

Seifert, Stefan et al.

Conference Paper — Published Version

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Suggested Citation: Seifert, Stefan et al. (2025) : Climate extremes, irrigation and farms' adaptation to climate change: The Danish case, XVIII EAAE Congress, August 26th - 29th 2025, Bonn, Germany, European Association of Agricultural Economists, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg, pp. 1-15

This Version is available at:

<https://hdl.handle.net/10419/324746>

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Climate extremes, irrigation and farms' adaptation to climate change: The Danish case

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Conference paper for the 18. EAAE Congress 2025 in Bonn, Germany

Abstract

Climate change impacts farms' risk profiles and farms' expected returns; yet farms seem to be reluctant to invest into adaption measures. Previous literature suggests that delayed adaptation is due to the real option nature of such investments: irreversibility, flexibility in timing, and (economic) uncertainty. We test these theoretical considerations by empirically examining irrigation uptake among Danish farms. We consider production inefficiency, market and weather risk, and experienced climate extremes as determinants of irrigation adoption behavior. Our analysis uses a panel of 1,104 farm-level observations from the FADN for 2007–2020 combined with weather, climate and price data. We model farms' persistent inefficiency using a 4-component stochastic frontier; a panel logit quantifying the effects of inefficiency, climate extremes, and price and weather volatility on adoption. Our results align with predictions from real options theory: higher market uncertainty lowers adoption rates, whereas exposure to extreme drought increases the probability of investing. Results also suggest that crop-market signals matter, suggested by higher adoption rates under greater potato price volatility, indicating anticipatory investment when upside price risk is salient. We find that higher farm-level efficiency is associated with a lower propensity to invest, pointing either to substitution toward other risk-management or yield-enhancing strategies, or to less binding water constraints on already efficient farms. Our current results therefore suggest that additional policy initiatives may be required to foster adaptation levels adequate for expected climate change development.

Keywords: irrigation investment, real option, Denmark, climate extremes

Acknowledgments: Authors Seifert, Hüttel, Britz, Kodama, Heckelei and Low gratefully acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – through CRC (SFB) 1502/1–2022 – project id: 450058266.

Introduction

Climate change alters weather conditions, translating into changes in a farm's risk profile and production efficiency, in turn influencing expectations on future farming returns. Farms can and should react to these changes by adapting farming structures to better cope with changed risk profiles, such as crop choices, irrigation uptake or expansion, or termination of farm branches (Challinor *et al.*, 2014). Despite these the well-documented vulnerability of farming systems, threatening global food security, adaptation reluctance, and barriers to adaption need to be overcome (IPCC, 2022).

Most of the adaptations imply substantial changes in the farming business and require investments. Such investment decisions have to be made under climatic and economic uncertainty affecting future returns and their distribution (e.g., Antle and Capalbo, 2010; Reilly and Schimmelpfennig, 2000). This includes (i) scientific uncertainty of how an observed slow change to the climate (e.g., radiative forcing under a given scenario) manifests itself in more frequent and severe weather extremes, and uncertainty about the climate's sensitivity to changes in the atmospheric composition; and (ii) socio-economic uncertainty regarding the difficulties in forecasting uncertainty, the impacts of climatic change, and society's reactions (Heal and Millner, 2014). Climatic uncertainty is highly dynamic over time, which means that decision-makers can update their knowledge through learning (Quiggin, 2008), making flexibility in the timing of adaptations central. Typically, adaptations are (partially) irreversible, i.e., investment costs cannot be (fully) recovered, and flexibility in timing offers an option value (Regan *et al.*, 2015; Guthrie, 2019; Ginbo, Di Corato and Hoffmann, 2021). Delaying adaptation can thus be beneficial (Wesseler and Zhao, 2019). This makes the real options approach suitable to investigate farms irrigation uptake (Wreford, Dittrich and van der Pol, 2020; Ginbo, Di Corato and Hoffmann, 2021).

In this paper, we investigate Danish farms' irrigation uptake to test the central hypothesis of the real options approach that farms' reluctance to adopt irrigation can be explained by weather and production risk, and experienced climate extremes. By expanding a real options model (Dixit and Pindyck, 1994) to incorporate productive inefficiency, economic uncertainty, and weather shocks, we hypothesize that farms hesitate to adopt irrigation under expected uncertainty in economic returns, whereas farms are more likely to adopt irrigation if climate extremes were experienced. We explicitly acknowledge that the farms' net returns depend on production efficiency via profit (Kumbhakar, 2001; Pieralli, Hüttel and Odening, 2017). That is, farms will delay irrigation uptake if they operate efficiently in their current system.

