Temperature effects on crop yields in heat index insurance

Janic Bucheli\textsuperscript{a,\*}, Tobias Dalhaus\textsuperscript{a,\textdagger}, Robert Finger\textsuperscript{a}

\textsuperscript{a} Agricultural Economics and Policy Group, ETH Zurich, Switzerland
\textsuperscript{b} Business Economics Group, Wageningen University, Netherlands

\section*{ARTICLE INFO}

\textbf{Keywords:}
Index insurance
Insurance design
Heat stress
Restricted cubic splines

\section*{ABSTRACT}

Heat can cause substantial yield losses in crop production and climate change is increasing the risk of this kind of damage. Weather index insurance can help to reduce the financial losses resulting from heat exposure. This paper introduces crop-specific payout functions based on restricted cubic splines in heat index insurance. The use of restricted cubic splines is a cutting-edge method to reflect empirically estimated temperature effects on crop yields and to estimate temperature-related yield losses. The integration of these temperature effects in payout functions facilitates insurance design and allows hourly temperatures to be used as the underlying index. An empirical analysis is used to assess heat stress effects for a panel of East German winter wheat and winter rapeseed producers, to calibrate insurance contracts accordingly and simulate the resulting risk reducing capacities. We find that the insurance scheme introduced here leads to statistically and economically significant out-of-sample risk reducing capacities for farmers, i.e. risk premiums are reduced by up to approximately 20\% at the median, in comparison to the uninsured status and at the actuarially fair premium. Moreover, we highlight that policy-makers can support the cost-efficient provision of market-based weather index insurance by fostering data collection and data provision.

\section{Introduction}

Heat stress is a major driver of crop yield losses and its relevance is growing due to climate change (Lobell et al., 2011a; Schlenker and Roberts, 2009; Asseng et al., 2015; Tack et al., 2015; Lesk et al., 2016; Ortiz-Boema et al., 2019). Insurance solutions can reduce the financial losses suffered by farmers, especially when on-field risk management reaches its limit. Therefore, insurance can be a viable complement to other risk management tools and improves adaptation to climate change (Miranda and Vedenov, 2001; Smith and Glauber, 2012; Di Falco et al., 2014).

In this paper, we introduce novel and crop-specific payout functions based on restricted cubic splines into a heat index insurance design to reflect empirically estimated hourly temperature effects on crop yields. Next, we use data for crop production in Eastern Germany to evaluate empirically the potential of this heat index insurance design to reduce financial downside risks from the perspective of farmers.

Weather index insurance\textsuperscript{1}, including heat index insurance, permits timely indemnification and the insurability of systemic and specific risks, such as heat stress, at low costs and can avoid moral hazard and adverse selection problems that can cause insurance market failure (Barnett and Mahul, 2007; Barnett et al., 2008; Vroege et al., 2019; Benami et al., 2021). For these reasons, private insurance suppliers have recently introduced several weather index insurance schemes in European agriculture. The European market for weather index insurance is strongly growing and contributes to close farmers’ protection gap for extreme weather events. Weather index insurance complements traditional indemnity insurances, which were already introduced in Europe towards the end of the 18th century and that cover less systemic weather risks (e.g. hail, snow pressure, storms) and geohazards (e.g. landslides). Especially drought risks received attention in weather index insurance markets, because droughts are difficult to insure with traditional indemnity

\textsuperscript{\*} Corresponding author.
\textsuperscript{\textdagger} E-mail addresses: jbucheli@ethz.ch (J. Bucheli), tobias.dalhaus@wur.nl (T. Dalhaus), rofinger@ethz.ch (R. Finger).

\textsuperscript{1} Other studies use the terms parametric weather insurance or weather index-based risk transfer product. An alternative index product is area yield insurance, e.g. widely used in the US (e.g. Harri et al., 2011; Ker and Tolhurst, 2019). A further comparison between area yield insurance and weather index insurance is beyond the scope of this paper.

https://doi.org/10.1016/j.foodpol.2021.102214
Received 8 July 2021; Received in revised form 21 December 2021; Accepted 25 December 2021
Available online 10 January 2022
0306-9192/© 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
insurances (e.g. Vroege et al., 2019; Bucheli et al., 2021). In contrast to drought risks, we are not aware of offered heat index insurance in Europe, even though it constitutes an important risk for crop production (e.g. Webber et al., 2020). The amount of indemnification in weather index insurance depends solely on a single underlying weather index, such as accumulated temperatures, and not on actual yield observations (Mahul, 2001; Turvey, 2001). This introduces basis risk, which reflects the possible difference between the actual loss and the amount of indemnification (Vedenov and Barnett, 2004; Clarke, 2016). Basis risk is one of the most important determinants of insurance uptake and must therefore be minimized (Elabd et al., 2013; Jensen et al., 2018). The choice of the insured time period, measurement errors in the (interpolated) weather data and the insurance design are to a certain extent controllable factors that influence basis risk in weather index insurance (e.g. Woodard and Garcia, 2008; Norton et al., 2012; Dalhaus et al., 2018).

Previous studies on heat index insurance have followed the design of financial call options and proposed linear payout functions using accumulated degree-days based on daily average temperature data as the underlying index (e.g. Richards et al., 2004; Turvey, 2005; Deng et al., 2008; Woodard and Garcia, 2008; Norton et al., 2012; Okhrin et al., 2013; Buchholz and Musshoff, 2014; Leppert et al., 2021). Accumulated degree-days indicate by how much and for how long temperature exceeds a pre-defined temperature threshold (D’Agostino and Schlenker, 2016). Previous studies on heat index insurance have used different temperature thresholds for the calculation of degree-days and have estimated marginal payouts with different methods but under the assumption of linear temperature-yield relationships above the predefined temperature threshold. These previous insurance designs face several pitfalls as highlighted by recent heat impact studies (e.g. Schlenker and Roberts, 2009; Lobell et al., 2011b; Blanc and Schlenker, 2017; Tack et al., 2017; Gammans et al., 2017; Ortiz-Bobea et al., 2019). More specifically, the estimation of yield losses and corresponding payouts in previous insurance designs is susceptible to not fully accounting for crop-specific, nonlinear temperature effects on yields and intra-day temperature variation. This provides an additional source of basis risk that can be reduced with the insurance design suggested in this paper.

Spline functions in combination with hourly air temperatures are considered superior to the use of accumulated degree-days and have been used to assess historical temperature effects on crop yields (e.g. Ortiz-Bobea et al., 2018; Dalhaus et al., 2020a; Dalhaus et al., 2020b) or to calibrate splines with historical data to project future temperature effects on yields under different climate change scenarios (e.g. Schlenker and Roberts, 2009; Ortiz-Bobea et al., 2019). Restricted cubic splines are particularly suitable to estimate nonlinear hourly temperature effects on specific crop yields and corresponding yield losses (Berry et al., 2014; D’Agostino and Schlenker, 2016; Blanc and Schlenker, 2017). This econometric method smoothly connects piecewise cubic estimates of crop yield responses to temperature exposures while using linear yield responses in the data-scarce tails of temperature distributions and without the need to define critical temperature thresholds a priori. However, empirically estimated temperature effects on crop yields derived using restricted cubic splines and hourly temperature data have not yet been applied to weather index insurance design.

We seek to bridge this research gap by developing a framework that incorporates restricted cubic splines in weather index insurance design. This allows the integration of an empirically estimated yield response function to hourly temperature exposure in insurance design. More specifically, we integrate restricted cubic splines into the payout function and use hourly air temperature instead of accumulated degree-days as the underlying index to obtain an insurance design that builds on a cutting-edge method to empirically estimate yield losses. In addition, this paper presents recent suggestions for heat insurance design.

