FARMERS' PREFERENCES FOR SATELLITE-BASED AND PRECIPITATION-BASED INDEX INSURANCE: INSIGHTS FROM GERMANY

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Abstract

Crop insurance and index insurance in particular is a promising tool for farmers to cope with rising climate risks. However, the demand of index insurance in Europe is low as current policies based on weather station data suffer from high basis risk. To reduce the basis risk, the use of satellite data is discussed. While this has been empirically shown, valid studies on insights into farmers' preferences for satellite-based index insurance are missing. We employ a discrete choice experiment with 127 German farmers to compare preferences for hypothetical satellite-based and precipitation-based index insurance. We also focus on the effect of partial subsidization on farmers' utility as the common agricultural policy allows for subsidization of index insurance to reduce premiums for farmers. We include other attributes like premium, strike level and payout as they were rated as important by farmers. Mixed logit model results show a preference for both index insurance policies against the opt-out. Furthermore, the average farmer has a statistically significant higher preference for the satellite-based against the precipitation-based index insurance. We find farmers to be more sensitive to subsidizing satellite-based index insurance. Our results highlight the potential of satellite data to increase farmers' demand for index insurance and are of interest for insurers and policymakers.

Keywords

satellite data, index insurance, risk management, discrete choice experiment

1. Introduction

Climate risks caused by climate change, especially droughts and heat waves, are expected to occur more often and affect larger areas in the temperate zone in Europe. This will adversely affect crop yields, increases income uncertainty for farmers and calls risk management to improve (Finger and El Benni, 2021; Harkness et al., 2020; Lunt et al., 2016). Crop insurance is commonly discussed in this context to ensure liquidity of farms. Yet, only a small proportion of farmers in Europe is insured against drought (MEUWISSEN et al., 2018) as no program like the US Federal Crop Insurance Program is in place (GLAUBER, 2013). In Germany, for example, less than 1% of farmers are insured against drought, even though the country was hit by a catastrophic nationwide drought in 2018. (BUNDESMINISTERIUM FÜR ERNÄHRUNG UND LANDWIRTSCHAFT, 2018; GERMAN INSURANCE ASSOCIATION, 2019). To increase farmers' demand, the common agricultural policy (CAP) established measures to support farmers in risk management and allowed subsidization of insurance for catastrophic events (EUROPEAN UNION, 2017).

Further, the concept of index insurance seems promising to increase demand among farmers, as it simplifies loss assessment and reduces moral hazard risk compared to traditional indemnity-based crop insurance (BARNETT and MAHUL, 2007). However, while these new insurance schemes are already well established in the USA and Canada, they are emerging too slowly in Europe to deal with the increasing climate risks (VROEGE et al., 2019). In particular, the intensively discussed high basis risk of policies based on weather station data does not fit the preferences of farmers (HEIMFARTH and MUSSHOFF, 2011). It is known that high basis risk makes index insurance unattractive even for risk-averse decision-makers, as it can even worsen the financial situation in the event of a claim (CLARKE, 2016). Moreover, increasing premiums, resulting from more frequent occurrence of droughts, discourage farmers from buying insurance even under fair premium conditions (DU et al., 2017). Therefore, making index insurance more attractive presents insurers and policymakers with a challenging task that should focus on improving the quality and pricing of policies to increase demand (HILL et al., 2016).

Satellite data (e.g. biomass data or soil moisture data) has received considerably research attention to reduce basis risk and improve hedging effectiveness of index insurance. Previous studies in developed and developing countries investigated various satellite indices for integrating into index insurance (e.g. BOKUSHEVA et al., 2016; TURVEY and MCLAURIN, 2012). In general, positive effects on hedging effectiveness or a reduction in basis risk were found. Surprisingly, there is a lack of literature on farmers' demand and their preferences for satellite-based insurance. VROEGE et al. (2021) point out that satellite data improve the number of insurance options. Moreover, satellite data can contribute to the development of individually tailored insurance (BUCHELI et al., 2021). However, insights into farmers' preferences and experiences with satellite data are needed to design future policies.

