Farm-level responses to weather trends

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Abstract

Assessing the effects of climate change on agricultural production is crucial for designing policies related to climate change and climate change mitigation. A large body of literature identified detrimental effects on crop yields around the globe under various climate change scenarios, while farm-level adaptation has been shown to mitigate the adverse effect of climate change on agricultural production. In this paper, we use a structural approach to examine farms' production responses to both expected and realized weather. We investigate how farmers adjust crop supply and input demand by estimating a system of output supply and input demand functions that controls for non-random crop selection. Using panel data on 1406 German crop farms (2005–2019), we find that both expected and realized weather outcomes determine farmers output supply and input demand, and that a drought shock has both immediate and lasting effects on farmers' production decisions.

Keywords Adaptation, climate change, profit function, structural model, weather shocks

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1 Introduction

By its very nature, agricultural production inherently depends on weather patterns (Ray et al. 2015). Rising mean temperatures along with changing precipitation regimes substantially alter growing conditions for crops (Lobell, Schlenker and Costa-Roberts 2011) and livestock (Gisbert-Queral et al. 2021). Globally, anthropogenic climate change has already caused significant losses in agricultural productivity (Ortiz-Bobea et al. 2021). The increasing frequency of extreme weather events, such as floods, droughts, or frost events, poses an additional threat to agricultural production (e.g., Trnka et al. 2014; Barlow et al. 2015; Pullens et al. 2019), and hence to food supply and quality (Dalhaus et al. 2020). The ability of farms to adjust to these environmental changes is crucial for the viability of the agricultural sector in the future.

In this paper, we use a structural approach to examine farms' production responses to both expected and realized weather, using farm-level accountancy data from 1406 German crop farms. The estimated parameters of the conditional input demand and output supply functions are used to simulate the immediate and lasting effects of the European drought shock in 2018. Being the second largest cereal producer in Europe (BMEL 2020), Germany constitutes a well suited case to study heterogeneous production adjustments to changing weather patterns because of its diverse weather and soil conditions as well as its relevance for European and global food production.

Previous studies concerned with the climate impact on agriculture largely rely on large-scale modelling approaches (e.g. Agnolucci et al. 2020; Rosenzweig and Parry 1994; Webber et al. 2018) or on statistical models using either panel data (Deschênes and Greenstone 2007; Schlenker and Roberts 2009) or cross-sectional data (Mendelsohn, Nordhaus and Shaw 1994). It has been argued that panel data models are limited in their capability to capture long-term adjustments and thus may overestimate the climate change impact (e.g., Carter et al. 2018; Mérel and Gammans 2021). The cross-sectional approach, also called the Ricardian approach, was designed to fully account for long-run adjustments to different climates. Recent applications include Bozzola et al. (2018), Ortiz-Bobea (2020), and Huang and Sim (2021). Exploiting the cross-sectional variation in economic farm returns and weather variates, it is however vulnerable to omitted variable bias (Carter et al. 2018; Ortiz-Bobea 2020). Neither of the mentioned approaches reveal *how* farmers adjust their production to different climatic conditions. For example, farmers may adjust the level of fertilizer use in the short run or replace heat-sensitive crops with warmth-loving crops (Reidsma et al. 2010). Structural models, on the other hand, retain parameter estimates that describe the farmer's decision-making process. Farmers' revealed decisions allow understanding the adaptation to climate change and response to weather events, supporting the development of improved projections and targeted policies to support adaptation to climate change. In the context of climate change, only few applications of structural models exist (e.g., Kaminski, Kan and Fleischer 2013; Yang and Shumway 2016; Sesmero, Ricker-Gilbert and Cook 2018).

Against this background, this paper assesses farmers' responses in output supply and input demand to weather trends, both in the short and in the longer run, using a structural approach. We formulate a profit model in which farmers decide on planned output and input levels conditional on weather expectations. During the cropping season, they respond to contemporaneous weather outcomes by adjusting variable inputs such as fertilizer. The profit function incorporates the weather variables as exogeneous shifters, which are interacted with price variables to capture heterogeneous crop-specific yield impacts of weather. Empirically, we estimate a system of crop-specific output supply and input demand functions, conditioned on both expected and realized weather outcomes. Finally, we use the estimated parameters to simulate the immediate and lasting effect of drought shock on farmers' input and output choices. Our case study relies on panel data from 1406 German crop farms (2005–2019) which are matched with local weather data.

We contribute to the understanding of climate impacts on agriculture by developing a structural model that takes into account farmers' behavioral responses to experienced weather outcomes in the more distant and the more recent past. This setting allows examining the short- and longer-term effects of extreme weather events, such as the European drought in 2018, on farmer's production decisions. The study is the first one to investigate weather impacts based on a structural model in EU agriculture, where crop rotation considerations may play a larger role compared to other regions. Contrary to previous studies in the context of climate impacts on agriculture, we account for non-random crop selection mechanism, as the use of farm level data combined with a fine distinction of several crop categories involves corner solutions to the profit maximization problem.

We find that both expected and realized weather outcomes determine farmers output supply and input demand, and that the effect of weather experienced in the more distant past differs from the effect of the more recent past. Results from a simulation approach show that a drought shock has both immediate and lasting effects on farmers' production decisions.

The paper proceeds as follows. In the next section, we introduce the conceptual model which describes the effects of both expected and realized weather on output supply and input demand. Section 3 presents the data and Section 4 elaborates on the empirical approach and the econometric framework, including non-random crop selection. Section 5 presents the results, before Section 6 discusses and concludes.

2 Conceptual Framework

We are interested in how past and current weather affects farmers output and input decisions. This is because weather can affect the relative profitability of individual crops. For example, beets and potatoes require high precipitation and cannot be grown in dry regions without irrigation (Döll and Siebert 2002; Siebert et al. 2013). Precipitation is also a limiting factor for winter wheat, while temperature is considered a limiting factor in maize and sugar beet production in Germany (Lotze-Campen et al. 2009). Cachorro and Gobin (2018) assess that rising temperatures under climate change will negatively affect summer crop yields, especially of sugar beet and potatoes. Crop models by Agnolocci et al. (2020) predict that a one percent increase in temperature relative to current average temperatures in Germany would benefit canola yields but reduce the yield of pulses. Considering extreme weather events, Webber et al. (2020) found that drought is an important driver of silage maize yields and, to a lesser extent, of barley and wheat in the east of Germany. In the same study, heat is found to be harmful to wheat yields, while canola and silage maize are less affected by unusually high temperatures. However, the effect of weather on farmers' production choices does not only depend on individual yield effects but especially on the *relative* profitability of each crop under different weather conditions. If warmer temperatures benefit maize yields more than sugar beets, for example, it can be rational to allocate resources away from sugar beets towards maize. Moreover, agronomic aspects from crop rotations must be considered if the crop portfolio is to be changed. Thus, farmers' production responses to changing weather patterns are difficult to assess *a-priori* and remain an empirical question.

Weather and production decisions

Our goal is to evaluate farmers responses in output supply and input demand to weather trends. To achieve this goal, we model farmers' decision making at the beginning of the crop season in two stages, following Chambers and Just (1989), assuming risk-neutral decision makers. In the first stage, farmers maximizes the expected profit from each crop given a fixed allocation of land. The crop-specific profit function is expressed as

$$\pi_c(p_c, r, l_c, s, w) = \max_{x_c, y_c}\big(p_c q_c - r x_c \colon q_c \in Q^c(x_c, l_c, s, w)\big) \quad , \tag{1}$$

where π_c is the expected maximum profit from producing crop c, given its expected price p_c, input prices r, area allocated towards the crop l_c, site-specific characteristics s, and expected weather outcomes w. In the second stage, the land input is allocated optimally across the crops, yielding the multi-crop profit function

$$\pi(p_c, w, l, s, w) = \max_{x,y}\left(\sum_{c=1}^{C}(p_c q_c) - \sum_{k=1}^{K}(r_k w_k) : q_c \in Q(x, l, s, w)\right) \tag{2}$$

The optimal land allocation made at the beginning of the crop season depends on expected weather, since weather affects the profitability of each crop as shown by $Q^c(\cdot)$ in equation (1). By standard results, the well-behaved profit function is non-decreasing in output prices, non-increasing in input prices, and homogeneous and convex in prices (Chambers 1988).