In our empirical analysis, we design heat index insurances for large-scale winter wheat and winter rapeseed producers in Eastern Germany and simulate their risk reducing capacities at the farm-level. The unsubsidized German market is organized by private insurance suppliers that offer traditional indemnity insurance and have recently introduced drought index insurance. However, heat stress currently remains an uninsurable risk. Eastern Germany is one of Europe’s main crop producing regions where farmers face a great, and indeed increasing, degree of heat stress (Trnka et al., 2014; Gnornott and Wechsung, 2016; Lüttger and Fehle, 2018; Senapati et al., 2021) which has significant implications for winter wheat and winter rapeseed, two major crops in this region (Donatelli et al., 2015; Weymann et al., 2015). We combine high resolution temperature and phenology data with panel data on farm-level yields to design contracts for different restricted cubic spline models. Subsequently, we use the expected utility model to simulate the out-of-sample risk reducing capacities of the payout functions based on restricted cubic splines and in comparison to the uninsured status. Our results show statistically significant out-of-sample risk reducing capacities for heat index insurance based on restricted cubic splines. We attribute considerable economic relevance to both heat exposure and the heat index insurance covering the most critical crop growth phases as suggested here.

Based on the restricted cubic spline model and strike level temperature, and assuming moderate risk-aversion, the heat index insurances implemented here reduce farmers’ risk premium at the median by 18.46% for winter wheat (20 °C strike level temperature) and by 21.42% to 20.66% for winter rapeseed (15 °C strike level temperature), at the actuarially fair premium and in comparison to the uninsured status. Our results are insensitive to various robustness checks such as the choice of the restricted cubic spline model and other levels of risk-aversion.

The remainder of this paper is structured as follows. We first present an economic framework of weather index insurance. In the following section, we introduce the novel insurance design based on restricted cubic spline functions. We then put forward our implementation of insurance design and risk analysis, followed by the case study and data. Next, we present our results that are followed by a discussion. Finally, we end the paper with concluding remarks and policy recommendations.

2. Economic framework of weather index insurance

The revenue realized from insured single-crop production $\tilde{W}_i$ of farm $i$ in year $t$ is a random variable with stochastic dependency on exogenous random weather shocks $\tilde{I}_t$ as illustrated in equation (1).

$$\tilde{W}_i = p \cdot \tilde{y}_i (\tilde{I}_t) + \tilde{x}_i (\tilde{I}_t) - \theta_i$$

(1)

$p$ is the price of the insured crop, which we assume to be non-random.

For instance, weather index insurance schemes are offered by the Vereinigte Hagel in Germany, Austrian hail insurance in Austria, Swiss hail insurance in Switzerland, Groupama in France, Agroseguro in Spain and Cooper-Gay in several European countries. The insurance design of their products is also influenced by the findings of previous research. This highlights the impact of scientific studies that address insurance design on practical implementations.

Most of these studies use common temperature thresholds of approximately 8 °C (growing degree-days), 18 °C (cooling degree-days) or 30 °C (heat degree-days), irrespective of crop and crop growth phases.

We compare our insurance design with the uninsured status because there is no comparable insurance implemented in Eastern Germany. Moreover, a systematic and fair comparison to another hypothetical design based on a form of degree-days is not straightforward, but the literature has shown the superiority of restricted cubic splines over degree-days to estimate temperature-related crop yield losses.
due to the availability of forward contracts that mitigate price risks.\(^5\) \(\hat{y}_n(I_{\theta})\) is the random yield of a specific crop that depends stochastically on random weather conditions captured with \(I_{\theta}\), \(\hat{x}_v\) is the insurance payout that depends on the random value of underlying index \(I_{\theta}\) and \(\theta\) is the insurance premium paid by the farmer. The use of farm-specific yields reflects the full exposure of spatially heterogeneous and farm-specific production risks that affect crop yields, which would be smoothed when yields are aggregated to higher levels (e.g. state-level) and thus would bias the estimates of farm-specific risk reducing capacities (Marra and Schurle, 1994; Webber et al., 2020). According to equation (1), adverse weather conditions captured in \(I_{\theta}\) reduce market revenues, comprising price \(p\) multiplied by yield \(\hat{y}_n(I_{\theta})\), but may increase the net insurance revenues, which comprise the insurance payout \(\hat{x}_v\) minus the non-random insurance premium \(\theta\). Therefore, the insurance compensates for low revenues due to low yields, thus reducing farmers' financial exposure to weather risks. However, crop yields \(\hat{y}_n\) do not depend solely on the captured weather conditions as shown in equation (2).

\[
\hat{y}_n = g(I_{\theta}) + \hat{e}_v
\]  

\(g(I_{\theta})\) is a function that approximates the impact of random weather conditions, indicated by \(I_{\theta}\), on yields \(\hat{y}_n\) and \(\hat{e}_v\) is an error term that summarizes the myriad of other production factors that are uncorrelated with the weather captured in \(I_{\theta}\) but influence crop yields (e.g. from weather captured in \(I_{\theta}\) independent pests and diseases, geohazards, management decisions, time trends, farm-fixed-effects such as soil properties and other weather events). The error term is the source of basis risk and limits the ability of the insurance to compensate for losses perfectly. Our research aims to integrate restricted cubic splines in combination with hourly temperature exposure, which is considered to be a cutting-edge method to estimate yield losses, in heat index insurance design so that we have an accurate estimation of \(g(I_{\theta})\) and can trigger adequate payouts.

The standard microeconomic model for individuals who face risks is the expected utility framework.\(^6\) Thus, we use this framework to assess overall gains from heat index insurance giving due consideration of different levels of risk-aversion that provide an incentive to reduce risk exposure. In this framework, a risk-averse farmer perceives an increase in the expected utility when the insurance reduces her/his temperature-related financial risk exposure (Di Falco and Chavas, 2009). This is illustrated in equation (3):

\[
EU\left(\hat{W}_s\right) = E\left[U\left(\hat{W}_s\right)\right] = U\left[E\left(\hat{W}_s\right) - R_i\right]
\]  

\(U(.)\) is a utility function mapping farmers’ preferences under risk, \(\hat{W}_s\) is the revenue realized by farmer \(i\) in year \(t\), \(E\) is the expectation operator

\(\hat{W}_s\) is the accumulated sum of hourly payouts during the crop’s critical growth phases starting in hour \(h_0 = 1\) and ending in hour \(h_e\). An hourly payout is triggered if temperature \(T_{\text{ib}}\) in hour \(h\) equals or exceeds the strike level temperature \(T_i\) and if we estimate a yield loss with the function \(f(T_{\text{ib}})\) due to temperature exposure \(T_{\text{ib}}\). Consequently, the strike level can be used to

\[R_i = E\left(\hat{W}_s\right) - U^{-1}\left[U\left(\hat{W}_s\right)\right]
\]

The power utility function \(U(.)\) depicted in equation (5) is especially suitable for risk-averse farmers seeking insurance because it has a diminishing marginal utility to increasing revenues and particularly reflects aversion to downside risks (e.g. Femenia et al., 2010). The inclusion of downside risks, i.e. going beyond a mean–variance analysis, is important because the insurance should reduce the probability of low revenues, i.e. downside risks. The utility function shown in equation (5) has been applied in many studies focusing on risk reductions in agriculture, including the use of insurance (e.g. Di Falco and Chavas, 2009; Femenia et al., 2010; Leblois et al., 2014; Kenduiywo et al., 2021; Vroege et al., 2021).

\[U\left(\hat{W}_s\right) = (1 - \alpha)^{-1} s\left(\hat{W}_s\right)^{1-\alpha}\]

\(\alpha\) is a coefficient of constant relative risk-aversion, which is a fitting description of farmers’ risk preferences (e.g. Di Falco and Chavas, 2009; Femenia et al., 2010).

Consequently, a farmer with risk preferences mapped by a power utility function benefits from taking out heat index insurance when the expected utility increases, which is equivalent to a decrease in the risk premium given the same level of expected wealth \(E\left(\hat{W}_s\right)\) for the insured and uninsured status. The actuarially fair premium\(^7\) is the expected payout from the insurance, i.e. \(\theta = E(\hat{x}_v)\), and results in the same level of expected wealth as the uninsured status. Note that we use the risk premium as an indicator of overall risk exposure/risk reducing capacity and not to estimate insurance uptake, which can be subject to factors other than expected utility maximization behavior (see Babcock, 2015; Du et al., 2017; Cao et al., 2019; Luckstead and Devadoss, 2019; Dalhaus et al., 2020a). An estimation of insurance uptake is beyond the scope of this paper, but decreasing risk premiums indicate potential interest in insurance uptake.

