1.5	1.5	–	65.6	75.7	32.8
12	–	20.7	17.5	88.1	–	93.8	–	–	–	10.5	6.3	262.1
13	13.1	14.3	10.1	–	17.2	23.3	8.4	20.2	110.2	98.1	78.3	–
14	–	15.9	–	12.3	–	–	8.9	7.7				
15	2.4	–	4.0	–	7.1	–	–	–				
16	35.1	15.8	22.3	8.5	187.0	104.9	206.0	190.3				
17	–	–	–	–	45.9	–	44.5	40.3	–	52.3	1.7	39.2
18					–	165.4	16.4	–				
19	27.8	26.0	22.9	11.1	10.8	44.7	45.4	50.2				
20	–	–	–	–	110.1	135.5	–	–				
21	28.5	28.1	32.3	43.4	13.1	11.9	26.2	7.3	89.5	–	175.3	–
22	19.0	–	29.9	18.7	–	7.9	15.3	–	2.4	18.2	4.1	23.7
23	20.7	29.2	35.0	31.4	63.7	91.3	60.4	46.4				
24	79.8	76.1	82.8	83.0	347.0	202.4	–	–	–	–	49.8	–

(continued)

Table A10. (Continued)

	Wheat				Rapeseed				Maize			
	Extended		Short		Extended		Short		Extended		Short	
ID	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat
25	–	13.9	–	–	–	–	–	–				
26	–	–	–	–	19.6	61.4	105.2	75.4	92.1	28.8	67.5	93.1
27	29.7	48.2	39.1	30.0	0.0	31.1	0.3	0.0				
28	–	18.0	–	15.0								
29	1.3	69.6	1.6	68.2	–	0.3	47.4	47.1	–	–	22.6	156.7
30	–	–	–	21.4	17.0	0.0	–	–	8.2	70.7	87.6	44.5
31	–	–	–	36.4	41.3	15.0	–	–				
32	10.9	7.8	12.5	10.2	0.0	–	104.0	–				
33	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
34	3.2	–	3.6	–	–	–	21.0	–				
35	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
36	55.9	15.2	48.1	8.3	56.6	–	8.3	26.9				
37	40.7	55.6	38.3	–	43.0	26.4	20.8	36.1				
38	68.6	62.3	36.3	78.6	1.0	–	–	–				
39	–	–	–	–	0.2	53.5	56.1	84.6				
40	25.0	21.7	12.1	29.7	146.5	81.0	0.0	0.0	16.8	135.6	49.3	79.8
41	73.6	85.6	60.6	77.5	–	89.2	–	–				
42	0.0	12.9	0.0	–	–	13.5	–	–	28.9	13.3	77.6	6.1
43					18.3	221.4	14.4	14.2				
44	–	18.5	–	29.4	56.8	31.2	48.9	36.1				
45	181.5	108.0	115.4	82.5	9.9	50.3	17.8	9.7				
46	11.5	3.2	37.7	66.6	63.1	62.9	23.0	40.4				
47	132.0	80.8	52.6	109.4								

(continued)

Table A10. (Continued)

	Wheat				Rapeseed				Maize			
	Extended		Short		Extended		Short		Extended		Short	
ID	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat
48	105.5	65.9	77.6	66.9	20.4	96.4	15.4	17.9	–	45.9	95.1	10.4
49	–	0.0	–	35.4	–	4.1	–	–	96.9	43.2	31.7	38.1
50	5.2	13.9	11.9	1.1	7.1	–	16.8	78.7				
51	51.0	45.6	41.6	40.3	0.0	103.3	–	–				
52	0.0	13.4	0.2	19.4	32.8	19.1	62.5	19.7	33.0	11.7	30.5	86.6
53	23.9	6.0	33.8	6.4	17.2	4.0	52.9	–	15.3	0.0	20.9	–
54	0.0	3.0	0.0	6.8	–	89.9	38.4	–	–	57.8	37.6	57.7
55	11.9	–	14.7	–	59.5	55.3	71.5	83.4				
56	73.8	–	2.3	–								
57	–	–	–	18.0	–	53.5	–	–	–	5.1	5.2	10.0
58	–	6.5	–	–	–	14.1	16.0	20.4	64.0	34.7	–	–
59	25.1	11.3	24.6	28.9	68.9	78.8	67.3	72.2	31.0	115.0	7.1	11.3
60	17.9	24.7	18.1	11.1	84.5	70.8	71.6	113.8				
61	6.3	5.9	5.8	4.5	62.6	39.0	65.4	43.9				
62	1.0	71.7	1.6	46.8	–	54.9	–	7.7				
63	156.4	103.0	151.1	169.7	19.8	57.4	50.5	37.7				
64					0.0	6.3	0.4	26.1	–	–	–	19.4
65	18.0	29.2	13.8	16.6	118.0	102.0	100.2	15.4	1.6	30.3	35.3	39.7
66	3.8	6.8	3.6	5.7	–	10.3	1.2	–	65.2	81.8	112.0	61.3
67	28.3	65.9	51.3	83.3					2.2	–	33.6	–
68	1.0	0.0	0.0	0.0	79.3	59.4	70.1	79.5	–	55.2	–	33.4
69	–	4.4	–	8.2	16.2	22.6	–	–				