This article provides first insights into preferences for satellite-based insurance. In particular, we investigate into farmers' overall preferences for satellite-based compared to precipitation-based index insurance. We also focus on the effect of partially subsidizing index insurance on farmers' utility. However, this study is more basic research on farmers' demand for satellite-based index insurance than it is aimed at precisely quantifying its market potential. As satellite-based insurance is hard to find in Europe, a discrete choice experiment (DCE) has been conducted with German farmers. In a hypothetical scenario, farmers could decide whether or not to insure themselves against drought by purchasing hypothetical index insurance policies. Specifically, they could choose between a satellite-based and a precipitation-based policy. To the best our knowledge, we are the first measuring farmers' preferences for a satellite-based insurance. Additionally, we are the first to study the influence of subsidized index insurance on farmers' utility. Herewith, we can contribute to the political discussion on government intervention to improve risk management on a national level. The results should provide guidance to insurers regarding the design of insurance products and give policymakers insights into how governmental support would change farmers' demand. The article is structured as follows. First, we give a brief overview on index insurance and satellite data in this context in particular. In section 3, the idea of the DCE approach and its methodology is explained. Additionally, our experimental setting is shown. We present and discuss the results of farmers' preferences in section 4. A conclusion ends up this article.

2. Index insurance and the potential of satellite data

The literature on index insurance mainly focus on meteorological indices like precipitation or temperature sums, but also indexes referring to water stress like evapotranspiration are discussed (LEBLOIS and QUIRION, 2013). However, the performance of such insurance schemes is affected by the distance to the next weather station, creating a geographical basis risk (HEIMFARTH and MUSSHOFF, 2011). Moreover, the correlation of the crop yield and the underlying index is imperfect, resulting in a mismatch of the payoff and the yield loss experienced by the farmer because the weather index is not the only determinant of the crop yield (JENSEN et al., 2016). Nevertheless, the majority of index insurance policies in Europe are currently based on weather station data (VROEGE et al., 2019). To reduce the problem of basis risk and increase the hedging effectiveness, several opportunities are under discussion. For one, gridded precipitation data is used to ensure a low geographical basis risk (DALHAUS and FINGER, 2016). Weighted daily precipitation data from different weather stations combined with orographic data are converted into a grid to interpolate precipitation between weather stations. Thus, heavy precipitation and zero precipitation observations at weather stations are not excluded, but remain in the data. This reduces the technical risk, since a failure of one weather station can be compensated.

Further, satellite data is under investigation given their availability in almost real time and their independency of the density and number of weather stations (QUIRING and GANESH, 2010).

Several indexes on biomass data, such as the normalized difference vegetation index (NDVI), are discussed. The NDVI describes the density and vigor of green biomass and is an indicator for the health of the vegetation (LEBLOIS and QUIRION, 2013). The NDVI is highly adapted to biomass assessment, while it shows an inconsistent relationship to crop yield. Due to this, the NDVI is primarily investigated for use in forage index insurance (TURVEY and MCLAURIN, 2012). Other studies focus on the vegetation condition index (VCI) and the temperature condition index (TCI). The VCI is a relative indicator that shows how vegetation develops between the minimum and maximum potential of a particular region, while TCI is a relative indicator of how favorable or unfavorable the thermal conditions are at the vegetation surface (KOGAN, 1995).

Even though these biomass indices show good results in terms of hedging effectiveness (BOKUSHEVA et al., 2016; MÖLLMANN et al., 2019a), it will face problems for practical integration. First, it cannot be accurately identified that the observed loss in yields due to the low index is drought-related (AGHAKOUCHAK et al., 2015). It is important that the interaction of the weather events and damage in a specific growth phase is clear (NIETO et al., 2010). Especially in spring, late frosts can cause damage to growing winter crops (MARTINO and ABBATE, 2019). Second, the use of high granularity increases the risk of moral hazard costs, as agricultural practices and potential diseases can also affect yields (WEBBER et al., 2020). If farmers notice their crops being in bad conditions, there is a risk to neglect crop protection and fertilization as the insurance would cover a defined damage. This would entail high monitoring costs for insurers and lead to higher premiums (CLEMENT et al., 2018) or requires a lower spatial resolution, which would be accompanied by a loss of hedging effectiveness. Third, there is a time lag between weather effects and indices such as NDVI, VCI and TCI. In the case of moderate heat stress, crops react with a time delay with reduced chlorophyll production (NIETO et al., 2010). In particular, drought periods towards the end of the insurance period could not be reflected in the index.