3. Using restricted cubic splines in insurance design

Equation (6) introduces our novel, crop-specific payout function that uses hourly air temperature as the underlying index, i.e. payouts depend solely on hourly temperature exposure. We use hourly temperature exposure to account for intra-day temperature variations and extremes.\(^8\)

\[\pi_a = p \times \sum_{h=1}^{h_e} \max \left\{ -f(T_{ib}), 0 \right\} \quad \text{if } T_{ib} \geq T_i \]

\[0 \quad \text{if } T_{ib} < T_i \]

The final payout \(\pi_a\) farmer \(i\) receives in year \(t\) is the accumulated sum of hourly payouts during the crop’s critical growth phases starting in hour \(h_0 = 1\) and ending in hour \(h_e\). An hourly payout is triggered if temperature \(T_{ib}\) in hour \(h\) equals or exceeds the strike level temperature \(T_i\) and if we estimate a yield loss with the function \(f(T_{ib})\) due to temperature exposure \(T_{ib}\). Consequently, the strike level can be used to

\(^5\) Price-yield correlations are very low at farm-levels, i.e. there is almost no natural hedge (Finger, 2012). Moreover, German crop producers usually use bilateral forward contracts to mitigate price risks, but rely less on future markets (Anastassiadis et al., 2014). Thus, price risks can be controlled but production risks remain a challenge and main source of revenue volatility. Bilateral forward contracts between a farmer and buyer even increase production risks because farmers must buy additional crops if their harvest falls short after the contractually agreed quantity.

\(^6\) See e.g. Dalhaus et al. (2020a) for extensions towards cumulative prospect theory. The here suggested improvements in weather index insurance would also result in superior outcomes for farmers under this concept.

\(^7\) We load the actuarially fair premium in a robustness check to account for the insurer’s internal expenses.

\(^8\) Lobell (2007) shows the importance of considering intra-day temperature variations to estimate crop yield responses. Moreover, Tack et al. (2015) and Gammans et al. (2017) compare hourly temperature exposure with daily average temperature exposure and find that hourly temperatures have higher predictive power for crop yields than daily average temperatures.
define the insured temperatures. The hourly payout triggered equals the estimated yield loss \((-f(T_{ah}))\) times the predefined crop price \(p\). If \(f(T_{ah})\) does not estimate a yield loss, there will be no hourly payout even if temperature \(T_{ah}\) exceeds the strike level \(T_s\).

The functional form of \(f(T_{ah})\), which is used to estimate the hourly marginal temperature effect on crop yields, is based on a restricted cubic spline specification that considers the full temperature exposure during critical crop growth phases. Once the knots that divide temperature into intervals have been defined\(^9\), restricted cubic splines smoothly connect the piecewise cubic estimates of marginal yield responses to temperatures within each temperature interval and force a linear yield response to temperatures beyond outer knots (Berry et al., 2014; Harrell Jr. 2015; Blanc and Schlenker, 2017). Consequently, restricted cubic splines reflect potentially nonlinear temperature effects on crop yields while linear relationships in the data-scarce tails of temperature distributions can reduce prediction errors (Blanc and Schlenker, 2017; Harrell Jr. 2015). Moreover, the estimated cubic yield responses within temperature intervals are flexible regarding their form and can also reflect potentially linear or quadratic relationships between crop yields and temperatures within that specific temperature interval. Consequently, restricted cubic splines are an ideal functional form to calculate payouts that reflect nonlinear hourly temperature effects. The remainder of this section provides step-by-step instructions regarding the calculation of hourly marginal temperature effects based on restricted cubic splines in the context of insurance design in which a single underlying index (here temperature) is used to estimate yield losses.

Firstly, we define the number of knots \(k\) and the knot locations \(k_1, \ldots, k_n\) to divide the temperature range into intervals (see Section 4 “Implementation of insurance design and risk analysis” for some practical suggestions). Secondly, restricted cubic splines require the calculation of \((k-2)\) new time series that are transformations of the original temperature time series \(T_{ah}\) (Blanc and Schlenker, 2017). Equation (7) derives the \((k-1)\) new hourly temperature series \(S_{ah}\) based on the hourly temperature \(T_{ah}\), where \(j\) indicates the number of the new time series with \(j \in \{1, \ldots, k-2\}\) (see Harrell Jr. (2015) and Harrell Jr. and Dupont (2019) for more details).

\[
S_{ah} = \max(\frac{T_{ah} - k_n}{k_n - k_1}, 0) + \max(\frac{T_{ah} - k_{n-1}}{(k_n - k_1)2^{3/2}}, 0) + \frac{k_n - k_{n-1}}{k_n - k_1} \left[ \max(\frac{T_{ah} - k_1}{(k_1 - k_n)2^{3/2}}, 0) + \frac{k_n - k_1}{k_n - k_1} \right] \]

Thirdly, we aggregate the hourly values over the period of critical crop growth phases starting in hour \(h_0 = 1\) and ending in hour \(H_{at}\) at farm \(i\) and in year \(t\). This is shown in equation (8). We aggregate the hourly values over the period of critical crop growth phases to match them with annual yield observations (see fourth step). More specifically, we aggregate the original temperature series \(T_{ah}\) and each of its \((k-2)\) transformations \(S_{ah}\) in this third step. This results in the \((k-1)\) aggregated variables \(X_{a1}, \ldots, X_{a(k-1)}\) that we have for each period of critical crop growth phases at farm \(i\) and in year \(t\). \(X_{a1}\) represents the aggregated hourly values of the original time series \(T_{ah}\) and \(X_{a(j+1)}\), the aggregated hourly values of the transformed time series \(S_{ah}\).

\[
X_{a1} = \sum_{k=1}^{H_{at}} T_{ah}
\]
\[
X_{a(j+1)} = \sum_{k=1}^{H_{at}} S_{ah}
\]

Fourthly, we estimate the farm fixed-effect model shown in equation (9) to estimate the effect of the aggregated variable while controlling for a time trend.

\[
y_{it} = \beta_1 X_{a1} + \beta_2 X_{a2} + \cdots + \beta_{k-1} X_{a(k-1)} + \beta_2 t + \beta_2 t^2 + \alpha_i + \epsilon_{it}
\]

In equation (9), \(y_{it}\) is the crop yield of farm \(i\) in year \(t\), the restricted cubic spline specification is denoted as \((\beta_1 X_{a1} + \beta_2 X_{a2} + \cdots + \beta_{k-1} X_{a(k-1)})\) and the deterministic quadratic time trend \((\beta_2 t + \beta_2 t^2)\) controls for technological progress in crop yields. In addition, we use farm fixed-effects \(\alpha_i\) to control for unobserved and time-invariant factors that influence crop yields at farm-level (e.g. soil quality). The error term \(\epsilon_{it}\) summarizes random factors which influence yields but are uncorrelated with temperature and control variables\(^{12}\). After this fourth step, we have calibrated the restricted cubic spline specification by estimating the aggregated temperature effects of specific temperature intervals on crop yields with temperatures measured during the most critical crop growth phases.

Finally, we use equation (10) to calculate the marginal yield response to an hourly exposure to temperature \(T_{ah}\), which is denoted as \(f(T_{ah})\) in the payout formula illustrated in equation (6).

\[
f(T_{ah}) = \beta_1 X_{a1} + \beta_2 X_{a2} + \cdots + \beta_{k-1} X_{a(k-1)} + \beta_2 t + \beta_2 t^2
\]

The \((k-1)\) coefficients \(\beta_1, \ldots, \beta_{k-1}\) are estimated regression coefficients from equation (9), \(T_{ah}\) is the temperature in hour \(h\) of the period of critical crop growth phases at farm \(i\) and in year \(t\), and the \((k-2)\) variables \(S_{ah}\) with \(j \in \{1, \ldots, k-2\}\) are values of temperature transformation \(j\) that we derive with equation (7).