(continued)

Table A10. (Continued)

	Wheat				Rapeseed				Maize			
	Extended		Short		Extended		Short		Extended		Short	
ID	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat	Stat	Sat
70	–	–	–	–								
71	–	–	–	60.5	–	18.9	4.0	–	–	21.3	23.9	17.9
72					25.6	29.0	–	–				
73	–	–	–	11.1					52.8	28.8	38.4	0.0
74	20.9	–	29.2	40.3	51.8	–	65.7	–	9.7	22.4	16.6	17.5
75	0.9	19.8	2.2	40.7	26.6	–	–	–	–	17.4	–	22.5
76	–	–	–	76.6	–	115.0	–	–				
77	4.5	3.5	10.4	2.1	–	77.4	46.3	90.8				
78	32.3	38.5	34.5	48.0	7.7	22.0	18.0	35.6				
79	47.5	49.3	9.5	20.2	81.3	92.6	70.3	6.2				
80	26.5	42.2	45.6	48.1	28.7	48.6	16.4	49.4	62.3	46.4	24.9	65.0
81	4.8	7.2	6.8	12.0	17.7	10.2	10.9	–	85.7	–	–	32.1
82	0.0	22.0	–	23.6					1.1	22.8	48.1	138.0
83	–	29.7	–	3.0	–	93.1	–	89.9	–	0.3	23.0	18.6
84	–	–	3.1	11.9	–	36.0	–	–				
85	–	–	–	0.7	–	–	48.6	–				
86	0.9	48.9	0.2	69.0	129.5	50.6	71.4	70.8	210.2	65.9	91.5	72.6
87	6.8	4.0	4.2	0.5	7.9	17.7	27.5	17.6	45.1	17.0	29.4	53.6
88	17.6	–	–	–	0.4	–	112.0	0.0	90.9	25.6	47.8	32.9
89	0.5	40.6	0.4	28.1	22.3	34.1	48.6	12.3	–	122.0	236.9	97.0

ID: farm identification number; grey areas: no yield data available; —: no identified drought risk; *X*: no satellite measurement possible.

Table A11. Overview on absolute risk premiums in €/ha for level of risk aversion $\alpha = 2$