By taking these constraints into account, other papers focus on soil moisture (ENENKEL et al., 2018). A drought-related reduced soil moisture combined with a decrease in evapotranspiration has negative effects on crop yields (SENEVIRATNE et al., 2010). Soil moisture is commonly described as the water content of the unsaturated part of the soil in m^3 of water per m^3 of soil, resulting in a volumetric soil moisture content. However, because measuring soil moisture on ground is costly and difficult, researchers investigate into globally available satellite-retrieved soil moisture (DE JEU and DORIGO, 2016). Likewise, sentinel satellites can provide soil moisture data with a spatial resolution of 1x1 km (BAUER-MARSCHALLINGER et al., 2019). Remotely sensed soil moisture data are also available with lower spatial resolution, which can depict entire regions (COPERNICUS CLIMATE CHANGE SERVICE, 2019). As these studies shown, satellite data is potentially suitable for insurance. It can provide farmers information on crop health status and soil moisture.

3. Discrete choice experiment

3.1. Conceptual framework

Within the field of DCEs, especially the stated preference approach is of huge interest for researchers and very commonly used. In contrast to revealed preference methods, stated-preference methods allow to measure preferences in hypothetical situations in the context of e.g. new products (LOUVIERE et al., 2000). Since insurance based on satellite data for crops is still hard to find in Europe and no real data can be used, we apply the stated preference approach. To measure peoples' preferences, DCEs are well established methodology in agricultural economics (e.g. SCHULZ et al., 2014) and have been used in the context of crop insurance as well (LIESIVAARA and MYYRÄ, 2014; MÖLLMANN et al., 2019b). The random utility theory of MCFADDEN (1974) is the baseline for all developed choice models. According to the theory, consumers do not derive utility from a good itself, only from the characteristics associated with the good. Accordingly, a consumer chooses the good from a set of goods that provides the maximum individual utility. Following HENSHER et al. (2015), the random utility U of an individual n for an alternative j in choice situation s can be divided into 2 parts, a modeled and observable component V_{nsj} and a non-modeled and non-observable component ε_{nsj}, such that:

$$U_{nsj} = V_{nsj}(\beta_n X_{nsj}) + \varepsilon_{nsj} \quad (1)$$

where X_{nsj} describes the vector of attributes of an insurance and personal and farm characteristics, β_n is a vector of individual-specific random coefficients and ε_{nsj} is an error term that is assumed as an independently and identically distributed extreme value. In a DCE, participants are presented with different decision situations in which they have to choose one out of several alternatives. These alternatives are characterized by certain attributes, which have different characteristics (levels) across the decision situations. A pre-defined varying of the levels over choice sets allows the preferences for alternatives and attributes to be determined (LIST et al., 2006). In order to avoid forced decisions and resulting contradictions and inconsistencies with the demand theory, the opt-out option as a further alternative is offered in each decision situation (HANLEY et al., 2002).

3.2. Estimation procedure

For analyzing choice data, LOUVIERE (2000) developed different econometric models. We apply the mixed logit model (MXL). The MXL allows for more flexible estimations of the random utility compared to the conditional logit model. It does not depend on the assumption on interdependence of irrelevant alternatives. Moreover, it allows for correlation of unobserved factors and varying parameter across the sample. According to HENSHER et al. (2015), the probability of a farmer n choosing alternative j in choice situation s is given by:

$$Prob\ (Choice_{ns} = j|\boldsymbol{X}_{nsj}, \boldsymbol{Z}_n \boldsymbol{v}_n) = \frac{exp(V_{nsj})}{\sum_{j=1}^{J_{ns}} exp(V_{nsj})} \quad (2)$$