Note that the payout depends solely on temperature exposure during critical growth phases and is independent of yields. However, we use historical farm-level yields to calibrate temperature effects on crop yields. We estimate the payout functions for each crop separately because temperature effects are likely to vary between crops. The restricted cubic spline model is independent of the strike level temperature, i.e. equations (7) to (10) always consider the full temperature exposure during critical growth phases.

4. Implementation of insurance design and risk analysis

This section provides details regarding the implementation of our payout function in heat index insurance design, the risk analysis and the software used to calibrate contracts and run our simulation.

\(^9\) Several strategies to divide temperature exposure into intervals, including a numerical derivation, are presented in the next section.

\(^{10}\) Aggregation bias is reduced by calculating the \((k-2)\) transformed temperature variables \(S_{ah}\) in a first step and then aggregating hourly temperature \(T_{ah}\) and the \((k-2)\) transformed temperature variables \(S_{ah}\) in a second step rather than the reverse procedure (Blanc and Schlenker, 2017).

\(^{11}\) The use of yields at farm-level prevents aggregation bias (e.g. to state-level) that smoothens yield volatility (Marra and Schurle, 1994) and allows for a farm-specific risk assessment.

\(^{12}\) Note that we do not control for dry conditions because the heat index insurance should compensate for any temperature-related yield losses that are estimated by a single underlying weather index. Most weather index insurance designs use a single underlying index to keep payout schedules simple and comprehensible. Thus, the payout function based on equation (9) also compensates for dry conditions correlated with temperatures (see also Auffhammer et al. (2013)) because this reduces basis risk in heat index insurance.
Temperature effects on yields vary across different crop growth phases and the timings of these phases exhibit a spatiotemporal variability \(^{13}\) (Rezaei et al., 2015; Ortiz-Boeben et al., 2019; Yu and Goh, 2019). Thus, the period in which weather is captured for the payout calculation should cover the growth phases most vulnerable to heat stress and reflect spatiotemporal differences in growth phase timings (Leblois and Quirion, 2013; Conradt et al., 2015). Therefore, in line with Dalhaus et al. (2018), we use interpolated phenological observations to define the period of temperature measurement. More specifically, we cover the growth phases from stem elongation to the beginning of milk ripeness for winter wheat (Porter and Gawith, 1999; Barnabas et al., 2008) and from bud formation to the beginning of full ripeness for winter rapeseed (Gan et al., 2004)\(^{15}\). As no high-resolution, historical data of hourly temperature is currently available, we approximate the hourly temperatures required in equations (6) to (10). More specifically, we fit daily double sine curves that pass from the daily minimum temperature to the daily maximum temperature and from there to the daily minimum temperature of the consecutive day to estimate within-day temperature curves. Subsequently, we read hourly temperatures from these approximated daily temperature curves. Snyder (1985), Tack et al. (2015), D’Agostino and Schlenker (2016) and Gammans et al. (2017) also have implemented such an approximation of hourly temperatures and find that these approximated hourly temperatures have a higher predictive power of crop yields than daily average temperatures. The calculation of restricted cubic splines requires the specification of at least three knots that divide temperature into intervals, whereby each knot specification results in a different restricted cubic spline model. We use four different knot-placement strategies (called Model 1 to 4 hereafter)\(^{15}\) that are suggested in other publications and compare their resulting risk reducing capacity.

The first three models use three knots, which is the minimum number of knots required for the calculation of restricted cubic splines. In Model 1, we follow the four-step procedure suggested in Harri et al. (2011) and Ker and Tolhurst (2019) to identify the farm fixed-effect model (see equation (9)) that results in the largest goodness of fit. Firstly, we define bounds for the lowest (at the 5% quantile of observed temperatures) and highest (95% quantile of observed temperatures) knot location. In addition, we set the minimum distance between two knots equal to 5 °C. Secondly, we calculate all the combinations of knot locations that can possibly result from the definitions in the previous step. Thirdly, we estimate the farm fixed-effect model shown in equation (9) for each possible knot combination and calculate the residual sum of squares (RSS) of the estimated models. Fourthly, we choose the model with lowest RSS as, given there are three knots\(^{16}\), this is the model with the largest fit.

Since the model with largest goodness of fit for the calibration sample does not necessarily provide the largest output-of-sample risk reducing capacity resulting from downside risk removal, we also consider three other models in addition to Model 1. In accordance with Ortiz-Boeben et al. (2018), Model 2 has three equally spaced knots placed over observed temperature records. In Model 3, we follow Harrell Jr. (2015) and place three knots at the 10%, 50% and 90% quantile of observed temperatures. In Model 4, we follow the suggestion of Blanc and Schlenken (2017) and use equal spaces of 5 °C between knots, setting the first knot at 5 °C (close to the 10% quantile of observed temperatures) and the fifth knot at 25 °C (close to the 90% quantile of observed temperatures).

We avoid the risk of overfitted payout functions by omitting data of farm \(i\) in insurance calibration, i.e. we derive knot locations and payout functions for each farm \(i\) by omitting observations of farm \(i\) in the panel regression shown in equation (9). Subsequently, we simulate the risk reducing capacity of farm \(i\) by inserting hourly temperatures during risk periods of farm \(i\) into the payout function that was calibrated without observations of farm \(i\).

### 4.1. Insurance design

#### 4.1.1. Insurance design

#### 4.1.2. Risk analysis

We use the economic framework introduced in Section 2 to simulate risk reducing capacities of the payout functions applied here. The yield observations needed to calculate revenues as shown in equation (1) are detrended using the panel’s quadratic time trend\(^{17}\). We set crop prices equal to 1 (i.e. revenues, payouts and premiums are in yield terms (decitons per hectare, i.e. 100 kg per hectare)) because German farmers can use bilateral forward contracts\(^{18}\) to mitigate price risks (Anastassiadis et al., 2014). In fact, the use of forward contracts even stimulates the need for crop insurance as low yields may imply contract penalties. We report relative changes in risk premiums for different payout functions and strike level temperatures as compared to uninsured crop production and then evaluate significant differences with non-parametric paired Wilcoxon signed rank tests. The results in the main paper are representative for moderately risk-averse farmers with a coefficient of constant relative risk-aversion \(\alpha\) equal to 2 (see equation (5)). In addition, we provide results for slightly \((\alpha = 0.5)\) and extremely risk-averse farmers \((\alpha = 4)\) in section S.3 of the supplementary online appendix to reflect the heterogeneity in observed risk preferences in Germany (Chavas, 2004; Maart-Noelck and Musshoff, 2014; Meraner and Finger, 2019; Iyer et al., 2020).

### 4.2. Risk analysis

The statistical software environment R (R Core Team, 2018) is used for data handling, computations and the creation of illustrations. The package “Hmisc” derives the transformed temperature variables shown in equation (7) (Harrell Jr. and Dupont, 2019). All codes are available in an online supplement to increase transparency and facilitate reproducibility.

### 4.3. Software

The statistical software environment R (R Core Team, 2018) is used for data handling, computations and the creation of illustrations. The package “Hmisc” derives the transformed temperature variables shown in equation (7) (Harrell Jr. and Dupont, 2019). All codes are available in an online supplement to increase transparency and facilitate reproducibility.

### 5. Case study and data

We design heat index insurance for winter wheat and winter rapeseed production in Eastern Germany, which is one of Europe’s main production regions for these two crops. Our analysis is based on crop yield data from 88 large-scale crop producers with over 1’000 ha each, which is considerably above the average size of German farms (see Fig. 1 for their location). Table 1 provides summarized statistics for crop yields, varying durations of risk periods (i.e. periods of critical crop

---

\(^{13}\) Timings of growth phases depend mainly on temperature and to a lesser extent on other weather variables and management decisions (Gerstmann et al., 2016).

\(^{14}\) This implies that our payout function is based on the assumption of temporal additive temperature effects on crop yields during these critical growth phases.