	Winter wheat					Rapeseed					Maize				
	Not	Extended		Short		Not	Extended		Short		Not	Extended		Short	
ID	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat
1	38.0	38.0	35.4	38.0	33.9	88.9	71.9	50.1	68.1	83.6	14.0	14.4	13.1	14.8	11.4
2	9.0	9.0	9.0	9.0	12.4	21.3	21.3	21.2	21.5	21.4	45.9	45.9	45.9	47.5	45.9
3	6.8	6.6	6.6	6.5	6.8	17.5	17.5	16.9	17.4	17.5	27.7	28.6	27.6	28.1	27.7
4	72.6	72.8	70.3	72.8	64.5	55.5	55.5	55.8	55.5	55.5					
5	11.2	11.2	10.9	11.2	9.2	25.7	17.0	21.7	23.7	23.7					
6	12.7	14.0	12.7	12.7	13.5	7.7	7.4	7.7	7.3	7.2					
7	22.3	15.1	17.0	16.7	18.4	95.7	49.2	90.9	66.8	95.7	152.5	144.6	152.5	152.3	159.4
8	20.2	20.2	20.2	20.2	24.0	48.2	48.2	48.2	50.1	48.2	92.5	92.5	92.5	92.5	92.5
9	11.0	10.4	10.9	11.0	10.5	22.4	18.1	25.8	20.3	20.2	119.3	111.0	104.9	105.4	119.3
10	20.1	14.1	9.4	20.1	19.4	24.4	24.4	24.4	24.8	24.4					
11	57.4	55.5	57.1	53.1	48.9	88.4	81.9	87.6	87.6	87.6	40.2	40.2	45.5	42.6	44.2
12	18.0	18.0	19.0	17.7	15.9	22.2	22.2	18.7	22.2	22.2	33.2	33.2	32.5	32.5	27.9
13	29.0	26.0	26.8	26.6	26.9	82.2	78.7	81.8	82.3	81.8	51.9	46.3	66.2	38.9	51.9
14	11.6	11.6	12.0	11.6	12.9	29.1	29.1	29.1	29.1	29.2					
15	9.7	9.4	9.7	9.9	10.2	20.4	20.2	20.4	20.4	20.4					
16	45.8	36.8	45.3	38.6	40.4	84.6	62.1	42.9	93.1	83.6					
17	19.0	19.0	19.0	19.0	21.3	25.9	24.3	25.9	26.3	27.4	10.5	10.5	11.8	10.1	10.1
18						47.7	47.7	30.1	44.4	47.7					
19	23.5	22.7	23.9	21.8	21.8	19.2	18.7	15.4	19.2	19.1					
20	14.6	14.6	14.6	14.6	14.6	38.7	34.9	42.5	38.7	38.7					
21	13.9	12.7	13.6	12.1	14.8	22.2	21.0	21.1	19.6	21.7	57.8	53.4	57.8	44.6	57.8
22	15.8	14.4	15.8	15.4	18.8	21.2	21.2	20.5	20.4	21.2	3.4	3.3	3.1	3.4	2.8
23	13.0	10.9	11.0	11.5	11.3	18.4	12.4	16.1	13.7	13.0					
24	16.8	11.2	7.6	10.6	11.9	100.4	82.5	115.6	100.4	100.4	19.0	19.0	19.0	14.8	19.0
25	8.1	8.1	7.6	8.1	8.3	22.0	22.0	22.0	22.0	22.0					

(continued)

Table A11. (Continued)

	Winter wheat					Rapeseed					Maize				
	Not	Extended		Short		Not	Extended		Short		Not	Extended		Short	
ID	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat
26	8.7	8.7	8.7	8.7	9.8	26.8	23.1	28.0	23.6	22.5	68.4	61.1	60.5	50.4	52.0
27	13.1	11.3	11.8	11.6	11.8	119.1	119.1	105.9	119.1	119.1					
28	46.8	46.8	45.8	46.8	43.2										
29	21.3	20.7	17.0	20.7	17.7	64.0	64.0	64.0	58.6	61.2	54.3	54.3	54.3	59.8	74.3
30	15.3	15.3	15.3	15.3	16.6	19.2	18.6	19.2	19.2	19.2	71.3	69.2	71.8	63.9	83.2
31	24.3	24.3	24.3	24.3	25.5	33.4	29.1	33.0	33.4	33.4					
32	20.3	19.1	19.5	19.7	17.2	41.0	41.0	41.0	49.6	41.0					
33	20.5	20.5	20.5	20.5	20.5	21.4	21.4	21.4	21.4	21.4					
34	17.5	17.0	17.5	17.0	20.8	41.4	41.4	41.4	41.3	41.4					
35	12.1	12.1	12.1	12.1	12.1	16.2	16.2	16.2	16.2	16.2					
36	29.8	29.7	28.0	29.9	28.5	42.0	34.5	42.0	39.1	41.8					
37	26.3	24.0	27.1	26.4	27.3	21.7	16.2	21.3	19.1	20.7					
38	30.0	27.2	19.6	27.0	23.3	30.6	30.6	30.6	30.6	30.6					
39	12.0	12.0	12.0	12.0	12.5	15.7	15.6	13.9	14.9	15.0					
40	60.3	48.9	55.0	54.4	51.5	41.3	28.6	33.8	41.3	41.3	74.1	74.3	84.8	64.1	77.2
41	41.6	45.4	52.6	43.5	41.6	36.0	36.0	30.5	36.0	36.0					
42	16.3	16.3	16.0	16.3	17.3	22.6	22.6	21.9	22.6	22.6	27.3	27.0	24.8	28.9	26.6
43						91.5	78.2	46.0	91.0	90.9					
44	11.0	11.0	10.9	11.0	9.2	45.6	44.3	39.3	42.7	41.5					
45	52.5	46.6	25.8	41.7	42.1	51.6	49.4	37.2	50.4	48.4					
46	40.3	37.9	39.5	32.5	34.5	42.6	35.6	28.6	42.5	37.8					
47	47.0	36.1	29.6	38.8	36.9										
48	40.7	41.0	37.9	39.9	34.2	78.4	69.2	71.6	75.2	74.7	52.7	52.7	46.0	49.4	53.7
49	15.0	15.0	15.0	15.0	13.6	28.8	28.8	28.7	28.8	28.8	32.0	39.6	30.7	32.0	31.9
50	11.7	11.6	10.3	11.8	12.0	35.1	35.2	35.1	33.4	38.6					