During the crop season, land allocation is fixed but farmers can adjust variable inputs (e.g., fertilizer) in response to actual weather realizations[1]. Hence, if realized weather deviates from expected weather, observed input use can deviate from assumed input use in the beginning of the season. Moreover, planned output may change because if realized weather conditions are most favorable for a particular crop, it is economically rational to allocate more resources (e.g., fertilizer) to this crop, because it increases its relative profitability compared to other crops. In addition, realized weather affects profits directly through its effects on yields. Therefore, similarly to Sesmero et al. (2018), we express the realized profit as a function of both expected and realized weather, i.e.

$$\pi = f(p_c, w, l, s, E[w], w) \tag{3}$$

Finally, farmer's output supply and input demand functions can be derived by taking the first derivative of this profit function (Hotelling 1932). The functional form of the output supply and input demand functions depend on the assumed functional form of the profit function, which are described below in the empirical framework. In summary, the described decision-making process highlights that farm profit, and hence output supply and input demand, through two channels: The first channel is through land-use adjustments by farmers based on their weather expectations, which carry a behavioral component (see below) and define the expected profitability of individual crops. The second channel is the direct influence of observed weather on yield, while allowing for short-term input adjustments during the crop season. Both channels have been investigated individually using reduced-form equations in the literature. Such models regress either land allocation decisions on weather expectations (e.g. Arora et al. 2020) or yield (or total production) on weather realizations (e.g. Lobell et al. 2008). Contrary to the reduced-form models, our structural approach retains parameter estimates that describe the farmer's decision-making progress, both on output and input choice, and thus allows simulating the impact of not weather trends and policy changes such as input taxes or subsidies.

Weather expectations

Farmers' expectations about the weather play an important role in their production decisions (Ding, Schoengold and Tadesse 2009; Alem et al. 2010; Ramsey, Bergtold and Heier Stamm 2020). We assume that expectations on weather outcomes are formulated on experienced weather in the past. That is, farmers form adaptive expectations (Nerlove 1958) regarding weather. Based on qualitative interviews with US farmers from the Midwest, Wilke and Morton (2017) infer that both the recent past and the more distant past influence farmer's expectations about future weather, but it remains unclear how they differentially influence current decisions. Similarly, Burke and Emerick (2016) state that it is unclear if farmers respond to short term weather shocks or longer-term weather and climate changes. From these observations, Ramsey et al. (2020) conclude that simply taking the average of past weather is not an

[1] The same argument may hold for price expectations. However, prices are often revealed after harvest and farmers use forward pricing to fix prices early. If this is the case, there is less scope to respond to price changes than to weather changes in the course of the crop season.

appropriate approximation to farmers' weather expectation. We follow their approach and express farmers' weather expectations as

$$E[w_{i,t}] = \omega_0 + \omega_s W(w_{i,t-1}, \dots, w_{i,t-r}) + \omega_l W(w_{i,t-r-1}, \dots, w_{i,t-R}) \quad , \tag{3}$$

where ω_0 is a reference expectation and ω_s and ω_l denote the farmers' weights put on the recent and more distant past, respectively. The recent and more distant past[2] are separated by year r. The effect of a weather event in the previous growing season on farmers' expectations for the current growing season thus depends on the magnitudes of ω_s and ω_l. While r (i.e., the cutting point between the more recent and more distance past) must be chosen *a-priori*, these weights will be determined by the data without any prior assumptions.

3 Data

Farm production data

We employ farm accountancy data from German crop producers over the period 2005-2019, provided by the Federal Ministry of Food and Agriculture. This data set is Germany's contribution to the EU Farm Accountancy Data Network (FADN). Germany is characterized by a declining South-North gradient in temperatures and limited precipitation combined with light soils in the East, making it an interesting case for studying weather effects on agricultural production. The sample is a rotating panel which is stratified according to region, type of specialization and economic size to ensure its representativeness for commercial agricultural holdings. For the empirical analysis, we group all crops into five categories: Cereals except corn (most importantly wheat, barley, and rye), corn for grain, protein crops (beans and peas), oilseed crops (mainly canola), and root crops (sugar beets, potatoes, and fodder beets). Crops within the individual crop categories have similar agronomic characteristics, such as water and nutrient demands, soil requirements, or planting and harvest times. Crop rotations between the groups are typically highly compatible (for example, root crops following cereals), while rotations within the same group are often more prone to common diseases (for example, wheat following barley or beans following peas).

In our sample of German crop farms, cereals are grown at 99 per cent of all farms (see Table 1), followed by root crops (67 per cent) and oilseed (61 per cent). Fodder (22 per cent) and protein crops (13 per cent) are grown by a smaller number of farms, underscoring the need to address crop selection. In terms of physical quantity, root crops are ahead of cereals and, with great distance, fodder crops, oilseed, and protein crops. Expected prices for each crop category are computed as lagged district (nuts2)-level weighted averages by dividing the sum of crop revenues in a specific region by the region's total quantity

[2] Ramsey et al. (2020) emphasize that in the expected-weather-formation process, the term "longer term" is not equivalent to a climatological notation of "long term".

produced. We chose regional average prices over farm-level prices for two reasons. First, the latter include quality premiums and discounts and therefore mask quality differences in the production quantity (see Reinhard et al. 2001 for a similar reasoning in milk production). Second, in our data set, farm-level prices are only reported for farms producing a specific crop, while the crop choice also depends on the price of alternative crops. Using regional prices, on the other hand, implicitly consider quality differences if farm-level revenue is divided by these prices, and are available for all farms even for crops they do not produce in the current year. As reported by the descriptive statistics in Table 1, oilseed achieves the highest price per decitonne in our sample, followed by protein crops, cereals, root crops, and fodder crops. The magnitudes of these prices are in line with those observed in the German market.

As for inputs, we consider two variable inputs (fertilizer and other material inputs) and three quasi-fixed inputs (land, labor, and capital). Fertilizer quantities and prices are approximated by combining information on expenses from the accountancy data with country-level application rates and unit prices for nitrogen, phosphate, potash, and calcium oxide. For other material inputs (seed, pesticides, material, energy, contract services, and water use), we calculate implicit quantities by dividing total expenses by a Tornquist price index calculated at the regional (nuts2-) level (e.g., Henry de Frahan et al. 2011):

$$r_{nt} = \sum_i \left(\frac{r_{it}}{r_{is}}\right)^{\frac{g_{int}-g_{ins}}{2}} with\ g_{int} = \frac{\sum_{f \in n} V_{ift}}{\sum_{f \in n} \sum_i V_{ift}} \tag{4}$$

where n denotes the nuts2-region, t denotes contemporaneous time, s is the basis year, r_{it} is the country-level price index of the i^{th} item in year t, and V are value shares. For quasi-fixed inputs, only quantities are required in our empirical specification. Land is measured in hectares, labor in annual working units (AWU), and capital use is approximated by deflated depreciation.

Weather data

Weather data are officially provided by the German Weather Service (DWD) at the 1x1 km grid level for the period 1960−2019. To match the weather records with the farm-level data, we aggregated them to the municipality (LAU, formerly nuts4) level[3]. There are more than 11,000 municipalities in Germany, and the average size of a municipality is about 33 square kilometers, allowing for a good approximation of weather outcomes at the farm level. In line with recent literature (Huang and Sim, 2020; Ramsey et al. 2020), we consider the following weather variables in the baseline model: Growing degree days between 8 and 32 °C (GDD), high degree days above 32 °C (HighGDD), precipitation in mm (PREC), and the number of dry days with less than 1 mm precipitation (DD). Growing degree days are calculated by fitting a sine curve over daily minimum and maximum temperatures as suggested by Schlenker and Roberts (2009). All weather variables are measured during the growing season March – August. These four weather variables capture both average climatic conditions (growing degree days and precipitation) as well as extreme weather events (high degree days and the number of dry days). We

[3] We used the municipalities of the year 2007 to consider border changes border during the observation period.

also include non-linear effects of growing degree days and precipitation in the empirical specification. Table 1 shows that the average year in our sample is characterized by 1550 growing degree days from March to August, and the yearly average sum of precipitation during this period is 423 mm. There are, on average, 160 dry days per year and 1.25 high degree days with a very large variation as indicated by the maximum and minimum values. As discussed above, we also include averages of recent and more distant weather observations to capture farmers' weather expectations, motivated by Ramsey et al. (2020). In particular, we add a lag structure that measures each variable based on years $t-1$ to $t-3$, indicated with $GDD1to3$, for instance, and based on years $t-4$ to $t-10$, indicated with $GDD4to10$.