Irrigation is an important example of a farm-level adaptation which mitigates yield and quality losses in drought periods in European agriculture (Webber *et al.*, 2016), especially as the likelihood of drought periods will increase. To test the hypothesis, our empirical procedure rests on three steps: (i) we assign climate and weather data from the European Climate Assessment Dataset to 1,104 Danish farms sampled from the Farm Accountancy Data Network (FADN) during 2007-2020 at NUTS-2; (ii) we estimate farm-specific persistent inefficiency using a 4-component stochastic frontier model; (iii) we run a panel-data logit model to quantify the impact of farm inefficiency, climate extreme events, price, and weather volatility on farms' probability to adopt irrigation.

Most previous real option studies on irrigation investments are based on simulations with normative character and demonstrate that adaptation reluctance can be explained by costly reversibility, uncertainty of future returns under climate change and economic risk, and managerial flexibility (Michailidis and Mattas, 2007; Carey and Zilberman, 2002; Seo *et al.*, 2008; Zhang, Wang and Li, 2018). The majority of studies focus on single sources of uncertainty such as output or water prices or are weather-related, while multiple sources of uncertainty, or the complexity of uncertainty related to climatic change and potential interactions, seem to be rarely modeled explicitly (Ginbo *et al.*, 2021).

Exceptions include joint modeling of price and yield uncertainty in simulations in farms' irrigation investment decisions (Heumesser *et al.*, 2012). Empirical studies with the aim to test hypotheses from the real options approach appear missing in the field of irrigation uptake or new water saving irrigation technology adoption.

The Farm Adaptation Model

We expand a traditional real options model that covers economic uncertainty from investments (see Dixit and Pindyck, 1994) and incorporate implications of farm productivity (Pieralli, Hüttel and Odening, 2017; Lambarraa, Stefanou and Gil, 2016), weather-related production risk (Reilly and Schimmelpfennig, 2000), and perceived weather shocks from climate extremes (Lee and Zhao, 2021) on farms' optimal irrigation investment timing.

The farm's technology is modelled as a function of weather and productivity levels. Irrigation uptake can reduce weather-related productive inefficiency u , and thus future volatility of production σ^u . The farm's return function from the investment considers uncertainty in future prices for crops produced with irrigation p_t , energy, and water prices needed for irrigation q_t . These are assumed to follow a stochastic process with respective volatility terms σ_p and σ_q . The value of the irrigation uptake (investment) can be summarized by the discounted net differences between the expected profits with (1) and without (0) irrigation:

$$V_t^{01}(p_t, q_t, w_t, u_t^0, u_t^1, \sigma^{u,0}, \sigma^{u,1}) = E \int_0^\infty [\pi_{t+s}^1 - \pi_{t+s}^0] \exp(-rs) ds \quad (1)$$

(u_t^0, u_t^1) denotes a set of productivity terms corresponding to each production system depending on weather realizations w_t , other production input prices relevant for generating profits, and r the discount rate. The core result of the real options model is that the adaptation investment will not be optimal when the expected return from irrigation uptake V_t^{01} is greater than the irreversible investment costs C^1 . The net return $V_t^{01} - C^1$ must exceed the option value OV^{01} . This option value "of waiting" represents the gain of delaying the investment to gather more information and learn about future operational profit under an uncertain future climate. Farm decision-makers will invest if:

$$V_t^{01}(p_t, q_t, w_t, u_t^0, u_t^1, a_t) > C^1 + OV^{01}(\sigma_p, \sigma_q). \quad (2)$$

If the option value increases as market uncertainties (σ_p, σ_q) increase, this leads to observed adaptation reluctance. If, however, the weather-induced variability of production without irrigation is higher, including severe weather shocks from climate extremes, this increases the value of the investment and incentivizes adaptation. Under a high productive efficiency of the non-adapted systems, the model predicts delayed adaptation.