(continued)

Table A11. (Continued)

	Winter wheat					Rapeseed					Maize				
	Not	Extended		Short		Not	Extended		Short		Not	Extended		Short	
ID	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat
51	21.1	20.9	21.7	20.8	21.0	62.5	62.5	56.3	62.5	62.5					
52	9.3	9.3	8.6	9.3	7.8	23.5	16.9	21.4	17.1	30.5	26.8	27.7	26.3	27.5	35.7
53	16.3	15.5	15.4	17.5	16.6	21.1	19.7	21.2	20.4	21.1	22.4	20.9	22.4	23.7	22.4
54	24.7	24.7	25.0	24.7	26.5	28.5	28.5	34.2	29.3	28.5	20.0	20.0	16.3	15.7	11.1
55	23.2	21.7	23.2	21.9	28.4	29.6	23.5	29.4	24.5	27.2					
56	15.0	16.0	15.0	14.8	18.8										
57	12.8	12.8	12.8	12.8	12.7	22.3	22.3	20.4	22.3	22.3	17.1	17.1	17.3	16.9	17.0
58	7.8	7.8	7.5	7.8	8.1	31.4	31.4	31.4	26.3	30.5	27.7	26.6	25.3	27.7	27.7
59	20.1	17.6	19.6	17.8	16.9	41.4	40.8	38.9	41.3	44.8	73.0	74.2	38.7	73.6	72.5
60	13.2	12.0	13.3	12.4	11.7	15.5	14.1	17.7	13.7	22.2					
61	15.0	13.4	14.6	14.0	14.7	24.2	16.1	25.7	17.8	21.6					
62	53.2	53.0	41.2	53.0	48.9	26.4	26.4	18.3	26.4	24.8					
63	42.6	35.7	32.6	32.7	35.2	28.8	28.1	21.4	28.6	27.4					
64						22.0	22.0	23.1	22.1	27.5	31.8	31.8	31.8	31.8	30.9
65	69.5	61.2	64.4	64.3	61.6	54.8	35.0	48.7	54.3	58.4	33.8	33.3	28.0	28.9	31.4
66	19.7	18.3	19.4	18.6	17.0	32.5	32.5	31.8	32.2	32.5	35.1	31.9	23.7	18.6	18.4
67	24.5	24.0	20.6	23.2	19.6						31.4	31.0	31.4	26.7	31.4
68	21.7	21.9	21.7	21.7	22.6	65.5	57.5	66.2	69.1	74.5	78.0	78.0	77.3	78.0	76.2
69	17.2	17.2	16.9	17.2	13.7	31.7	29.0	29.1	31.7	31.7					
70	13.9	13.9	13.9	13.9	14.5										
71	20.7	20.7	20.7	20.7	18.6	22.0	22.0	20.1	22.3	22.0	12.7	12.7	9.8	11.4	10.0
72						32.0	29.0	40.5	32.0	32.0					
73	10.7	10.7	10.7	10.7	11.6						30.6	30.7	27.9	27.4	30.6
74	18.0	16.6	18.0	17.1	22.9	28.7	23.2	28.7	22.6	28.7	14.1	12.6	15.1	12.8	13.4