Table 1. Descriptive statistics for all farms in the sample, 2005-2019

Statistic	Mean	St. Dev.	Min	Max
Cereals quantity (dt)	9,153.68	16,196.80	0.00	359,546.70
Oilseed quantity (dt)	1,324.04	2,813.87	0.00	58,417.00
Root crops quantity (dt)	11,389.74	20,041.21	0.00	402,123.00
Protein crops quantity (dt)	114.52	655.88	0.00	18,468.00
Fertilizer quantity (kg pure nutrients)	75.73	142.73	-20.15	2,496.60
Other material input (const. EUR)	1,118.57	1,569.25	4.06	17,876.70
Cereals price (EUR/dt)	13.80	3.50	4.10	21.77
Oilseed price (EUR/dt)	33.37	7.57	17.52	62.24
Root crops price (EUR/dt)	6.83	3.03	1.49	43.04
Protein crops price (EUR/dt)	16.25	7.42	0.00	53.88
Fertilizer price (EUR/1000 kg)	431.92	71.33	327.66	537.13
Other materials price (index)	94.50	11.33	67.22	114.19
Cereals area > 0 (yes or no)	0.99	0.12	0.00	1.00
Oilseed area > 0 (yes or no)	0.61	0.49	0.00	1.00
Roots area > 0 (yes or no)	0.67	0.47	0.00	1.00
Protein area > 0 (yes or no)	0.13	0.34	0.00	1.00
Total area (ha)	217.85	325.46	0.00	5,223.25
Labor (Annual working unit)	2.45	4.82	0.00	118.00
Depreciation (EUR)	435.61	712.05	0.00	13,674.86
Number of growing degree days (8-32 °C), Mar-Oct	1,551.45	165.50	1,045.06	2,204.47
Precipitation (mm), Mar-Oct	423.65	97.32	222.24	882.90
Number of high degree days > 32 °C, Mar-Oct	1.25	1.64	0.00	14.55
Number of dry days (precipitation <1mm), Mar-Oct	160.25	14.15	106.00	192.00

Note: Number of observations: 9259

4 Empirical Framework

Output supply and input demand functions

We approximate the farm profit in (3) with a normalized quadratic functional form. In line with the theoretical framework, the profit function includes expected and realized weather outcomes as profit shifters and the weather variables are interacted with output and input prices (see also Sesmero et al. 2018). With 5 crops, 2 variable inputs, 3 quasi-fixed inputs, 6 weather variables (including the nonlinear forms), and r_1 being the price of the normalizing input x_1, the profit function takes the following form:

$$\begin{aligned}\tilde{\pi} = \beta_0 &+ \sum_{c=1}^{5} \beta_c^p \tilde{p}_c + \beta_2^r \tilde{r}_2 + \sum_{m=1}^{3} \beta_m^z z_m + \sum_{j=1}^{6} \beta_j^w w_j + \sum_{j=1}^{6} \beta_j^{E[w]} E[w]_j + \frac{1}{2} \sum_{c=1}^{5} \sum_{c'=1}^{5} \beta_{cc'}^{pp} \tilde{p}_c \tilde{p}_{c'} \\ &+ \frac{1}{2} \beta_{22}^{rr} \tilde{r}_2 \tilde{r}_2 + \frac{1}{2} \sum_{m=1}^{3} \sum_{m'=1}^{3} \beta_{mm'}^{zz} z_m z_m + \frac{1}{2} \sum_{j=1}^{6} \sum_{j'=1}^{6} \beta_{jj'}^{ww} w_j w_j \\ &+ \frac{1}{2} \sum_{j=1}^{6} \sum_{j'=1}^{6} \beta_{jj'}^{E[w]E[w]} E[w]_j E[w]_j + \sum_{c=1}^{5} \beta_{c2}^{pr} \tilde{p}_c \tilde{r}_2 + \sum_{c=1}^{5} \sum_{m=1}^{3} \beta_{cm}^{pz} \tilde{p}_m z_m \\ &+ \sum_{c=1}^{5} \sum_{j=1}^{6} \beta_{cj}^{pw} \tilde{p}_c w_j + \sum_{c=1}^{5} \sum_{j=1}^{6} \beta_{cj}^{pE[w]} \tilde{p}_c E[w]_j + \sum_{m=1}^{3} \beta_{2m}^{rz} \tilde{r}_2 z_m + \sum_{j=1}^{6} \beta_{2j}^{rw} \tilde{r}_2 w_j \\ &+ \sum_{j=1}^{6} \beta_{2j}^{rE[w]} \tilde{r}_2 E[w]_j + \sum_{m=1}^{3} \sum_{j=1}^{6} \beta_{mj}^{zw} z_m w_j + \sum_{m=1}^{3} \sum_{j=1}^{6} \beta_{mj}^{zE[w]} z_m E[w]_j + \epsilon_\pi \end{aligned} \tag{5}$$

The tilde over a variable indicates that the variable has been normalized by the price of the first variable input, e.g., $\tilde{\pi} = \pi / r_1$. The division of profits and all prices by the numeraire makes the function homogeneous in prices. Convexity can be imposed by Cholesky factorization (Lau 1978; Diewert and Wales 1987). The output supply and input demand functions are obtained by taking the first derivatives of the function in (5) with respect to output prices and input prices (Hotelling 1932):

$$q_c = \frac{\partial \tilde{\pi}}{\partial \tilde{p}_c} = \beta_c^p + \sum_{c'=1}^{5} \beta_{cc'}^{pp} \tilde{p}_{c'} + \beta_{ck}^{pr} \tilde{r}_2 + \sum_{m=1}^{3} \beta_{cm}^{pz} z_m + \sum_{j=1}^{6} \beta_{cj}^{pw} w_j + \sum_{j=1}^{6} \beta_{cj}^{pE[w]} E[w]_j + \epsilon_c \tag{6}$$

$$-x_2 = \frac{\partial \tilde{\pi}}{\partial \tilde{r}_2} = \beta_2^r + \sum_{c=1}^{5} \beta_{c2}^{pr} \tilde{p}_c + \beta_{22}^{rr} \tilde{r}_2 + \sum_{m=1}^{3} \beta_{2m}^{rz} z_m + \sum_{j=1}^{6} \beta_{2j}^{rw} w_j + \sum_{j=1}^{6} \beta_{2j}^{rE[w]} E[w]_j + \epsilon_k \tag{7}$$

Estimating the system of equations in (6) and (7) identifies the effect of expected and realized weather on the farmers' choices of output supply and input demand[4].

[4] Equations (6) and (7) could also jointly be estimated with the profit function in (5). However, this approach often results in multicollinearity problems (Arnade and Kelch 2007). Although (6) and (7) identify many but not all parameters from the original profit function, the identified parameters are sufficient to for our purposes, as they allow evaluating price elasticities of supply and demand as well as the marginal effects of weather variables on profit-maximizing output and input levels.