where and $\boldsymbol{X}_{nsj}$ represents the K attributes of alternative j a farmer n facing in choice situation s and β_n are the parameters to be estimated for the attributes. $\boldsymbol{Z}_n$ is set of M characteristics of farmer n influencing the mean of the taste parameters and $\boldsymbol{v}_n$ describes a vector of random variables with zero means, knowing variances and zero covariances. We apply the Wald test to analyze if differences in coefficients of satellite-based and precipitation-based index insurance differ statistically significant from zero.

3.3. Experimental design

In our study, we offer farmers a satellite-based and a precipitation-based policy. We use winter wheat as the related crop because winter wheat is the most important crop in Germany and is grown in at least the whole country (DESTATIS, 2021). To give practical implications, we consider the discussion on satellite and meteorological indexes presented in section 2 in the design. Therefore, to minimize the risk of moral hazard and to avoid high control costs and thus high loadings, we provide farmers a satellite-based soil moisture index. The index is based on the volumetric soil moisture values (m^3 water/m^3 soil) measured during the insurance period. As ranges of soil moisture can differ even at short distance depending on soil type and absolute level (MITTELBACH and SENEVIRATNE, 2012), we offer an index with high spatial resolution (1x1 km). For the precipitation-based index insurance, we provide farmers an index based on gridded precipitation data with a spatial resolution of 1x1 km. Within these grids, the sum of precipitation per m^2 during the insured period is interpolated (DALHAUS and FINGER, 2016). Policies based on this index are currently offered by insurers in our study region (VEREINIGTE HAGEL, 2020). The insured period of a policy usually refers to a fix calendar period (e.g. April to June). However, different latitudes and altitudes result in differences in vegetation periods throughout Germany (GERSTMANN et al., 2016). Following DALHAUS et al. (2018), we focus on the critical phenological phase, since crops vulnerability changes across the different growth phases. For wheat, the most vulnerable time frame for damage by water lacking is between stem elongation and milk ripeness (ACEVEDO et al., 2002).

In practice, farmers can determine the sum insured per ha themselves. The sum insured may be the expected market price multiplied by the expected yield for the insured crop. However, farmers can choose individually a sum that is above or below the expected revenues as well. To take the differences in yield potential and risk attitudes into consideration, farmers could choose 1,000€, 1,250€ and 1,500€ per ha in advance of the experiment. The premiums and the payout of the insurance refer to the selected sum. In particular, they are calculated proportionally. Hence, premiums and payouts for 1,500€ sum insured are 50% higher than for 1,000€. We derived the attributes and levels for the final design of the experiment from the literature on DCEs in insurance context and the pilot study, which was conducted in May 2021 with 15 German farmers. As part of it, farmers were asked to rate the relevance of various attributes in the decision-making progress for purchasing insurance on a Likert scale. According to the results, the four most important attributes are the amount of premium, the level of subsidization, the respective strike level and the amount of payout. Table 1 shows the attributes and levels used in the experiment.

Table 1: Attributes and levels of the alternatives

Sum insured per ha[a]	1,000€, 1,250€, 1,500€
Attribute	**Levels**
Premium	2%, 4%, 6%, 8% (based on sum insured)
Subsidy level	0%, 25%, 50% of the premium
Strike level	20%, 25%, 30% expected loss in yields
Payout	20%, 30%, 40% (based on sum insured)
Weather data source:	Precipitation index: The index is based on the interpolated precipitation per m^2 calculated proportionally from various weather stations in your region by using gridded data with a spatial resolution of 1x1 km during the insured period (stem elongation to milk ripeness). Satellite index: The index is based on values of the volumetric soil moisture (m^3 water/m^3 soil) measured by satellites by means of radar radiation at 5-10 cm soil depth on your land with a spatial resolution of 1x1 km during the insured period (stem elongation to milk ripeness).

[a]The sum insured per ha has to be determined by the farmers in advance of the experiment. It is constant across all choice sets.