(continued)

Table A11. (Continued)

	Winter wheat					Rapeseed					Maize				
	Not	Extended		Short		Not	Extended		Short		Not	Extended		Short	
ID	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat	Insured	Stat	Sat	Stat	Sat
75	35.2	35.2	29.5	34.9	32.2	44.4	39.5	44.4	44.4	44.4	39.4	39.4	37.0	39.4	38.5
76	34.5	34.5	34.5	34.5	30.5	41.1	41.1	54.3	41.1	41.1					
77	22.6	22.3	22.5	23.0	22.3	63.0	63.0	49.8	55.0	59.6					
78	31.9	32.0	30.8	32.3	29.6	21.0	20.3	18.6	21.6	25.6					
79	46.8	28.2	33.4	39.8	40.2	67.1	56.6	56.2	65.6	67.6					
80	17.1	14.0	16.1	14.9	14.0	30.6	23.1	21.9	26.7	30.8	36.4	27.6	26.7	25.6	31.3
81	14.6	14.0	14.2	14.2	12.7	25.0	22.3	24.2	24.1	25.0	121.0	125.4	121.0	121.0	125.9
82	10.2	10.2	8.4	10.2	8.9						40.1	39.9	35.6	33.4	22.1
83	15.4	15.4	12.5	15.4	15.4	31.5	31.5	31.8	31.5	28.6	20.7	20.7	20.7	20.6	19.5
84	8.1	8.1	8.1	7.9	11.1	19.0	19.0	21.7	19.0	19.0					
85	10.2	10.2	10.2	10.2	11.3	42.4	42.4	42.4	42.4	42.4					
86	32.8	32.6	29.1	32.8	23.8	98.4	76.7	86.9	91.7	98.5	86.9	91.4	65.5	73.6	74.5
87	38.7	35.3	38.3	36.7	33.7	27.0	25.7	27.3	28.5	27.3	49.2	48.9	41.7	45.2	34.2
88	20.4	20.3	20.4	20.4	23.6	38.2	38.2	38.2	46.0	38.2	44.5	39.9	43.7	38.3	39.5
89	27.3	27.1	20.1	27.1	18.9	24.8	21.8	18.1	26.8	23.2	40.7	40.7	40.6	33.4	33.6

ID: farm identification number; grey areas: no yield data; *X*: no satellite measurement possible.

Table A12. Results with strike level defined with mean yields[c] instead of quantile approach (equation (A3))

Crop	Phase	Index	Compared to no insurance			Compared to station-based insurance		
			Ø Relative RP change[a]	Confidence interval (95%)	p-value[b]	Ø Relative RP change	Confidence interval (95%)	p-value
WHEAT	Extended	Station	−4.66	(−6.7, −2.6)	0			
		Satellite	−9.34	(−12.5, −6.2)	0	−4.82	(−7.7, −2)	0
	Short	Station	−4.26	(−6.4, −2.1)	0			
		Satellite	−7.33	(−10.6, −4)	0	−2.94	(−6.1, 0.2)	0.02
RAPESEED	Extended	Station	−7.47	(−10.1, −4.9)	0			
		Satellite	−6.81	(−10.5, −3.1)	0	2.38	(−2.7, 7.5)	0.44
	Short	Station	−2.41	(−4.4, −0.4)	0.01			
		Satellite	0.95	(−1.4, 3.3)	0.55	4.21	(1, 7.4)	0.98
MAIZE	Extended	Station	−2.44	(−5.3, 0.4)	0.01			
		Satellite	−9.01	(−14.2, −3.8)	0	−5.95	(−11.8, −0.1)	0.05
	Short	Station	−12.34	(−17.3, −7.3)	0			
		Satellite	−8.42	(−14.7, −2.1)	0.02	6.41	(−1.8, 14.6)	0.96