Non-random crop selection

Farmers typically do not grow all considered crops. The decision to grow a certain crop in a specific year depends on the relative expected profitability of crops, which is in turn influenced by weather expectations as well as economic, agronomic, and political factors. Thus, from an econometric point of view, farmers self-select into different cropping schemes. Estimating the output supply functions for the entire sample without consideration of this self-selection results in biased parameter estimates, as we only observe a farms' production levels for crops whose profitability is above a certain (latent) threshold. The system of equations (6) and (7) with censored dependent variables y_{it} for observation i at year t can be written as

$$y_{cit} = d_{cit} \times y^{*}_{cit}, \;\; d_{cit} = I(d^{*}_{cit} > 0) \tag{8}$$

$$y^{*}_{cit} = \boldsymbol{X}_{cit}\boldsymbol{\beta}_c + \alpha_{ci} + \epsilon_{cit} \tag{9}$$

$$d^{*}_{cit} = \boldsymbol{Z}_{cit}\boldsymbol{\delta}_c + \eta_{ci} + u_{cit} \tag{10}$$

where y^{*}_{cit} and d^{*}_{cit} are latent variables for the outcome equation and selection equation, respectively, and ϵ_{cit} and u_{cit} are the corresponding error terms. Vectors $\boldsymbol{X}_{cit}$ and $\boldsymbol{Z}_{cit}$ hold the explanatory variables for the outcome and selection equations, and they can share common elements. The function I is an indicator function such that d equals one if $d^{*}_{cit} > 0$. Finally, α_{ci} and η_{ci} are farm- and crop-specific fixed effects. To obtain consistent estimates of output supply and input demand functions, we follow the two-step approach developed by Shonkwiler and Yen (1999)[5]. In the first step, we estimate the probability that a farm grows a specific crop as a function of quasi-fixed inputs, lagged land shares, price expectations, and a time trend with probit regressions. Using the probability density function $\phi_{cit}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c)$ and the cumulative distribution function $\Phi_{\text{cit}}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c)$ of the crop-specific selection equations, we then estimate the system of equations in the second step as (Shonkwiler and Yen 1999):

$$E(y^{*}_{cit}|\boldsymbol{X}_{cit}\boldsymbol{\beta}_c) = \Phi_{\text{cit}}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) \times [y_{cit}(\boldsymbol{X}_{cit}\boldsymbol{\beta}_c)] + \mu_c \phi_{cit}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) + \epsilon_{cit}, \tag{11}$$

where now ϵ_{cit} is an error term with $E[\epsilon_{cit}] = 0$.

The system of equations are estimated in the form of (11) using iterated feasible generalized nonlinear squares, which converges to the maximum likelihood estimator (Zellner 1962). To account for possible correlations between individual heterogeneity α_{ic} and the error terms of the crop selection and outcome equations, we use fixed-effects estimation along the lines of Chamberlain (1984) and Mundlak (1978) by adding the farm-level averages of each independent variable to each regression equation. To consider the uncertainty in the parameters obtained from the first-stage probit regressions, standard errors are obtained using non-parametric bootstrapping with 1000 replications.

[5] Studies using this approach in the agricultural economics literature include, amongst others, Sckokai and Moro (2006), Laukkanen and Nauges (2014), and Roosen et al. (2022).

Since prices and expected weather are contained both in the selection equation and in the structural equations, unconditional elasticities must account for changes in both equations. For example, the semi-elasticity of output c with respect to expected outcome of weather $E[w_j]$ is given by

$$\varepsilon_{q_c,w_j} = \frac{\partial q_{cit}}{\partial Ew_{jit}} \times \frac{1}{q_{cit}}$$

$$= \left(\Phi_{\mathrm{cit}}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) \times \frac{q_{cit}(\boldsymbol{X}_{cit}\boldsymbol{\beta}_c)}{\partial Ew_{jit}} + \frac{\partial \Phi_{\mathrm{cit}}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c)}{\partial EW_{jit}} \times [q_{cit}(\boldsymbol{X}_{cit}\boldsymbol{\beta}_c)] + \mu_c \times \frac{\partial \phi_{cit}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c)}{\partial EW_{jit}} \right) \times \frac{1}{q_{cit}} \tag{12}$$

$$= \left(\Phi_{\mathrm{cit}}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) \times \beta_{cj}^{pw} + \phi_{cit}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) \times [q_{cit}(\boldsymbol{X}_{cit}\boldsymbol{\beta}_c)] \times \delta_{cj} - \mu_c \times (\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) \times \delta_{cj} \times \phi_{cit}(\boldsymbol{Z}_{cit}\boldsymbol{\delta}_c) \right) \times \frac{1}{q_{cit}}$$

Simulation of farm responses to an extreme weather event

It is not always meaningful to interpret the (semi-)elasticities of various weather variables in isolation, as they are usually interdependent. For example, the *ceteris paribus* interpretation of the number of dry days requires to hold total precipitation fixed. Simulation exercises can therefore help to better understand the effect of weather outcomes on production choices. In addition, transformative events such as droughts may have different impacts on farmers' behavior than incremental events such as gradual changes in temperature (Wilke and Morton 2017). Hence, we assess the short- and longer-term effects of an extreme weather event by simulating farm-level responses to a one-year drought shock over a period of 10 years, based on the estimated parameters from the profit system. As an exemplary case, we use the 2018 German drought which led to severe losses across crops in Germany (Webber et al. 2020). For this purpose, we suppose that a drought shock takes place in period $t = 0$. In $t = -1$, we set all weather variables to their long-term average value (e.g., over the past 30 years). This period serves as benchmark for the following years. In $t = 0$, the realized weather variables are set to the German average values in the drought year 2018, while the lagged variables are still equal to their long-term averages. The drought shock further influences the 1to3-years lagged variables in the first three years following the shock, and the 4to10-years lagged variables in years four to ten after the shock. The detailed formula to compute these variables, as well as their descriptive statistics, are presented in the appendix. The simulated levels of output supply and input demand are obtained by plugging these simulated weather variables into the regression equations, using the estimated parameters from the output supply and input demand functions.

5 Results

First-stage regression results: Crop choice

The results from the first-stage regressions reveal how expected weather, along with prices and quasi-fixed inputs, affects crop choice. The full parameter estimates from the probit regressions are reported in Table A.1 in the Appendix. As the estimated coefficients of a probit regression have no direct interpretation, we compute the average partial effects of expected weather outcomes on the probability of crop selection. Following Ramsey et al. (2020), we add the partial effects of the more recent and more distant pasts to compute the net effect of weather expectations. Figure 1 shows that cereal production does not respond to changes in any of our four weather variables, when evaluated at the sample mean. This result is expected, because nearly all farm observations in our sample engage in cereal production. More expected growing degree days slightly decrease the probability of corn and oilseed production, more expected high degree days slightly decrease corn for grain production, and higher expected precipitation increases the likelihood of protein production. All other relationships are not statistically significant at the 5%-level, suggesting that other factors (possibly prices, agronomic aspects, or policy environments) may be more important drivers of crop portfolio changes within the considered crops.

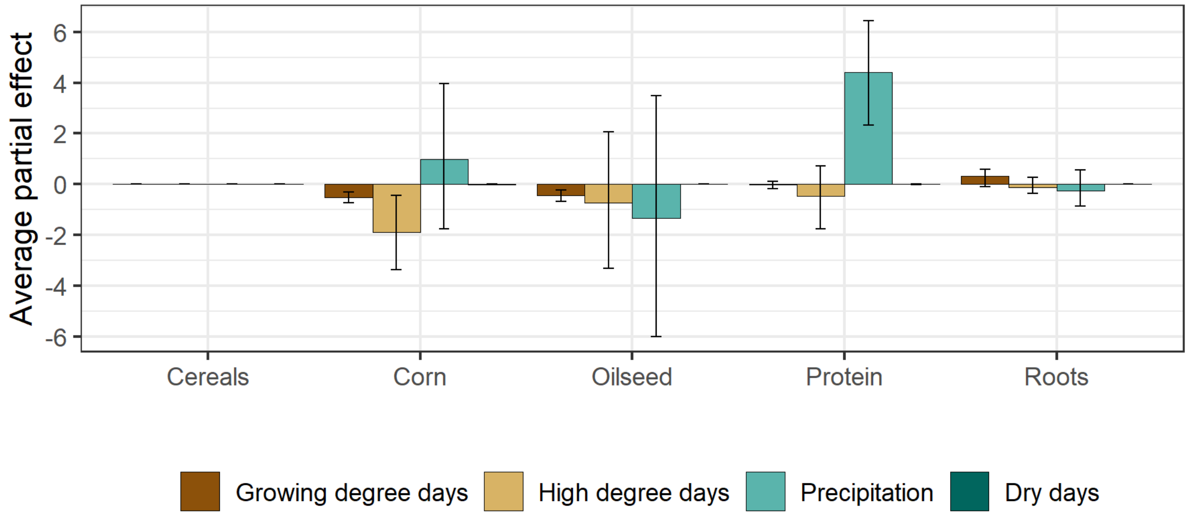

Figure 1. Weather effects on crop choice at the sample mean. Vertical bars indicate 95%-confidence intervals obtained from non-parametric bootstrapping.