\(^{15}\) Other knot-placement strategies and corresponding results are shown in the supplementary online appendix.

\(^{16}\) In addition, we compare this nonlinear model based on three knots with the nonlinear models with largest goodness of fit based on four and five knots using the Akaike Information Criterion (AIC). See S.3 of the supplementary online appendix for more details. The AIC favors all nonlinear models over linear models.

\(^{17}\) The Akaike Information Criterion favors a quadratic trend over a linear trend in our panel. Note that we use observed yields to estimate temperature effects in equation (9) while controlling for technological progress with a quadratic time trend.

\(^{18}\) We have no information about the actual use of bilateral forward contracts between farmers and buyers in our sample, e.g. which farms actually use forward contracts or which contract terms (quantity, quality and prices) are used. However, we know that German crop producers use regularly these forwards (Anastassiadis et al., 2014).
growth phases) and historical temperatures within these periods. The critical heat risk period for winter wheat starts when the growth phase “stem elongation” commences (on average 26 April) and ends when the growth phase “milk ripeness” starts (on average 29 June). The risk period for winter rapeseed starts when the growth phase “bud formation” commences (on average 14 April) and ends when the growth phase “ripeness” starts (on average 12 July).

Irrigation is not widespread in crop production in our case study region (Siebert et al., 2015; United Nations, 2020a) and we are not aware of any insurance product that uses restricted cubic splines to calibrate payout functions. In general, the German insurance market is open for various private insurance suppliers, the number of offered weather index insurances is growing19 and the government does not provide or prescribe insurance solutions. There is no premium subsidy in Germany, there is only a value-added tax deduction. The German government has provided ad hoc disaster payments for extreme drought exposure (e.g. 2003, 2018), but never for heat exposure during critical growth phases of winter wheat or winter rapeseed (Odening et al., 2007; Vroege and Finger, 2020). Some insurance providers tailor weather index insurance to the individual needs of farmers and mostly use drought indices as the underlying index. For instance, depending on the insurance provider, farmers can choose the underlying index, strike levels and period of index measurement, which also results in farm-specific payouts and premiums.

5.1. Yield data

The German insurance broker “gvf VersicherungsMakler AG” provided the unbalanced yield panel consisting of 88 farms with records of yield per hectare and from 1995 to 201820. Of these 88 farms, 77 produce winter wheat and winter rapeseed, 7 produce winter wheat but no winter rapeseed and 4 produce winter rapeseed but no winter wheat. The total number of yield records is 1’316 for winter wheat (from 84 farms) and 1’262 for winter rapeseed (from 81 farms) and the median number of records per farm for both crops is 16. We use farm-specific yield data to reflect farm-specific production risk affecting crop yields to the full, i.e. we consider any factor that affects crop yield volatility at the farm-level.

5.2. Phenology data

We derive crop-, farm- and year-specific phenology data from the PHASE model (PHenological model for Application in Spatial and Environmental sciences) that interpolates the timing of growth phases based on a modified growing degree-days approach while also considering elevation (Gerstmann et al., 2016; Möller et al., 2020). The model uses a digital elevation model and daily average temperatures to interpolate phenological observations into 1 km x 1 km raster files. The German Meteorological Service (DWD) publishes phenological observations from a network of approximately 1’200 voluntary reporters who follow standardized criteria to report the timing of growth phases (Kaspar et al., 2015). It has been proved that index insurance based on phenological observations outperforms monthly aggregated weather exposure and crop modelling approaches (Dalhaus and Finger, 2016; Dalhaus et al., 2018).

5.3. Temperature data

We derive daily minimum and maximum temperatures at each farm, which we require to approximate farm-specific daily temperature curves as explained in Section 4.1 “Insurance design”, from the publicly available gridded datasets E-OBS version 20e with a spatial resolution of 0.1° x 0.1° (~11 km x 11 km) and monthly updates. Each grid contains daily minimum and maximum temperatures based on cutting-edge interpolation techniques developed by climatologists and meteorologists and with the aim to minimize measurement errors in interpolated temperature data. More specifically, the interpolation is based on the mean value of a 100-member ensemble that uses station-derived observations collected by the European Climate Assessment and Dataset (ECA&D) (see Cornes et al., 2018 for technical details). Each model of the 100-member ensemble uses several surrounding weather stations to interpolate temperature data into grids. The station network currently consists of approximately 19’100 weather stations across Europe with highest density in Central Europe, including Eastern Germany (see Fig. 1 in Cornes et al., 2018 for an overview and www.ecad.eu for detailed documentation). This dataset has been used to assess the magnitude and frequency of daily temperature (extremes), to monitor ongoing climate change and to estimate temperature effects on crop yields in Europe (e.g. Gammans et al., 2017; Cornes et al., 2018; Ma et al., 2020).

Leppert et al. (2021) show that interpolated data based on simpler interpolation techniques than applied in E-OBS (e.g. kriging) already improves the performance of weather index insurance compared to matching to the closest weather station. Moreover, gridded datasets provided by experts in climatology and meteorology are truthful, of highest quality, complete (i.e. no missing data due to technical failure of a weather station), frequently refined, and cut transaction costs in insurance design because there is no need to identify a suitable weather station or its substitutes in case of technical failure (Auffhammer et al., 2013; Dalhaus and Finger, 2016).

6. Results

We first present the estimated temperature effects and corresponding payouts that are based on restricted cubic splines. Subsequently, we show the simulated out-of-sample risk reducing capacities of the insurance proposed here and illustrate the economic relevance of payouts. The four different models (called Model 1 to 4 hereafter) result from the

---

19 For example, the Vereinigte Hagel (https://vereinigte-hagel.net), Versicherungskammer Bayern (www.vkb.de), Hagelgilde VVAG (https://www.hagelgilde.de), Wetterheld (www.wetterheld.com) and gvf VersicherungsMakler AG (www.gvf.de) are insurance suppliers that tailor drought index insurance contracts and premiums in Germany (all last accessed 18.10.2021).

20 Farm-level yield data prior to the completed translational phase of German reunification (before the early nineties) is not comparable to current production systems, i.e. longer time-series would be better but are not available in Eastern Germany.
The estimated average temperature effect, which is certain temperature is exceeded. This exposure to heat stress results in of insurance design and risk analysis.

Note: 84 winter wheat and 81 winter rapeseed producers with yield records between 1995 and 2018. Risk period is the duration of temperature measurements. dt is deci-ton, ha hectare, d day and °C degree Celsius. Hourly temperatures are measured within risk periods.

### 4.4. Crop-Specific Risk Positions

Four knot placement strategies introduced in Section 4 “Implementation of insurance design and risk analysis”.

#### 6.1. Estimated temperature effects and payouts

We find nonlinear temperature effects on crop yields during the crop’s most critical growth phases with harmful impacts on yields once a certain temperature is exceeded. This exposure to heat stress results in slightly curved yield responses and corresponding payouts that become linear once the last knot is overshot. Moreover, we find that temperature effects differ between winter wheat and winter rapeseed.

Fig. 2 (Fig. 3) shows the estimated hourly temperature effects for winter wheat (winter rapeseed) in the left column and the corresponding hourly payouts in the right column. Each row represents one of the four restricted cubic spline models based on one of the four knot placement strategies. The last row illustrates a histogram of temperature exposure within the most critical growth phases. The y-axis in each sub-panel displaying hourly temperature effects (left column) represents the absolute deviation from a farm-specific expected yield in deci-tons per hectare (dt/ha) for an hourly exposure to the temperature on the x-axis. Within each of these sub-panels, the inner line in dark-red shows the estimated average temperature effect, which is $f(T_{th})$ in the payout function described in equation (6), and the two outer lines in dark-red represent the 95% confidence bands that we correct for contemporaneous spatial dependence. The y-axis in each sub-panel in the right column shows the payout in deci-tons per hectare (dt/ha) for an hourly exposure to the temperature on the x-axis if the temperature is above the strike level. The inner dark-blue line shows the payout and outer dark-blue lines represent the 95% confidence bands. Note that the confidence bands are presented here for illustrative purposes and have no influence on the calculation of payouts and the following risk analysis. The functions illustrated apply to a farm chosen at random from the sample and regression outputs are shown in section S1 of the supplementary online appendix. Note that these functions vary slightly between farms because we calibrate payout functions by omitting data of farm i to avoid overfitting.