[a] $\text{Ø } Relative\ RP\ Change = \text{Ø}\left((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i}\right)$

[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

[c] $S_{i,v} = \frac{\left(\frac{1}{N_t}\sum_{t=1}^{N} Y_{i.t}\right) - \beta_{0i,v}}{\beta_{1i,v}}$

Table A13. Risk premium reduction with individually tailored insurance time frame according to highest risk reduction

Crop	Phase	Index	Compared to no insurance			Compared to station-based insurance		
			Ø Relative RP change[a]	Confidence interval (95%)	p-value[b]	Ø Relative RP change	Confidence interval (95%)	p-value
WHEAT	Individually optimized	Station	−5.86	(−7.8, −3.9)	0.00			
		Satellite	−9.79	(−12.9, −6.6)	0.00	−4.27	(−7, −1.6)	0.01
RAPESEED	Individually optimized	Station	−9.31	(−11.7, −6.9)	0.00			
		Satellite	−8.69	(−11.4, −6)	0.00	1.88	(−2, 5.8)	0.76
MAIZE	Individually optimized	Station	−9.06	(−12.4, −5.8)	0.00			
		Satellite	−11.13	(−15.6, −6.7)	0.00	−1.73	(−6.5, 3)	0.26

[a] $\text{Ø } Relative\ RP\ Change = \text{Ø}\left((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i}\right)$.

[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

Table A14. Risk premium reduction with a split sample (2005-2015)

Crop	Phase	Index	Compared to no insurance			Compared to station-based insurance		
			Ø Relative RP change[a]	Confidence interval (95%)	*p*-value[b]	Ø Relative RP change	Confidence interval (95%)	*p*-value
WHEAT	Extended	Station	−4.51	(−6.9, −2.1)	0.01			
		Satellite	−1.67	(−4.8, 1.4)	0.27	3.97	(0.2, 7.7)	0.96
	Short	Station	−3.07	(−4.6, −1.5)	0.04			
		Satellite	−2.27	(−4.8, 0.3)	0.35	0.99	(−1.6, 3.6)	0.88
RAPESEED	Extended	Station	−12.14	(−15.4, −8.9)	0.00			
		Satellite	−8.02	(−11.2, −4.8)	0.00	7.26	(2.2, 12.3)	1.00
	Short	Station	−2.39	(−4.7, −0.1)	0.10			
		Satellite	0.04	(−2.2, 2.3)	0.94	3.30	(0.5, 6.1)	0.94
MAIZE	Extended	Station	−1.14	(−2.7, 0.4)	0.69			
		Satellite	−6.43	(−10.1, −2.8)	0.01	−5.14	(−9.1, −1.2)	0.00
	Short	Station	−7.38	(−11.1, −3.6)	0.00			
		Satellite	−4.53	(−10.3, 1.3)	0.06	3.85	(−2.4, 10.1)	0.90

[a] $Ø\ Relative\ RP\ Change = Ø\ ((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i})$

[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

Table A15. Out-of-sample risk premium change with pooled quantile regression and therefore no single-farm tailoring

Crop	Phase	Index	Compared to no insurance			Compared to station-based insurance		
			Ø Relative RP change[a]	Confidence interval (95%)	*p*-value[b]	Ø Relative RP change	Confidence interval (95%)	*p*-value
WHEAT	Extended	Station	−3.52	(−4.8, −2.2)	0.00			
		Satellite	−2.26	(−4.5, −0.1)	0.00	1.38	(−0.7, 3.5)	0.34
	Short	Station	−2.55	(−3.6, −1.5)	0.00			
		Satellite	−3.14	(−5.4, −0.9)	0.00	−0.60	(−2.7, 1.5)	0.01
RAPESEED	Extended	Station	−5.63	(−7.1, −4.2)	0.00			
		Satellite	−3.72	(−5.4, −2)	0.00	2.28	(0.4, 4.1)	0.97
	Short	Station	−3.29	(−4.7, −1.9)	0.00			
		Satellite	0.33	(−0.9, 1.6)	0.57	4.01	(2.6, 5.4)	1.00
MAIZE	Extended	Station	−1.37	(−4.4, 1.7)	0.11			
		Satellite	−1.47	(−6.5, 3.5)	0.04	1.13	(−5.9, 8.2)	0.13
	Short	Station	−7.47	(−11.1, −3.9)	0.00			
		Satellite	−1.17	(−6.9, 4.6)	0.38	7.78	(0.6, 15)	0.99