Second-stage regression results: Price and weather elasticities

The model fit and full parameter estimates of the system of output supply and input demand functions are presented in Tables A.2 and A.3 in the appendix. Table 2 reports own- and cross price elasticities with respect to crop output levels and variable input levels, evaluated at the sample mean. As described above, price and weather elasticities contain the effects of prices and weather both in the selection equations and in the output supply and input demand equations. To account for uncertainty in both stages, the 95%-confidence intervals are again obtained from bootstrapping. Parameter estimates for which the confidence interval does not include zero are written in bold. From economic theory, we expect that optimal output quantities increase in own prices and optimal input quantities decrease in own prices. This is the case for all estimated elasticities that are significantly different from zero. For example, evaluated at the sample mean, cereals supply increases by 0.33% if cereal prices increase by 1%, and fertilizer demand decreases by 0.77% if the fertilizer prices increase by 1%. Own-prices elasticities of protein, root, and corn output are insignificant, indicating that output levels of these crops are not highly influenced by their prices in the short term. Protein crops may be primarily grown for environmental reasons and sugar beet production is usually linked to delivery rights issued by sugar factories (see, e.g., Wimmer and Sauer 2020), which can explain the price inelastic supply of these crops. Contrary to own-price elasticities, cross-price elasticities, can take either sign because there may be synergies between crops or crop-rotational requirements. If this is the case, the optimal supply of one crop increases with enhanced supply of the other crop. For example, an increasing oilseed price does not only enhance oilseed production but also cereals and protein production, mostly at the expense of corn production.

Table 2. Own- and cross price elasticities of supply and demand

	Q Cereals	Q Protein	Q Oilseed	Q Roots	Q Corn	X Fertilizer	X Others
P Cereals	**0.325**	**0.557**	**0.429**	-0.036	**-0.507**	**0.734**	**0.310**
	(0.232;0.421)	(0.225;0.913)	(0.248;0.608)	(-0.106;0.065)	(-0.933;-0.087)	(0.568;0.903)	(0.16;0.452)
P Protein	0.016	0.062	**0.098**	-0.017	0.157	-0.004	**0.025**
	(-0.035;0.065)	(-0.083;0.212)	(0.014;0.182)	(-0.065;0.034)	(-0.025;0.364)	(-0.051;0.04)	(0.013;0.038)
P Oilseed	**0.149**	**0.917**	**1.443**	0.019	**-0.461**	-0.071	**1.009**
	(0.081;0.214)	(0.553;1.302)	(1.185;1.682)	(-0.037;0.084)	(-0.894;-0.077)	(-0.229;0.091)	(0.837;1.175)
P Roots	0.010	-0.051	-0.012	0.121	-0.077	-0.081	0.092
	(-0.028;0.05)	(-0.235;0.118)	(-0.085;0.064)	(-0.123;0.347)	(-0.658;0.537)	(-0.13;-0.028)	(-0.14;0.379)
P Corn	-0.032	0.022	**-0.172**	0.024	-0.241	-0.008	-0.039
	(-0.089;0.022)	(-0.195;0.258)	(-0.261;-0.087)	(-0.272;0.339)	(-0.735;0.285)	(-0.12;0.098)	(-0.072;-0.004)
W Fertilizer	**-0.199**	-0.083	**0.651**	0.011	-0.103	**-0.769**	-0.062
	(-0.246;-0.155)	(-0.459;0.301)	(0.411;0.884)	(-0.058;0.109)	(-0.741;0.535)	(-0.997;-0.539)	(-0.167;0.043)
W Others	**-0.269**	**-1.425**	**-2.438**	-0.122	**1.232**	0.198	**-1.335**
	(-0.393;-0.138)	(-2.155;-0.756)	(-2.832;-2.013)	(-0.503;0.187)	(0.128;2.302)	(-0.14;0.534)	(-1.729;-0.985)

Note: Elasticities are evaluated at the sample means. For example, at the sample mean, a 1%-increase in cereals price increases cereals supply by 0.325%. 95%-Confidence intervals (95%-CI), presented in parentheses, are obtained using non-parametric bootstrapping. Parameter estimates for which the 95%-CI does not include zero are written in bold.

Next, we evaluate how optimal output supply and input demand respond to changes in past and contemporaneous weather. Because weather realizations in the lagged structures (e.g., GDD1to3 and GDD4to10) essentially arise from the same signal, they can be best interpreted by looking at their combined effect on the outcome variables (Ramsey, Bergtold and Stamm 2021). Table 3 displays elasticities of crop supply and input demand with respect to the four considered weather variables. It is important to recall that these elasticities do not represent pure weather-yield effects. Instead, they indicate how the profit-maximizing supply of individual crops change under different weather conditions. If a particular crop is not affected at all by a certain weather condition, but other crops planted at the same farm are negatively affected, it can be rational for the farmer to allocate more resources (e.g., labor, capital, fertilizer, or other material inputs) to the crop that is not affected, as this crop increases its relative profitability. Thus, we would observe a positive effect on output supply of this particular crop, although there is no direct yield effect. According to our results, growing degree days during the current growing season decrease the supply of cereals and protein crops, precipitation increases the supply of protein crops, more growing degree days increase protein crops supply and decrease root crops supply, and dry days increase oilseed supply. The ceteris paribus effects of past weather differs from the effects of realized weather. For example, experiencing high growing degree days in the past increases farmers' supply of cereals, oilseed, and root crops, and experiencing dry days in the past decreases the supply of protein and oilseed crops.

Table 3. Semi-elasticities for weather and production decisions

	Q_Cereals	Q_Protein	Q_Oilseed	Q_Roots	Q_Corn	X_Fertilizer
Observed weather						
GDD	**-1.470**	**-0.807**	-0.956	4.004	3.502	**-2.196**
	(-2.257;-0.665)	(-3.528;2.043)	(-2.603;0.572)	(-0.418;8.278)	(-5.313;12.073)	(-3.595;-0.752)
PREC	0.578	**2.703**	0.389	2.153	-1.846	**1.105**
	(-0.023;1.175)	(0.709;5.232)	(-0.778;1.521)	(-0.484;4.643)	(-5.956;2.147)	(0.036;2.13)
GDD High	-0.001	**0.028**	0.000	**-0.044**	-0.020	**0.020**
	(-0.005;0.004)	(0.008;0.051)	(-0.012;0.011)	(-0.056;-0.034)	(-0.048;0.007)	(0.013;0.026)
Dry Days	0.722	-4.412	**4.536**	7.360	-6.423	**15.961**
	(-1.335;2.851)	(-12.734;4.078)	(0.347;8.928)	(-0.378;15.437)	(-23.196;9.405)	(12.639;19.272)
Past weather						
GDD	**4.014**	-2.729	**20.376**	**23.075**	-11.929	**52.762**
	(0.986;7.108)	(-18.345;12.109)	(11.088;29.719)	(12.263;34.449)	(-42.99;18.952)	(43.829;61.753)
PREC	**6.626**	8.362	0.944	1.938	9.391	-6.557
	(2.609;10.769)	(-6.891;23.628)	(-7.417;8.885)	(-18.449;22.089)	(-18.754;39.183)	(-17.43;4.488)
GDD High	0.037	-0.127	**0.415**	**-0.195**	-0.170	**0.320**
	(-0.007;0.083)	(-0.376;0.099)	(0.303;0.529)	(-0.342;-0.035)	(-0.517;0.171)	(0.244;0.401)
Dry Days	14.091	**-215.174**	**-32.424**	60.589	-65.250	23.499
	(-0.577;28.134)	(-284.903;-154.933)	(-66.164;-2.208)	(-1.729;124.193)	(-168.515;37.299)	(-0.976;48.28)

Note: Semi-elasticities are evaluated at the sample means. For example, at the sample mean, a increase in GDD by 1000 days increases cereals supply by 1.470%. Confidence intervals, presented in parentheses, are obtained using non-parametric bootstrapping.