A comparison of the four models for a given crop shows that different knot placement strategies result in different payouts, although the differences for winter wheat at a strike level temperature of 20°C (top right sub-panel) results in median out-of-sample risk reducing capacities between 18.46% (Model 3) and 19.62% (Model 4). The median out-of-sample risk reducing capacity for winter rapeseed at a strike level temperature of 15°C (bottom left sub-panel) varies between 14.21% (Model 3) and 20.66% (Model 4). A strike level temperature of 20°C (bottom right sub-panel) results in median out-of-sample risk reducing capacities between 11.15% (Model 3) and 15.93% (Model 4). In general, the distribution of risk reducing capacity is similar across models for a given crop and strike level temperature. Risk reducing capacities tend to decrease if the strike level temperature shown here increases (moving from the left to the right column in Fig. 4), because less harmful temperature exposure is covered. In our sample, the risk premiums for insured winter wheat and winter rapeseed production are significantly lower than risk premiums for uninsured winter wheat and uninsured winter rapeseed production at the actuarially fair premium and at Bonferroni-adjusted p-values.

The payouts are also of economic relevance as illustrated in the following example. When the payout function based on Model 1 is used to cover winter wheat, the average payout across all farms and years is 9.23 deci-tons per hectare (11.17% of the sample’s expected wheat yield per hectare) for a strike level of 20°C and 4.56 deci-tons per hectare (5.52% of the sample’s expected wheat yield per hectare) for a strike level of 25°C. Using the payout function based on Model 1, the average payout across all farms and years for winter rapeseed, is 16.31 deci-tons

21 The almost linear form of payout functions suggests that piecewise linear splines, which show similar negative temperature effects than restricted cubic splines (e.g. Blanc and Schlenker, 2017), can also be used in our payout function. The advantage of restricted cubic splines is the flexibility regarding the functional form, i.e. responses to temperatures between knots are not restricted to a linear form while responses in the data-scare tails (below the lowest knot or above the largest knot) are by definition linear to avoid inaccurate estimates due to data-scarcity.

22 Section S.4 of the supplementary online appendix shows risk reducing capacities for other coefficients of constant relative risk-aversion to reflect the heterogeneity in observed levels of risk-aversion.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Variable</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter wheat</td>
<td>Detrended yield [dt/ha]</td>
<td>29.24</td>
<td>82.66</td>
<td>83.13</td>
<td>124.04</td>
<td>14.26</td>
</tr>
<tr>
<td></td>
<td>Duration risk period [d]</td>
<td>48.00</td>
<td>65.32</td>
<td>65.00</td>
<td>87.00</td>
<td>6.41</td>
</tr>
<tr>
<td></td>
<td>Hourly temperatures [°C]</td>
<td>-4.75</td>
<td>14.53</td>
<td>14.16</td>
<td>36.38</td>
<td>5.74</td>
</tr>
<tr>
<td>Winter rapeseed</td>
<td>Detrended yield [dt/ha]</td>
<td>8.31</td>
<td>37.63</td>
<td>38.62</td>
<td>57.01</td>
<td>8.01</td>
</tr>
<tr>
<td></td>
<td>Duration risk period [d]</td>
<td>65.00</td>
<td>90.55</td>
<td>91.00</td>
<td>117.00</td>
<td>7.85</td>
</tr>
<tr>
<td></td>
<td>Hourly temperatures [°C]</td>
<td>-14.15</td>
<td>14.23</td>
<td>13.97</td>
<td>38.48</td>
<td>6.10</td>
</tr>
</tbody>
</table>

per hectare (43.34% of the sample’s expected rapeseed yield per hectare) for a strike level of 15 °C and 10.98 deci-tons per hectare (29.18% of the sample’s expected rapeseed yield per hectare) for a strike level of 20 °C. Taking the German price-level in 2018 (last year in our panel), which is 17.03 Euros per deci-ton for winter wheat (United Nations, 2020b), the monetized average payout across all farms and years is 157.19 Euros per hectare (11.17% of the sample’s expected wheat revenue) for a strike level of 20 °C and 77.66 Euros per hectare for a strike level of 25 °C (5.52% of the sample’s expected wheat revenue). In the case of winter rapeseed and a price of 34.91 Euros per deci-ton (United Nations, 2020b), the monetized average payout across all farms and years is 569.38 Euros per hectare (43.34% of the sample’s expected

---

**Fig. 2.** Hourly temperature effects and hourly payouts for winter wheat and different models. Note: Different scales and units on axes. Dotted vertical lines in left column show knot locations. 1’000 block bootstraps, with observations blocked by year, derive the 95% confidence bands (account for potential contemporaneous spatial dependence within one year). Each of these 1’000 block bootstraps is plotted. The statistical uncertainty is shown for illustration but is irrelevant for payout function. The different models result from the different knot specifications. Model 1 sets knots to maximize the goodness of fit, Model 2 to divide the temperature range equally, Model 3 sets knots at certain quantiles and Model 4 has 5 °C between knots (see Section 4 “Implementation of insurance design and risk analysis”). dt/ha is deci-tons (dt) per hectare (ha).
rapeseed revenue) for a strike level of 15 °C and 383.31 Euros per hectare (29.18% of the sample’s expected rapeseed revenue)\textsuperscript{23} for a strike level of 20 °C.

\textbf{6.3. Summary of robustness checks}

We summarize findings from five robustness checks we conducted. In the first robustness check, we change the strike level temperature. See section S.2 of the supplementary online appendix for details. Lowering the strike level temperature to 13 °C or lower for both crops (Fig. S1), i.e. full coverage of estimated harmful temperatures, results in similar out-of-sample risk reducing capacities as shown in Fig. 4. Increasing the strike level temperature to 30 °C for winter wheat and to 25 °C for winter

\textsuperscript{23} These relatively large average yearly payouts for winter rapeseed and a strike level of 15 °C or 20 °C result from numerous hourly payouts within the period of index measurement, particularly towards the end of this period. Although we find largest out-of-sample risk reducing capacities for low strike level temperatures, farmers might have liquidity constraints and be unable to purchase insurance with a low strike level temperature in this case (e.g. Gasaburi and Willis, 2018).
rapeseed, i.e. focusing solely on extreme temperatures, still results in significant out-of-sample risk reducing capacities, albeit lower than in the initial specifications (Fig. 4).

In a second robustness check, we use four or five knots for Models 1 to 3 (Model 4 already has five knots) because the payout function depends on the knot specification. See section S.3 of the supplementary online appendix for detailed results and illustrations. As shown in Fig. 4, we find similar out-of-sample risk reducing capacities (Fig. S4 and Fig. S7) for these supplementary models and conclude that the knot placements implemented here are not an important driver of risk reducing capacities. In addition, we find that increasing the number of knots improves the goodness of fit for winter rapeseed but not for winter wheat.

Thirdly, we run our simulation under the assumption of slightly ($\alpha = 0.5$) and extremely risk-averse farmers ($\alpha = 4$) (Fig. S8 and Fig. S9) to reflect the heterogeneity in observed risk preferences in Germany (Chavas, 2004; Maart-Noelck and Musshoff, 2014; Meraner and Finger, 2019; Iyer et al., 2020). See S.4 of the supplementary online appendix for detailed results and illustrations. As expected, we find that relative out-of-sample reductions in risk premiums tend to increase with a growing level of constant relative risk-aversion. At a given level of risk-aversion, strike level and crop, the models still result in similar out-of-sample risk reducing capacities. In addition, risk premiums of insured production are significantly lower than risk premiums of uninsured production for the levels of constant relative risk-aversion ($\alpha = 0.5, 2, 4$) considered here.