The attribute "premium" describes the amount to be paid annually per ha. Premiums for a particular farm are composed of the fair premium, which depends on the long-term damage, and the loading factor including the production costs of the policy and the margin of the insurer. However, calculation of fair premiums was not possible due to unknown risk exposure of participating farmers. According to the largest insurer in Germany, premiums for drought insurance start from 2% up to 10% of the insured sum (VEREINIGTE HAGEL, 2020). Hence, we use the respective value for 2%, 4%, 6% and 8% of the insured sum for both policies. DU et al. (2017) identify that higher expenditures for premiums even under fair conditions reduce farmers' willingness to insure. MÖLLMANN et al. (2019b) show that an increased premium for revenue insurance and whole farm insurance declines the probability to insure. Therefore, we expect a negative effect of the premium on farmers' utility.

Under CAP, subsidies of up to 65% of the annual premium for insurance are allowed (EUROPEAN UNION, 2017). Based on this, farmers are presented with a subsidy of 0%, 25% or 50% of the premium. We expect an increase in utility with a higher subsidy level due to the reduction in the premium. MUSSHOFF et. al (2014) show for farmers in our study region that an explicit communication of a subsidization leads to an increased demand for index insurance even the exactly costs for farmers are not affected. Further, they find that farmers nevertheless perceive a subsidy as an indicator for economically beneficial alternatives. We want to identify whether this effect depends on the subsidized index.

The attribute "strike level" is defined as the threshold for the respective index. Based on historical yield and index observations, the corresponding value of the index for the average yield can be quantified (CONRADT et al., 2015a). More precisely, a specific quantile of the yield corresponds to a specific value of the index which can be used as the threshold value. We set up a minimum expected loss in yields of 20% in order to meet the legal requirements for partial subsidization (EUROPEAN UNION, 2017). If the interpolated precipitation per m^2 during the insurance period is below the amount that corresponds to a 20% lower yield than the long-term average, the farmer receives a payout. Regarding the satellite index, the farmer receives a payout if the average value of volumetric soil moisture during the insurance period is at least below the corresponding average soil moisture that will cause a 20% yield loss. Furthermore, we offer farmers a strike level of 25% and 30% and expect a decrease in utility. The attribute "payout" describes the amount of compensation that farmers would receive per ha in the event of claim. According to the findings of LIESIVAARA and MYYRÄ (2014), we assume an increasing payout to have a positive effect on farmers' utility. We offer a fixed payout, since current policies in Germany also offer a fixed payout (VEREINIGTE HAGEL, 2020).

Our DCE with two alternatives results in a full-factorial design of 11,664 possible choices $(4x3x3x3)^2$. Results from the pilot study were used to take prior information for all integrated utility parameters into account. Additionally, we use them to reduce the number of choice sets to 12 to increase practicability and avoid overburdening farmers (BECH et al., 2011). We create a D-efficient design with a D-error of 0.0058 (ROSE and BLIEMER, 2009). Furthermore, we randomize the order of all choice sets between the respondents to minimize order effects (CARLSSON et al., 2012). Table 2 shows an exemplary choice set. In each situation, the opt-out was also offered to the farmers as the "no insurance" alternative.

Table 2: Exemplary choice set for insuring 1,500€ per ha

	Precipitation index	Satellite index	No insurance
Index	Sum of precipitation per m^2 proportionally calculated based on the various weather stations by using gridded data with a spatial resolution of 1x1 km	Volumetric soil moisture measured by satellites using radar radiation at 5-10 cm soil depth with a spatial resolution of 1x1 km	
Premium	90€	90€	
Subsidy level	25%	50%	
Strike level	20% expected loss in yields	30% expected loss in yields	
Payout	300€	600€	
I choose:	○	○	○

3.4. Sample collection

An online survey among German farmers was conducted in June 2021. Farmers who grow wheat as part of their crop rotation were allowed to participate. Farmers were invited via social media and online forums. Furthermore, farmers who had already participated in previous surveys were invited to participate via an e-mail distribution list. The survey was divided into four sections. First, information on socio-economic and farm business characteristics was required. Second, we investigate farmers' current climate risk management as well as the economic effect of climate change on the farm over the past several years. Third, the DCE was conducted. Finally, farmers' knowledge, experiences with insurance as well as their trust and understanding of index insurance in particular were investigated.