Simulation results

As outlined above, the individual weather effects must be interpreted with care because the *ceteris paribus* interpretation is not always sensible. For example, it may be rarely the case that the number of dry days changes without a change in total precipitation. To obtain a better understanding of how different weather outcomes both in the past and in the current year change crop supply and production decisions, we simulate the production outcomes of a weather shock in the following section. The weather variables are set to hypothetical values as explained in section 4. All other observed variables (e.g., prices and quasi-fixed inputs) are set to their sample means. Figure 3 shows the change in output supply and fertilizer demand after the drought shock in $t = 0$, with $t = -1$ (i.e., the long-term average) as the base year. The drought shock increases protein supply compared to its long-term average, while output levels of all other crops were below average in the drought year. Oilseed supply suffered the most from the shock

(-40 percent supply). Fertilizer use is also significantly reduced by the shock, consistent with lower growth potential of crops. Figure 3 further shows that the drought shock has long-lasting effects on output supply and input demand. Oilseed supply and fertilizer demand remain at reduced levels in the three subsequent years, before oilseed supply returns to its original level and fertilizer use is even increased four years after the shock. Cereals production return to their original level immediately after the shock, while the supply of fodder, roots, and protein crops is enhanced in the three years after the shock.

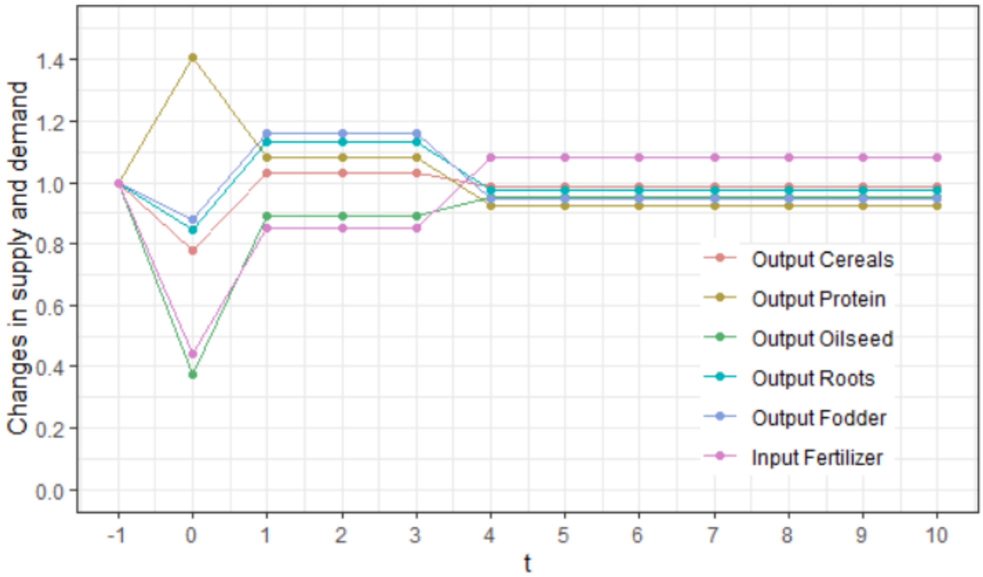

Figure 3. Simulated changes in crop supply and fertilizer demand after a drought occurring in $t = 0$.

6 Discussion and Conclusion

In this paper, we assessed farmers' response in crop supply and input use to weather trends. We hereby assume that farmers form weather expectations based on experienced weather outcomes distinguishing between the more recent and more distant past. The theoretical framework shows that expected weather affects production choices mainly through land allocation decisions, while realized weather affects output directly through yield effects and indirectly through farmers' input adjustments. Econometrically, we consider non-random crop selection using a two-stage approach, consisting of a first-stage probit regression to assess crop choice probabilities and a second-stage system of output supply and input demand equations. Based on the estimated parameters, we estimate price and weather elasticities that consider their marginal effects in both the probit model and the structural equations.

Price elasticities are primarily evaluated to assess the economic consistency of the model. In line with economic theory, statistically significant own-price elasticities of crops are positive and own-price elasticities of fertilizer and other variable inputs are negative. The findings further demonstrate that elasticities with respect to realized weather are different from elasticities with respect to expected weather. Since effects of individual weather variables are different to interpret in isolation, we assess the effect of a specific weather event using a simulation procedure. We find that a drought event reduces the supply of all crop categories except for protein crops in the year of the event, and has lasting effects on farmers' production choices in the years following the event. For example, oilseed supply is reduced by 40% in the drought year and returns to its original level after three years. Fertilizer use is also reduced in the drought year, consistent with reduced growth potential of plants, and is even increased in subsequent years, potentially to compensate for the supply losses caused by the drought.

An important limitation of our approach is that it does not allow to explicitly disentangle land and yield elasticities. For this purpose, land allocation choices must be incorporated in addition to crop choices (e.g., Fezzi and Bateman 2011; Kaminski et al. 2013) or shadow price equations must be derived for each crop area allocation (e.g., Arnade and Kelch 2007). Incorporating contemporaneous and expected weather effects in such models is subject to further research. Furthermore, there may be interdependencies between the choice of one crop and the output level of another crop, an issue that is addressed by Lacroix and Thomas (2011) and Chakir and Thomas (2022).

Despite these limitations, the empirical results presented in this paper have implications for policy. Most importantly, they highlight that both contemporaneous weather and experienced weather affects output supply and input demand. Moreover, weather experiences in the more recent past have a different effect on output decisions than weather experiences in the more distant past, implying that there is a behavioral component in farmers' formulation of weather expectations. Thus, both gradual changes in temperature and extreme weather events affect crop farmers' portfolio choice, and policies designed to reduce greenhouse gas emissions and to support farmers in climate change adaptation must consider these farm-level responses. The paper highlights that farm-level responses to weather trends are key in the assessment of the consequences of climate change in terms of output supply and input demand.