In the fourth robustness check, the actuarially fair premium is loaded to account for the insurance provider’s internal costs and profit margins in an unsubsidized market. See section S.5 of the supplementary online appendix for detailed results and illustrations. We find that different models still exhibit similar risk reducing capacities for a given crop and strike level, although these risk reducing capacities do decrease (Fig. S10 and Fig. S11). In our case study, a loading of 5% on the actuarially fair premium means that, in terms of expected utility, a majority of farms are no longer any better off with insurance and in comparison to being uninsured. In contrast to the results in Fig. 4, we also find that an increase in the strike level temperature may increase risk reducing capacities (e.g. from 20°C to 25°C for winter wheat) when the premium is not actuarially fair.

In a fifth robustness check, we use lower partial moments of first (expected shortfall) and second (downside variance) order as complementary risk measures to the expected utility model. See section S.6 of the supplementary online appendix for detailed results and illustrations (Fig. S12 and Fig. S13). The results confirm our findings in terms of statistical and economic significance and show that the here suggested insurance scheme reduces downside risk exposure of farms.

7. Discussion

Previous research detected nonlinear and crop-specific hourly temperature effects (e.g. Schlenker and Roberts, 2009; Gammans et al., 2017; Tack et al., 2017; Ortiz-Bobea et al., 2019) and highlighted the
superiority of restricted cubic splines based on hourly air temperatures over the use of accumulated degree-days to estimate these nonlinear relationships (Berry et al., 2014; D’Agostino and Schlenker, 2016; Blanc and Schlenker, 2017). However, a payout function that uses restricted cubic splines to empirically estimate temperature effects on crop yield losses has not yet been incorporated into weather index insurance design. This paper aims to bridge this research gap by proposing a novel payout function based on the use of restricted cubic splines in weather index insurance design and illustrates its application for large-scale winter wheat and winter rapeseed producers in Eastern Germany.

7.1. Implications for the German insurance market

For our case study in which our novel payout function compensates only for harmful temperatures during the most critical crop growth phases, we find economically relevant and statistically significant out-of-sample reducing capacities of total production risks of up to approximately 20% at the median, at the actuarially fair premium and compared to the uninsured status. Therefore, this paper provides, after Buchholz and Musshoff (2014), a second study that finds risk reducing capacities of heat index insurance in Germany.

The reported out-of-sample risk reducing capacities show removals of production risks. Production risks remain the main source of revenue variability, as especially forward contracts are used to mitigate price risks (Anastassiadis et al., 2014). The use of these forwards even increases the demand for production risk management instruments, as potential yield losses below contract specifications require compensation payments. This also motivates the increasing demand for crop insurance in Germany. A profound analysis of combining insurance with forwards is beyond the scope of this paper. Here, we introduce a novel insurance design and show that heat index insurance can have farm-specific risk reducing capacities and can cover so far uninsurable heat risks in Germany.

Various other risks than temperatures during most critical crop growth phases affect crop yield volatility. Next to farm-individual but uninsurable effects of management decisions that explain of up to 50% of yield variability in Germany (e.g. crop rotation, pest management, nutrient management), other weather effects than temperatures also affect crop yields in Germany (Ray et al., 2015; Albers et al., 2017; Webber et al., 2020). In contrast to currently uninsurable heat stress, there already exist insurance products to cover these weather risks (e.g. hail, snow pressure, frost, floods, droughts, storms). We conclude from this that adding heat index insurance with median out-of-sample risk reducing capacities of up to approximately 20% to currently existing insurance can be a viable add-on to cover so far uninsurable heat risks in German crop production.

Heat index insurance is particularly suitable to cover heat stress because it overcomes moral hazard and adverse selection problems, Moreover, on-site loss adjustment of heat damages required in traditional indemnity insurance is challenging and thus not offered. While several studies look into the determinants of indemnity insurance uptake (e.g. Möllmann et al., 2019; Knapp et al., 2020), much less is currently known about the determinants of weather index insurance uptake in Europe. Doherty et al. (2021) provide an optimistic outlook but more studies that also can build on the rich body of literature in developing countries (e.g. Jensen et al., 2018; Patt et al., 2009) are needed. Finally, the outcome of current debates on premium subsidies will also affect uptake rates.

7.2. Key aspects for insurance design with the novel payout function

Our case study highlights several key aspects for a heat index insurance design based on restricted cubic splines. Firstly, we find that the expected critical hourly temperature, i.e. the point at which yields start to fall below average, is approximately 20 ºC for winter wheat and 15 ºC for winter rapeseed. In the case of winter wheat, our critical temperature is lower than the critical temperature previously identified in heat impact studies applying similar statistical methods (e.g. Schlenker and Roberts, 2009; Tack et al., 2015; Gammans et al., 2017). These previous heat impact studies focused on other regions and entire growing seasons. In contrast, we focus solely on the most heat-vulnerable growth phases (i.e. around end of April to end of June for winter wheat and in accordance with timings of critical growth phases). These critical growth phases occur mainly before the warmest period of the year in Eastern Germany (i.e. July and August). In addition, since we only control for a time trend and farm fixed-effects to increase the prediction power of the underlying index (i.e. temperature) on crop yield losses and thus decrease basis risk, our temperature effects differ from previous heat impact studies, in that they also capture variables that are correlated with temperatures (e.g. dry conditions). We are not aware of any study that uses a similar method to estimate temperature effects on yields of winter rapeseed.

Secondly, and in line with previous research, we find nonlinear temperature effects on crop yields, in the form of decreasing yields, once the critical temperature threshold has been passed. In our case study, this translates into crop-specific payout functions that are slightly nonlinear for exposure to low heat stress, but become, by definition, linear for moderate and extreme heat stress (after the last knot has been overshot). Consequently, differences in forms are not large compared to fully linear payouts previously applied in heat index insurance design (e.g. Deng et al., 2008; Woodard and Garcia, 2008). However, and in contrast to previous insurance designs, the crop-specific payout functions introduced here are calibrated with restricted cubic splines. This facilitates insurance design. The restricted cubic splines directly estimate the critical temperature threshold, i.e. the point at which yields of a specific crop start to fall, so that we do not need to specify a form of degree-days to account for nonlinear temperature effects. Moreover, the restricted cubic splines directly derive the slope of the payout function in accordance with estimated marginal yield responses of a specific crop to hourly temperature exposure.

Thirdly, the risk reducing capacities of high strike level temperatures (e.g. 30 ºC) are low compared to strike level temperatures that also consider low and moderate heat stress (e.g. 20 ºC). Exposure to low and moderate heat stress occurs more frequently than exposure to extreme heat stress and its overall impact might therefore exceed the overall impact of extreme heat stress. This effect of accumulated low and moderate heat stress is overlooked when the strike level temperature is too high (e.g. 30 ºC) and decreases the risk reducing capacity of the heat index insurance.

Fourthly, we find that different payout functions based on different restricted cubic spline models result in very similar out-of-sample risk reducing capacities. Consequently, the number of knots and their placement (based on the model with largest goodness of fit, equally spaced over observed temperatures or at certain temperature quantiles) are not an important driver of risk reducing capacities of the heat index insurance suggested here.

7.3. Considerations for practical implementation of the novel payout function

For practical implementation, the payout function introduced here must be calibrated individually for each production system, crop and climate because heat stress exposure and temperature effects vary across climates and crops (e.g. Teixeira et al., 2013). Moreover, we recommend to frequently recalibrate the payout function to make use of longer time.

---

24 A discussion on premium subsidies can be found in Smith and Glauber (2012), Coble and Barnett (2013) and Belasco et al. (2020) but is beyond the scope of this paper. We point towards alternative policy support in section Conclusion.
series with yield and temperature data and to account for changing temperature effects on crop yields due to ongoing technological progress and climate change (Fuchs and Wolff, 2011; Tack et al., 2018).