4. Results and discussion

4.1. Descriptive statistics

127 farmers fully completed the survey. Table 3 shows the socio-economic characteristics. The farmers are about 42 years on average and thus younger than the average German farmer (53

years). 84% claim farming as their main occupation which is above the German average (48%). Therefore, the average farmer cultivates 201 hectares which lies above the German average (63 hectares). In addition, the sample consists of 93% conventional farmers which lies close to the German average (90%). Our sample is equal in terms of gender distribution to the German average (10% are female farmers). The proportion of farmers who have completed an agricultural degree is 57% and lies far above the German average of 12%. 53% of farmers also keep livestock, which is lower than the German average (67%) (GERMAN FARMERS FEDERATION, 2021). Our sample is more highly educated, larger and younger than the average German farmer. Likewise, CONRADT et al. (2015b) mention that the use of phenology data for insurance requires a high level of understanding. This could also be applied to the use of satellite data. Moreover, young, large and highly educated farmers have been identified as the core group for precision agriculture adoption (e.g. MICHELS et al., 2020). Satellite-based insurance could also first be adopted by these farmers.

Table 3: Descriptive statistics (n=127)

Variable	Mean	SD	Min	Max
Age in years	42.08	13.68	22	75
Conventional farmer (yes=1, no=0)	0.93	-	0	1
Farm size in ha	200.66	267.92	5	2,300
Female (yes=1, no=0)	0.10	-	0	1
Fulltime farmer (yes=1, no=0)	0.84	-	0	1
Livestock owner (yes=1, no=0)	0.53	-	0	1
University degree (yes=1, no=0)	0.57	-	0	1

4.2. Farmers' overall preferences for insurance and their attributes

Table 4 presents the estimation results for the determinants of farmers' preferences for index insurance. Results of the Wald test are given in Table 5, indicating if the difference between the corresponding preference estimates for satellite-based and precipitation-based insurance attributes is statistically significant different from zero. Furthermore, we investigate whether policy attributes (premium, subsidy level, strike level and payout) have a different effect on farmers' preferences for satellite-based and precipitation-based insurance. The alternative specific constants (ASCs) for the two policies are dummy-coded variables und must be seen in relation to the opt-out. As MUSSHOFF et al. (2014) show that explicit communication of the subsidy despite unchanged actual costs increases demand, we interpret the effect of the attributes "premium" and "subsidy level" separately for the purpose of our study.

The statistically significant positive values for the ASCs in Table 4 indicate that farmers have, on average, an increase in utility by choosing insurance compared to the opt-out. Furthermore, the coefficient for satellite-based insurance is higher indicating a higher preference for the satellite-based insurance on average. The statistically significant results of the Wald-test in Table 5 confirm that the preference of farmers for satellite-based compared to precipitation-based differs from zero at 1% significance level (Wald chi-square statistic of 82.68). From Tables 4 and 5, we can conclude that farmers' preferences for satellite-based insurance is statistically significantly higher than their preference for precipitation-based. We credit this finding to farmers' understanding that using the high-resolution satellite index can increase a police's hedging effectiveness and reduce the geographical basis risk. Considering the preferences of farmers, insurers should increasingly incorporate satellite data into the development of index insurance. As a first step, satellite data could be integrated into existing policies based on weather station data. This could already increase their attractiveness for farmers.