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Appendix

Table A. 1. Results from the first-stage probit regressions

Variable	Cereals	Protein	Oilseed	Roots	Corn
Intercept	0.000	-1.691	-0.519	-0.071	0.662
	(0;0)	(-2.282;-1.071)	(-1.765;0.604)	(-0.211;0.041)	(-0.149;1.42)
P Cereals	0.000	-0.636	0.609	-0.066	0.410
	(0;0)	(-0.98;-0.314)	(-0.057;1.292)	(-0.145;0.063)	(0.027;0.78)
P Protein	0.000	0.028	0.127	-0.015	-0.117
	(0;0)	(-0.058;0.123)	(-0.012;0.282)	(-0.043;0.02)	(-0.221;-0.022)
P Oilseed	0.000	-0.417	0.477	0.002	0.087
	(0;0)	(-0.581;-0.261)	(0.136;0.781)	(-0.027;0.033)	(-0.066;0.253)
P Roots	0.000	0.109	-0.329	0.061	0.243
	(0;0)	(-0.197;0.434)	(-0.976;0.295)	(-0.099;0.156)	(-0.092;0.582)
P Corn	0.000	0.006	0.023	-0.002	0.120
	(0;0)	(-0.108;0.121)	(-0.26;0.303)	(-0.026;0.027)	(-0.018;0.256)
W fert	0.000	0.004	0.095	-0.001	0.003
	(0;0)	(-0.012;0.019)	(0.06;0.129)	(-0.004;0.003)	(-0.016;0.023)
K Land	0.000	0.184	0.466	0.016	0.096
	(0;0)	(0.092;0.28)	(0.009;0.961)	(-0.073;0.059)	(-0.051;0.261)
K Labor	0.000	-0.001	-0.006	0.002	-0.006
	(0;0)	(-0.006;0.005)	(-0.015;0.003)	(-0.002;0.004)	(-0.011;0)
K Capital	0.000	-0.006	0.013	-0.001	-0.021
	(0;0)	(-0.02;0.008)	(-0.057;0.077)	(-0.01;0.02)	(-0.05;0.012)
Trend	0.000	0.004	0.015	0.000	0.001
	(0;0)	(0;0.009)	(0.004;0.026)	(-0.001;0.001)	(-0.005;0.008)
L.Share Cereals	0.000	-0.045	0.207	0.003	-0.532
	(0;0)	(-0.177;0.076)	(0.004;0.395)	(-0.021;0.034)	(-0.75;-0.319)
L.Share Protein	0.000	0.574	0.229	-0.001	-0.499
	(0;0)	(-0.039;1.128)	(-0.117;0.58)	(-0.031;0.033)	(-0.76;-0.247)
L.Share Oilseed	0.000	-0.095	0.673	0.002	-0.571
	(0;0)	(-0.243;0.03)	(0.392;0.968)	(-0.024;0.038)	(-0.794;-0.354)
L.Share Roots	0.000	-0.028	-0.451	0.317	-0.521
	(0;0)	(-0.186;0.12)	(-0.685;-0.217)	(-0.092;0.586)	(-0.739;-0.312)
Gdd1to3	0.000	0.516	-1.010	0.152	2.654
	(0;0)	(-1.142;2.294)	(-4.958;2.683)	(-0.384;0.478)	(0.568;4.774)
Gdd1to3^2	0.000	-0.470	-0.738	-0.127	-1.895
	(0;0)	(-1.747;0.721)	(-3.308;2.053)	(-0.37;0.277)	(-3.363;-0.449)
Prec1to3	0.000	-1.589	0.676	0.115	-0.011
	(0;0.001)	(-2.513;-0.655)	(-1.662;2.895)	(-0.239;0.372)	(-1.414;1.316)
Prec1to3^2	-0.001	4.418	-1.345	-0.268	0.992
	(-0.002;0)	(2.323;6.444)	(-5.993;3.492)	(-0.848;0.56)	(-1.754;3.952)
GddHigh1to3	0.000	0.000	0.010	-0.001	-0.008
	(0;0)	(-0.007;0.007)	(-0.002;0.021)	(-0.002;0.002)	(-0.015;-0.001)
DD1to3	0.000	7.840	-0.121	0.208	2.323
	(0;0)	(5.627;10.071)	(-5.33;4.924)	(-0.424;0.695)	(-0.301;4.969)
Gdd4to10	0.000	-3.472	-0.141	-0.481	-0.204
	(0;0)	(-6.161;-0.763)	(-5.242;5.201)	(-1.164;0.579)	(-3.877;3.204)
Gdd4to10^2	0.000	2.174	-1.051	0.360	0.358
	(0;0)	(0.048;4.26)	(-5.096;2.86)	(-0.464;0.898)	(-2.136;3.065)
Prec4to10	0.000	0.664	-0.731	-0.020	-0.403
	(-0.001;0)	(-2.129;3.566)	(-7.742;5.818)	(-0.593;0.533)	(-3.54;2.549)
Prec4to10^2	0.001	1.122	-4.904	-0.047	0.857
	(0.001;0.003)	(-5.831;7.741)	(-20.099;11.318)	(-1.319;1.395)	(-5.944;8.077)
GddHigh4to10	0.000	-0.006	0.005	-0.001	0.009
	(0;0)	(-0.024;0.012)	(-0.031;0.044)	(-0.006;0.005)	(-0.012;0.029)
dd4to10	0.000	18.924	-29.881	-0.275	0.286
	(0;0.001)	(13.806;23.846)	(-41.287;-18.656)	(-1.231;0.989)	(-5.968;6.453)

Note: Each column presents an individual regression. The dependent variables are binary variables that take the value 1 if the crop (e.g., cereals) is grown and 0 otherwise. Confidence intervals are obtained using non-parametric bootstrapping.

Table A. 2. Regression diagnostics of the profit system

Dependent variable	Estimated parameters	RMSE	R-squared
Cereal output	37	4.732	0.935
Protein output	37	0.322	0.765
Oilseed output	37	1.099	0.875
Roots output	37	12.788	0.692
Fodder output	35	9.384	0.352
Fertilizer input	30	0.071	0.756

Note: Estimation is based on 9,259 observations. The six equations are simultaneously estimated using iterated feasible generalized nonlinear squares.

Table A. 3. Parameter estimates for the profit system

Variable	Coeff.	95%-CI	Variable	Coeff.	95%-CI
Cereal crops supply			P Corn	0.343	(-2.447;3.395)
Intercept	51.064	(42.946;60.822)	W Fertilizer	0.002	(-0.018;0.023)
P Cereals	20.106	(14.432;26.033)	K Land	3.3	(0.518;5.938)
P Protein	0.825	(-1.828;3.422)	K Labor	-0.039	(-0.191;0.084)
P Oilseed	3.806	(2.072;5.478)	K Capital	-0.35	(-0.888;0.133)
P Roots	1.257	(-3.385;6.005)	Trend	0.133	(0.075;0.199)
P Corn	-2.147	(-5.944;1.424)	GDD	0.539	(-8.45;10.263)
W Fertilizer	-0.386	(-0.477;-0.301)	GDD^2	-2.822	(-9.573;3.291)
K Land	35.512	(23.525;47.842)	Prec	10.255	(4.037;17.782)
K Labor	0.098	(-0.135;0.32)	Prec^2	-25.355	(-40.443;-12.823)
K Capital	0.504	(-0.575;1.414)	GddHigh	0.049	(0.013;0.09)
Trend	-0.044	(-0.121;0.036)	DryDays	-7.768	(-22.559;7.628)
GDD	-17.289	(-30.392;-3.956)	GDD1to3	-11.641	(-35.992;10.542)
GDD^2	5.987	(-3.114;14.873)	GDD1to3^2	2.854	(-13.045;20.227)
Prec	11.308	(2.567;19.967)	Prec1to3	18.157	(4.276;33.004)
Prec^2	-28.334	(-45.085;-11.243)	Prec1to3^2	-50.268	(-79.106;-24.473)
GddHigh	-0.005	(-0.044;0.033)	GddHigh1to3	0.021	(-0.083;0.126)
DryDays	6.448	(-11.84;25.419)	DryDays1to3	-29.419	(-64.607;2.649)
GDD1to3	63.597	(36.834;91.172)	GDD4to10	-15.267	(-47.259;19.637)
GDD1to3^2	-45.526	(-64.967;-26.577)	GDD4to10^2	4.507	(-22.941;29.45)
Prec1to3	71.063	(51.167;92.49)	Prec4to10	26.859	(0.207;52.972)
Prec1to3^2	-113.408	(-157.053;-73.994)	Prec4to10^2	-82.137	(-135.34;-29.738)
GddHigh1to3	0.08	(-0.036;0.192)	GddHigh4to10	-0.304	(-0.617;-0.009)
DryDays1to3	112.022	(69.216;153.923)	DryDays4to10	-98.534	(-177.921;-25.723)
GDD4to10	25.954	(-10.984;64.118)	φ Protein	-0.482	(-0.567;-0.414)
GDD4to10^2	-34.515	(-64.448;-5.986)	*Oilseed supply*		
Prec4to10	21.829	(-29.008;74.577)	Intercept	0.224	(-3.593;3.995)
Prec4to10^2	-44.331	(-157.117;63.102)	P Cereals	3.806	(2.072;5.478)
GddHigh4to10	0.254	(-0.068;0.591)	P Protein	0.717	(-0.134;1.525)
DryDays4to10	13.877	(-95.298;119.243)	P Oilseed	6.222	(5.116;7.351)
φ Cereals	-0.084	(-1.38;1.406)	P Roots	0.533	(-0.617;1.81)
Protein crops supply			P Corn	-2.357	(-3.456;-1.307)
Intercept	-7.049	(-14.5;1.057)	W Fertilizer	0.015	(-0.019;0.05)
P Cereals	0.825	(-1.828;3.422)	K Land	9.323	(5.168;14.055)
P Protein	0.911	(-0.438;2.337)	K Labor	0.095	(0.003;0.189)
P Oilseed	0.717	(-0.134;1.525)	K Capital	0.106	(-0.109;0.312)
P Roots	-0.191	(-3.234;2.703)	Trend	-0.093	(-0.125;-0.06)

(continued on next page)