In the empirical model, we distinguish between transient productive inefficiency, which differs by production system, and time persistent productive inefficiency, which is typically attributed to farm management and does not depend on the production technology. As we only observe the same farm in the irrigated or non-irrigated system, a counterfactual measure of productive transient inefficiency would be needed. As this is not available, we use farms' persistent inefficiency before adaptation in the empirical framework.

To test the model's predictions, we relate measures for the core real option variables—future economic and weather volatility, persistent productive inefficiency—and a set of control variables, e.g., location specificities. These are summarized in Z determining farms' probability for irrigation

uptake $P[d_{it}^{irr} = 1|Z]$ where d_{it}^{irr} denotes an indicator variable that equals one in the period where a farm has taken up irrigation. This is modelled as a panel logit model.

Background, data and variables

The Danish crop farming sector

Denmark's agricultural sector is a cornerstone of its economy and land use, with about two-thirds of its area devoted to farming (Statistics Denmark, 2025b). Danish crop farms operate on average 75 ha; full-time farms average at around 200 ha (European Commission, 2021). Main cultivated crops include cereals, rapeseed, sugar beets, and potatoes, with the latter usually exhibiting a high demand for irrigation (European Commission, 2021). Among potato-growing farms, around 50% their income comes from potatoes (European Commission, 2024).

Soil conditions vary to some extent across the country. The dominant soil types are moraine-derived clay loams in the eastern regions (Zealand, Funen). These clay-rich soils are naturally fertile, with high nutrient-holding capacity and water retention, making them particularly suitable for intensive arable farming. The western regions (Jutland) exhibit high shares of potato and fodder production, where less fertile sandy soils prevail. Sandy soils are more prone to leaching, and require higher levels of fertilization and irrigation to sustain comparable yields (Damme and Andersen, 2018; Thomsen, 1986).

Since 2000, Denmark has experienced notable shifts in climate patterns with warmer temperatures and longer growing seasons. Precipitation levels remained, however, fairly stable averaging between 900 and 1100mm annually in the western region, and 500-600 mm annually in the eastern region (DMI, 2025). Downside weather risks increased notably after 2000 with more frequent droughts (e.g., 2011 and 2018) and heatwaves (e.g., 2018 and 2019), and heavy rainfall events (e.g., 2011) also increased (DMI, 2025).

As a result of higher temperatures, shifting precipitation patterns, and increased (spring) drought frequencies, irrigation has been noted as beneficial for crop farming in nearly all years after 2000 (Damme and Andersen, 2018). Shares of irrigated land have increased since 2000, averaging around 9% of the total agricultural area in 2021 (World Bank, 2025). Climate change impacts are expected to further increase needs for irrigation (DANVA, 2008; Seidenfaden *et al.*, 2022).

Farm-level data and variables

We base our analysis on data from the Farm Accountancy Data Network (FADN) (European Commission, 2024) for Denmark covering 2007-2020. We consider crop farms according to the FADN classification and include specialist COP farms (cereals, oilseeds, and protein crops), specialist general field crop farms, and mixed crop farms. We restrict the sample to farms with at least three consecutive annual observations. We remove farms with unobserved crop outputs or arable land use, and farms with more than 10% income from tourism in at least one sample year.

We use the share of irrigated land to identify farms' uptake of irrigation. The dummy variable d_{it}^{irr} indicates whether farm i 's share of irrigated land in period t is zero ($d_{it}^{irr} = 0$), or greater than zero ($d_{it}^{irr} = 1$). Farms with irrigation throughout their observed period are excluded from the sample. Thus, we divide the sample into "never irrigating farms" ($d_{it}^{irr} = 0 \forall t$), and farms with "irrigation uptake" ($d_{it}^{irr} = 1$ in some period). For the latter, we consider only farms that start irrigation during their observation period but show at least two consecutive years with no irrigated land.

This selection results in 5,233 observations (N_T) of 1,104 farms, with on average 3.7 years in the sample (see Table 1), where 98 farms adopted irrigation; 1,006 farms never irrigated. The uptake of irrigation is nearly uniformly distributed after 2009, with a pronounced spike in 2012 potentially as a response to the 2011 drought (no uptake is observed before due to the required two years without irrigation). The share of irrigated land for the whole sample increases steadily over the observation period from around 3% (2007) to around 11% (2020). For farms that adopt irrigation, shares of irrigated lands range between 40% and 50% in most periods.