An increase in premium is associated with high losses in farmers' utility for both policies. Thus, we can confirm the findings from other studies in the context of crop insurance (LIESIVAARA and MYYRÄ, 2014; MÖLLMANN et al., 2019b). In particular, if the premium for the satellite index increases by 2% of the sum insured, the average farmer has a decreased utility of 1.06 (-0.53•2). For the precipitation index, the result can be interpreted in the same way. Wald test results suggest that the difference between farmers' utility for the premium for satellite-based and precipitation-based insurance is statistically significant different from zero at 1% significance level (Wald chi-square statistic of 145.25). Considering the price range in the experiment, 2% means an increase in the premium per ha of 20 to 30€, depending on the sum insured, which is a comparatively high amount of money. Since not all sources of satellite data are freely available and the calculation of the indices is more demanding than for weather station data, the production costs for satellite-based insurance can be higher, which would be reflected in a higher loading factor. Further, DU et al. (2017) highlight that more frequent droughts increase fair premiums and discourage farmers from buying. As for our farmers an increase in premiums for satellite-based insurance has a stronger negative effect on utility, high loadings combined with high fair premiums represent a potential demand problem especially for satellite-based insurance and should be considered by insurers.

Table 4: Estimation results of the MXL (n=127)

Variable	Mean coefficient (Standard error)	SD[a] coefficient (Standard error)
ASC precipitation[b]	1.76** (0.85)	1.41*** (0.52)
xPremium	-0.42*** (0.05)	-
xSubsidy in 10%[c]	0.27*** (0.05)	0.25*** (0.06)
xStrike level	-0.13*** (0.03)	0.06*** (0.01)
xPayout	0.11*** (0.02)	0.08*** (0.01)
ASC satellite[b]	2.42*** (0.76)	2.50*** (0.33)
xPremium	-0.53*** (0.05)	0.15** (0.06)
xSubsidy in 10%[c]	0.31*** (0.05)	0.20** (0.08)
xStrike level	-0.08*** (0.03)	0.06** (0.01)
xPayout	0.07*** (0.01)	0.04*** (0.01)
Goodness of fit		
Log of simulated likelihood	-1,101.47	
LR-statistic (χ^2)	717.84	
Prob > chi2	0.00	
AIC	2,240.94	
BIC	2,363.07	

[a]SD indicates standard deviation. Only SD coefficients with statistical significance at the 10%, 5% and 1% levels are shown.
[b]Alternative specific constant (ASC): dummy-coded-variable with a value of 1 for the insurance alternative and 0 for "no insurance".
[c]Indicating the average preference estimate for an increase in subsidy level by 10%.
*, ** and *** represents statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5: Wald test results of differences in coefficients for both insurance products

Test	Wald statistic	Prob > chi2
Precipitation = Satellite	82.68***	0.000
Precipitation premium = Satellite premium	145.25***	0.000
Precipitation subsidy level = Satellite subsidy level	105.63***	0.000
Precipitation strike level = Satellite strike level	86.25***	0.000
Precipitation payout = Satellite payout	165.26***	0.000

*, ** and *** represents statistical significance at the 10%, 5% and 1% levels, respectively.

We observe from Table 4 that for our surveyed farmers, on average, subsidizing satellite-based insurance has a statistically significant higher positive effect on utility. If a subsidy of 25% is offered compared to no subsidy, the utility of the average farmer increases by 0.78 (0.31•2.5) for satellite-based and 0.68 (0.27•2.5) for precipitation-based index insurance. We confirm this finding by the results of the Wald test in Table 5 which show that the difference between farmers' preference for a 10% increase in subsidy level for satellite-based insurance to precipitation-based insurance is statistically significantly different from zero at 1% significance level (Wald chi-square statistic of 105.63). It is known that farmers may perceive subsidy as an indicator of the relative economic advantage of alternatives even if actual costs remain unchanged (MUSSHOFF et al., 2014). Based on our findings, we can specify that the perceived economic advantage from a subsidy depends on the particular insurance subsidized. More specifically, our farmers perceive the satellite-based as the more economically advantageous insurance. If policymakers' aim is to get as many farmers as possible to buy insurance on a fixed budget, satellite-based insurance should be subsidized as a priority because the leverage effect seems to be higher than for weather station-based insurance. If index insurance is thereby adjusted to farmers' preferences, the effect of a subsidy could persist over time (HILL et al., 2016). However, it should be noted that subsidizing only satellite-based insurance would cause providers to focus on developing satellite-based insurance and neglect alternative products.