Tabelle A. 2 *(continued from previous page)*

Variable	Coeff.	95%-CI	Variable	Coeff.	95%-CI
GDD	-2.116	(-7.554;2.958)	P Corn	-3.195	(-15.198;9.826)
GDD^2	0.578	(-2.868;4.225)	W Fertilizer	0.004	(-0.055;0.068)
Prec	2.674	(-0.655;5.94)	K Land	2.54	(-18.069;24.089)
Prec^2	-9.121	(-15.459;-2.757)	K Labor	-0.014	(-0.193;0.156)
GddHigh	0	(-0.021;0.019)	K Capital	1.22	(-1.117;3.862)
DryDays	8.135	(0.649;16.022)	Trend	0.15	(-0.007;0.309)
GDD1to3	38.565	(25.957;51.457)	GDD	23.123	(-29.573;73.536)
GDD1to3^2	-29.478	(-38.929;-20.323)	GDD^2	-16.584	(-48.233;16.474)
Prec1to3	27.272	(20.304;34.62)	Prec	-6.49	(-28.316;15.205)
Prec1to3^2	-42.859	(-57.772;-28.564)	Prec^2	1.714	(-39.451;42.981)
GddHigh1to3	0.15	(0.101;0.198)	GddHigh	-0.068	(-0.159;0.025)
DryDays1to3	21	(1.769;40.064)	DryDays	-21.283	(-77.266;32.498)
GDD4to10	52.301	(34.421;70.542)	GDD1to3	2.262	(-82.478;86.179)
GDD4to10^2	-43.006	(-57.225;-29.159)	GDD1to3^2	0.948	(-56.064;58.711)
Prec4to10	-24.387	(-42.665;-6.077)	Prec1to3	-1.695	(-58.62;52.001)
Prec4to10^2	55.547	(15.74;94.308)	Prec1to3^2	-13.749	(-102.346;81.473)
GddHigh4to10	0.556	(0.417;0.7)	GddHigh1to3	-0.067	(-0.328;0.191)
DryDays4to10	-4.276	(-47.274;33.787)	DryDays1to3	-31.156	(-138.866;71.156)
φ Oilseed	-0.803	(-0.878;-0.739)	GDD4to10	-31.702	(-142.606;75.308)
Roots crops supply			GDD4to10^2	32.789	(-48.2;117.107)
Intercept	-6.524	(-57.026;34.751)	Prec4to10	58.477	(-59.495;178.659)
P Cereals	1.257	(-3.385;6.005)	Prec4to10^2	-112.353	(-362.716;138.766)
P Protein	-0.191	(-3.234;2.703)	GddHigh4to10	-0.468	(-1.264;0.301)
P Oilseed	0.533	(-0.617;1.81)	DryDays4to10	-124.763	(-363.812;121.442)
P Roots	14.943	(-21.403;51.677)	φ Corn	-1.479	(-1.795;-1.199)
P Corn	2.164	(-23.267;29.04)	*Fertilizer demand*		
W Fertilizer	0.083	(0.029;0.134)	Intercept	-0.471	(-0.604;-0.347)
K Land	13.018	(-4.438;38.207)	P Cereals	-0.386	(-0.477;-0.301)
K Labor	-0.301	(-1.027;0.446)	P Protein	0.002	(-0.018;0.023)
K Capital	4.052	(-1.947;8.977)	P Oilseed	0.015	(-0.019;0.05)
Trend	0.536	(0.203;0.851)	P Roots	0.083	(0.029;0.134)
GDD	89.006	(-2.365;176.43)	P Corn	0.004	(-0.055;0.068)
GDD^2	-61.859	(-117.493;-3.234)	W Fertilizer	0.013	(0.009;0.016)
Prec	35.126	(-20.725;86.579)	K Land	-0.33	(-0.456;-0.219)
Prec^2	-47.835	(-162.36;78.917)	K Labor	-0.001	(-0.004;0.002)
GddHigh	-0.511	(-0.647;-0.384)	K Capital	-0.003	(-0.013;0.008)
DryDays	84.64	(-4.468;177.477)	Trend	0.011	(0.01;0.012)
GDD1to3	153.882	(10.533;299.616)	GDD	0.214	(0.013;0.411)
GDD1to3^2	-94.865	(-195.313;3.444)	GDD^2	-0.068	(-0.201;0.068)
Prec1to3	-67.998	(-216.745;77.943)	Prec	-0.14	(-0.269;-0.006)
Prec1to3^2	270.774	(-59.75;608.977)	Prec^2	0.258	(-0.009;0.51)
GddHigh1to3	-0.899	(-1.437;-0.419)	GddHigh	-0.001	(-0.002;-0.001)
DryDays1to3	224.608	(-49.236;505.863)	DryDays	-1.213	(-1.471;-0.969)
GDD4to10	353.092	(178.821;531.538)	GDD1to3	-0.744	(-1.15;-0.327)
GDD4to10^2	-250.983	(-381.281;-124.814)	GDD1to3^2	0.627	(0.338;0.911)
Prec4to10	-53.588	(-384.31;276.596)	Prec1to3	-0.087	(-0.374;0.207)
Prec4to10^2	404.657	(-286.482;1098.233)	Prec1to3^2	-0.282	(-0.904;0.318)
GddHigh4to10	-1.203	(-2.617;0.259)	GddHigh1to3	-0.004	(-0.006;-0.003)
DryDays4to10	476.341	(-128.404;1077.511)	DryDays1to3	-0.629	(-1.333;0.068)
φ Roots	-20.008	(-20.877;-19.101)	GDD4to10	-3.172	(-3.673;-2.738)
Corn supply			GDD4to10^2	2.057	(1.728;2.439)
Intercept	-106.272	(-155.932;-62.95)	Prec4to10	0.473	(-0.243;1.182)
P Cereals	-2.147	(-5.944;1.424)	Prec4to10^2	-1.537	(-3.077;0.014)
P Protein	0.343	(-2.447;3.395)	GddHigh4to10	-0.02	(-0.025;-0.015)
P Oilseed	-2.357	(-3.456;-1.307)	DryDays4to10	-1.158	(-2.653;0.304)
P Roots	2.164	(-23.267;29.04)			

Note: Profit system is estimated as iterated seemingly unrelated regression (SUR) using the *systemfit* (Henningsen and Hamann, 2019) package in R. The Φ-parameters are obtained from first-stage probit regressions for each crop. Confidence intervals are obtained using non-parametric bootstrapping.

Simulation of weather shock

To simulate farmers responses to a drought shock (using the 2018 drought shock as example) in year $t = 0$, we compute the following weather variables for years $t = -1$ (i.e., one year before the shock) until $t = 10$:

$$
\begin{aligned}
&GDD_{t-1} = GDD_{LTA} \ ; \\
&GDD_{t} = GDD_{2018} \ ; \\
&GDD_{t+s} = GDD_{LTA} \ , s = 1,2,\dots,10; \\
&GDD1to3_{t-1+s} = GDD_{LTA} \ , s = 0,1; \\
&GDD1to3_{t+s} = \frac{1}{3} GDD_{2018} + \frac{2}{3} GDD_{LTA} \ , s = 1,2,3; \\
&GDD1to3_{t+s} = GDD_{LTA} \ , s = 4,5,\dots,10; \\
&GDD4to10_{t+s} = \frac{1}{3} GDD_{LTA} \ , s = 1,2,3; \\
&GDD1to3_{t+s} = \frac{1}{7} GDD_{2012} + \frac{6}{7} GDD_{LTA} \ , s = 4,5,\dots,10;
\end{aligned} \tag{10}
$$

The following table shows the resulting simulated weather variables:

	Observed weather				Weather1to3				Weather4to10			
t	**GDD**	**PREC**	**GddHigh**	**DD**	**GDD**	**PREC**	**GddHigh**	**DD**	**GDD**	**PREC**	**GddHigh**	**DD**
-1	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154
0	1.780	0.356	1.499	0.162	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154
1	1.259	0.451	0.111	0.154	1.433	0.419	0.574	0.157	1.259	0.451	0.111	0.154
2	1.259	0.451	0.111	0.154	1.433	0.419	0.574	0.157	1.259	0.451	0.111	0.154
3	1.259	0.451	0.111	0.154	1.433	0.419	0.574	0.157	1.259	0.451	0.111	0.154
4	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155
5	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155
6	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155
7	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155
8	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155
9	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155
10	1.259	0.451	0.111	0.154	1.259	0.451	0.111	0.154	1.333	0.438	0.310	0.155