[a] *Ø Relative RP Change* $= Ø\ ((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i})$. Tick size and strike level of each farm *i* derived with pooled quantile regression using data of other farms with same crop but leaving out data of farm *i*.
[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

Table A16. Risk premium change when designing a new insurance each year, always omitting data from the insured year

Crop	Phase	Index	Compared to no insurance			Compared to station-based insurance		
			Ø Relative RP change[a]	Confidence interval (95%)	*p*-value[b]	Ø Relative RP change	Confidence interval (95%)	*p*-value
WHEAT	Extended	Station	−0.12	(−1.3, 1)	0.16			
		Satellite	−1.29	(−3.5, 0.9)	0.01	−1.08	(−3.2, 1)	0.00
	Short	Station	0.94	(0, 1.9)	0.71			
		Satellite	−1.92	(−4.3, 0.4)	0.00	−2.79	(−5, −0.5)	0.00
RAPESEED	Extended	Station	−2.29	(−3.5, −1.1)	0.00			
		Satellite	−2.90	(−4.5, −1.3)	0.00	−0.45	(−2.2, 1.3)	0.09
	Short	Station	−1.59	(−2.9, −0.3)	0.05			
		Satellite	2.48	(1.2, 3.8)	1.00	4.36	(3, 5.8)	1.00
MAIZE	Extended	Station	−0.60	(−3.2, 2)	0.19			
		Satellite	−0.28	(−6.7, 6.2)	0.11	1.32	(−6.8, 9.5)	0.11
	Short	Station	−10.06	(−14.2, −5.9)	0.00			
		Satellite	−1.26	(−7.7, 5.1)	0.33	11.00	(2.8, 19.2)	1.00

[a] $Ø\ Relative\ RP\ Change = Ø\left((RP_{I,i} - RP_{no_I,i})/RP_{no\_I,i}\right)$. Tick size and strike level of each farm *i* derived with quantile regression leaving out year *t*.

[b] H0: The sample mean of the risk premium in the tested scenario (in rows) is larger or equal than in the comparison scenario (in columns).

European Review of Agricultural Economics Vol **48 (2)** (2021) pp. 315–337
doi:10.1093/erae/jbab002
Advance Access Publication 25 January 2021

Does family farming reduce rural unemployment?

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Received October 2019; final version accepted January 2021

Abstract

This article investigates the causal relationship between family farming and rural labour markets. To this end, we combine farm accountancy data and public labour market statistics at the district level (NUTS-3) for the years 2008–2013. While cross-sectional regressions reveal a strong and robust negative correlation between the share of family farm labour and unemployment rate in a region, fixed-effects panel data regressions suggest this is not causal. Instead, we find evidence that cultural differences in work ethic spuriously connect family farming with unemployment. Thus, supporting family farming to fight rural unemployment is not an effective strategy in Germany.

Keywords: Family Farming, Rural Unemployment, Labor Markets, Culture, Work Ethic

JEL classification: R23, Q12, J2, J4, Z13

1. Introduction

A considerable share of farm income in the Organisation for Economic Co-operation and Development (OECD) countries comes from public support. In the European Union, producer support amounts on average to a third of agricultural factor income and more than half of farm family income (Matthews, 2019). The welfare effect of these payments depends fundamentally on what they achieve, e.g. in terms of beneficial societal outcomes (Garrone *et al.*, 2019; Louhichi *et al.*, 2018; Pe'Er *et al.*, 2019; Rizov, Davidova and Bailey, 2018) and taxpayer preferences (Ellison, Lusk and Briggeman, 2010; Finger and El Benni, this issue; Mittenzwei *et al.*, 2016; Variyam and Jordan, 1991; Variyam, Jordan and Epperson, 1990).

In many countries around the world, there is a strong societal and political preference for small family farms, and many societal benefits are ascribed to them. In Germany, this is called 'Bäuerliche Landwirtschaft'. To support it,

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