Furthermore, the higher the loss threshold of the policy, the less likely farmers will choose insurance. Table 4 shows that a strike level of 25% compared to 20% is associated with a statistically significant loss in utility by 0.65 (-0.13•5) for the precipitation index and 0.40 (-0.08•5) for the satellite index for the average farmer. We confirm this finding by the results of the Wald test in Table 5 which show that the difference between farmers' preference for a higher strike level for satellite-based insurance to precipitation-based insurance is statistically significantly different from zero at 1% significance level (Wald chi-square statistic of 86.25). Thus, a higher strike level of the precipitation-based policy has a higher negative effect on farmers' utility compared to the satellite-based. We observe from Table 4 that a higher payout is positively associated for both policies. In detail, the average farmer derives an increase in utility of 1.10 (0.11•10) given an increase in payout from 20% to 30% of the sum insured for the precipitation-based and 0.70 (0.07•10) for the satellite-based. The statistically significant results of the Wald test confirm at 1% significance level, that the coefficients differ from zero (Wald chi-square statistic of 165.26). Therefore, we conclude that an increased payout has a higher effect on the preference for the precipitation-based insurance.

5. Conclusion

The relevance of climate risk management in Central Europe has grown especially since the catastrophic drought in 2018. However, farmers still lack sufficient insurance schemes to cope with climate risks. Satellite data have the potential to improve the hedging effectiveness and reduce the basis risk of index insurance. As no literature deals with farmers' preferences for satellite-based index insurance, we conduct a DCE to explore farmers' preferences for index insurance in Germany. We investigated farmers' preference for using satellite data compared to weather station data. We include different insurance policy attributes (premium, subsidy level, strike level and payout) as these are of high importance to farmers when making insurance decisions. Our sample has, on average, a higher preference for the satellite-based than for the precipitation-based index insurance. We also show that the leverage effect off a subsidization is higher for the satellite-based index insurance.

Our results provide preliminary insights into preferences of German farmers for satellite-based index insurance. As farmers, on average, prefer satellite data, insurers can increasingly incorporate them into the design of new policies. By integrating satellite data into policies based on weather station data or by developing purely satellite-based policies, insurers could better tailor index insurance to farmers' preferences. Policymakers can be advised that a partial subsidization will increase the demand for drought insurance in general. As farmers are, on average, more sensitive to subsidizing satellite-based index insurance, policymakers could focus on subsidizing these policies if they want to achieve the highest possible proportion of farmers to purchase index insurance with a given budget. However, it should be noted that this could lead to a steering effect of insurers, as they would focus exclusively on the development of satellite-based insurance.

With regard to debate on reliability and validity of DCEs (RAKOTONARIVO et al., 2016), we argue that the decision behavior of the surveyed farmers follows the standard assumptions of rational choice theory and thus theoretical validity is given. We claim this given the statistically significantly negative coefficients for "premium" and the statistically significantly positive coefficients for "payout" for both policies (MAS-COLELL et al., 1995). Additionally, the insured sum per ha does not affect farmers' preferences. Since premiums and payouts are calculated proportional to the sum insured, there is no economic advantage between the different sums insured. Thus, a rational farmer makes the same decisions regardless of the sum insured. However, further research is needed to validate these findings. First, the integration of socio-economic and farm characteristics can further identify factors influencing farmers' preferences. Second, given the statistically significant standard deviation of the estimated coefficients, research interest could be dedicated to heterogeneity in preferences to identify potential target groups for satellite-based index insurance. Third, given the young and highly educated sample, a larger and more representative sample is needed to strengthen the results. Furthermore, the knowledge of fair premiums would be of interest to investigate the effect of the farm-specific risk exposure. Future research should also focus on developing countries and the low educated farmers, as the preferences in the high educated European context may not directly applicable. Especially since many of these countries do not have a comparably dense network of weather stations, farmers could prefer satellite data as their use can significantly reduce the basis risk.

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