Sufficient historical temperature and yield records must be available for the estimation of nonlinear temperature effects. There may not be sufficient farm-specific yield records available to empirically estimate temperature effects with restricted cubic splines for each individual farm. Therefore, we use a farm fixed-effect model consisting of yield records from similar large-scale farms to calibrate payout functions. However, the tailoring of the payout function applied here to cover farm- and crop variety-specific heat risks is a promising field for future research, also to support these current developments observed in practice. It may also entail the definition of specific coverage levels using a deductible and a maximum payout as well as the optimal choice of the strike level temperature and sample for the fixed-effect model used to calibrate payout functions. Moreover, the payout function also works with other levels of data and risk aggregation (e.g. with county-level yields and weather data) so that risk coverage at different geographical levels is possible (see also Weber et al., 2015).

7.4. Additional qualitative advantages of the novel payout function

Our novel payout function not only offers the possibility of economically relevant, out-of-sample risk reducing capacities, but also has several other advantages. It is applicable in any farming system that fulfills its data requirements and facilitates insurance design, particularly by integrating empirically estimated temperature effects on crop yields in the payout function. Consequently, the payout function can calibrate itself based on the empirical temperature-yield relationship so that farmers and insurers only have to agree on contract specifics, such as the strike level temperature. This will reduce insurance providers’ transaction costs because insurance calibration can be automated. Cost-efficient insurance provision is of paramount importance because there is very little leeway to load the actuarially fair premium, especially in unsubsidized markets with voluntary insurance uptake. Another advantage of the payout formula proposed here is that if the required data is updated regularly, upcoming payouts within the period of temperature measurement can be monitored since the final payout is the sum of hourly payouts. This increases financial planning security and could trigger additional adaptation measures, such as irrigation. Since payouts do not depend on actual yield levels, they can be paid out in (e.g. monthly) installments during the period of temperature measurement and could thus cover additional expenditures (e.g. irrigation). Finally, the use of air temperature rather than degree-days as the underlying index in heat index insurance could make the insurance product easier to understand and this is an important determinant of insurance uptake (Patt et al., 2009; Hill et al., 2016).

Integrating restricted cubic splines in payout functions may also be promising for hazards other than heat. For instance, while a growing body of literature predicts that heat stress will become the largest climatic driver of crop yields in the future, other risks, such as droughts, are also likely to increase (e.g. Semenov and Shewry, 2011; Weber et al., 2018; Ortiz-Bobea et al., 2019). While our insurance design also compensates for drought risks correlated with temperature, future research could apply our framework in drought index insurance design (see e.g. Maestro et al., 2016; Bucheli et al., 2021), and further investigate the optimal insurability of compound weather risks (see e.g. Zscheischler et al., 2018; Haqiqi et al., 2021). Finally, the payout formula applied here can be brought together with other components of insurance design that are likely to increase adoption rates, such as the implementation of multi-annual insurance contracts (see e.g. Dalhaus et al., 2020a; Doherty et al., 2021).

8. Conclusion

In this paper, we propose a novel payout function for heat index insurance design based on restricted cubic splines and simulate its risk reducing capacities for winter wheat and winter rapeseed producers in Eastern Germany. The restricted cubic splines empirically estimate temperature effects on crop yields, which then translate into corresponding payouts.

We find heat stress to be an important production risk with nonlinear effects on crop yields, but almost linear payouts in the heat index insurance. The heat index insurance proposed here results in significant out-of-sample risk reducing capacities for the majority of the farms considered and at the actuarially fair premium. The payouts and corresponding risk reducing capacities are also of economic relevance and thus show the economic relevance of heat stress in Eastern Germany. Moreover, we argue that the advantages of payout functions based on restricted cubic splines outweigh the challenges involved because they facilitate insurance calibration, have the potential to lower transaction costs, can trigger additional adaptation measures and may improve comprehensibility and transparency compared to previous heat insurance design.

The insurance design based on restricted cubic splines estimates proposed here allows a flexible and straightforward implementation into insurance practice. The introduction of this kind of insurance scheme onto the market is likely to strengthen farmers’ ability to cope with heat risks and adapt to ongoing climate change. However, this approach relies on farm-level yield data which means that farmers must be willing to share yield data with insurance providers in order to benefit the most from the insurance scheme proposed here. In addition, insurance provision must be cost-efficient. The increasing availability of high-resolution data, for example from precision farming applications, will facilitate this process (e.g. Woodard, 2016; Finger et al., 2019) and reduce transaction costs.

Policy-makers should acknowledge market-based heat index insurance as a viable tool to reduce the financial losses resulting from temperature-related risk exposure. There remains an insurance gap between insurance products available to farmers and an increasing heat stress pressure also in European countries with growing weather index insurance markets such as Germany. Heat index insurance allows farmers to better cope with their individual heat risk exposure and without disincentivizing other short-term adaptation measures that may prevent yield losses because payouts are independent of actual yields. As an alternative or complement to costly premium subsidies, policy-makers and research institutes can support cost-efficient insurance provision and basis risk reductions by supplying software for secure data exchange and providing high-quality and up-to-date weather and phenology data. Finally, well-functioning insurance markets that also incentivize loss prevention and climate change adaptation may reduce the need for ad hoc disaster payments, which are considered to be of low efficiency and costly.

Our payout function is generally applicable and future research should assess its performance in other regions, for other heat-susceptible crops and also for other hazards than heat stress. Moreover, risk reducing capacities may be enhanced by tailoring contract specifics, such as the strike level, to farm-specific risk exposure. Further research should aim at developing payout functions based on empirically

25 Formally, this can be written as $\pi_{\text{final}} = \min\{\max\{\pi_{\text{max}}, \pi \text{ deductible} \}, \pi_{\text{max}}\}$ with $\pi_{\text{final}}$ being the final payout for farm $i$ in year $t$, $\pi_{\text{max}}$ the payout calculated in equation (6), $\pi$ the deductible and $\pi_{\text{max}}$ the maximum payout.

26 Tailored insurance solutions with farm-specific premiums are offered to crop producers in Eastern Germany. This tailoring does not introduce moral hazard problems when the insurance premium is adjusted to bespoke agreements because the payout is independent of crop yields. Farm-specific premiums eliminate adverse selection problems.

27 In Europe, several insurance providers, such as Cooper-Gay, gvf VersicherungsMakler AG or Swiss Re, already use automated underwriting tools that tailor index-based insurance solutions to farmers’ needs.
estimated temperature effects for farmers in regions where data is scarce. Finally, the application of weather index insurance in the context of compound weather risks and sustainable agriculture opens an important line of further research.

Authors contribution

All authors conceptualized the study, contributed to the methodology, data curation and evaluation, visualization and interpretation. JB led the development of the data curation, statistical data analysis, analyzed the data and wrote the initial draft of the paper and codes. All co-authors assisted with writing, reviewing and editing the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to express their gratitude to the anonymous reviewers for their thorough reading and helpful remarks and suggestions. We would like to thank the "gfv Versicherungsmakler AG", especially S. Mahler, for providing yield data and the "Deutscher Wetterdienst" for publicly providing weather and phenology data.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2021.102214.

References


Anastassiadis, F., Feil, J.-H., Musshoff, O., Schilling, P., 2014. Analysing farmers’ decisions. We would like to thank the reviewers for their thorough reading and helpful remarks and suggestions. We would like to thank the "gfv Versicherungsmakler AG", especially S. Mahler, for providing yield data and the "Deutscher Wetterdienst" for publicly providing weather and phenology data.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2021.102214.

References


Anastassiadis, F., Feil, J.-H., Musshoff, O., Schilling, P., 2014. Analysing farmers’ decisions. We would like to thank the reviewers for their thorough reading and helpful remarks and suggestions. We would like to thank the "gfv Versicherungsmakler AG", especially S. Mahler, for providing yield data and the "Deutscher Wetterdienst" for publicly providing weather and phenology data.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2021.102214.

References


Anastassiadis, F., Feil, J.-H., Musshoff, O., Schilling, P., 2014. Analysing farmers’ decisions. We would like to thank the reviewers for their thorough reading and helpful remarks and suggestions. We would like to thank the "gfv Versicherungsmakler AG", especially S. Mahler, for providing yield data and the "Deutscher Wetterdienst" for publicly providing weather and phenology data.