The resulting sample shows characteristics similar to full-time farms in Denmark (Statistics Denmark, 2025a) with average farms sizes above 200 ha. Crop farms taking up irrigation tend to be larger than never irrigating farms in terms of utilized arable land (Table 1), with corresponding higher labor inputs, farm capital and material expenditures.

Table 1: Descriptive statistics by irrigation uptake, mean values averaged over all obs., monetary values in nominal terms

Variable	Never irrigating ($N_{nirr} = 1,006$)		Irrigation uptake ($N_{irr} = 98$)	
	Mean	SD	Mean	SD
Labor (AWU)	1.778	1.856	2.633	2.182
Average farm capital (T€)	1,439.53	1,858.20	1,855,245	1,865,256
Arable land (ha)	207.88	228,76	276.47	297.08
Materials (T€)	62.61	82.36	113.48	139.89
N_T	4,807		426	

Note: Data from the Farm Accountancy Data Network FADN (European Commission, 2024). Detailed descriptive statistics cannot be reported due to data privacy protection. AWU denotes agricultural work units. T€ denotes thousand Euros.

Irrigation investment costs can vary substantially, for instance, if water storage and infrastructure investments are also needed. Moreover, costs depend on irrigation technology, which remains unobserved by us. To consider a farm's observed potential investment cost for irrigation uptake (C^1), we use the change in average farm capital before and after the uptake. We therefore run an auxiliary regression using the change in the average farm capital per hectare as the dependent variable. The independent variables include the adaptation investment dummy variable (d_{it}^{irr}) interacted with a trend variable to capture intertemporal price changes, the farm size, and the farm size change in terms of UAA. Using the prediction of the per-hectare farm capital change for the different time trend realizations, our estimates correspond to 900-1400€/ha capital change due to an investment in irrigation (C_t^1). We also consider the variance of the pre-irrigation revenues from cropping as a measure of the productivity variance without irrigation (σ_q).

Weather data and variables

To acknowledge the role of weather realization for crop farm production, we use weather and climate data from the European Climate Assessment Dataset (Cornes *et al.*, 2018). We assign climate and weather information to a farm using the observed location at the NUTS-2 level by spatially averaging observed weather over a 0.25° grid (Wimmer and Finger, 2025).

We use the average and the minimum monthly de Martonne drought index (Martonne, 1942) for each farm (lagged in time by one year) to capture drought months :

$$dMI = \frac{P}{T+10'} \quad (3)$$

where P is the total daily precipitation, and T is the daily mean temperature. Therefore, lower (higher) dMI values refer to drier (wetter) conditions. We average daily dMIs over the months of the growing season (April – August) to obtain average monthly drought indices for each NUTS-2 region. We calculate the average dMI within a year (\overline{dMI}_t) and retrieve the minimum monthly average dMI (dMI_{\min}).

We also acknowledge that, besides gradual changes in the climate, extreme events under climate change may play an important role to stimulate adaptation decision (Berrang-Ford, Ford and Paterson, 2011; Füssel, 2007). We acknowledge such climate extremes through indicator variables for the severe droughts in 2011 and 2018. The variables, *Post 2011 drought* and *Post 2018 drought* equal one in the year after the drought to relate adaptation decisions to extreme event occurrence.

Descriptive statistics for the weather indicators (see Table 2) show only minor differences between never irrigating farms and farms taking up irrigation in terms of the dMI drought indicators. Mean values for the post-drought dummy variables suggest, however, higher uptake of irrigation in the years following the drought events.

Table 2: Descriptive statistics of weather variables by farm type

Variable	Never irrigating ($N_{nirr} = 1,006$)		Irrigation uptake ($N_{irr} = 98$)	
	Mean	SD	Mean	SD
Average dMI_{t-1}	2.507	0.539	2.821	0.519
Min dMI_{t-1}	0.972	0.504	1.028	0.482
Post 2011 drought	0.057		0.235	
Post 2018 drought	0.058		0.071	

Price data and volatility variables

We approximate output market price volatility using monthly crop prices from (Statistics Denmark, 2025a). Due to unavailable potato price data in the observations period, we use corresponding data for the German Federal State of Schleswig-Holstein, neighboring Denmark (AMI, 2025).

Using prices p_{cm} for crop c in month m ($m = 1, \dots, M = 12$), we calculate the price volatility for crop c in year t as

$$\sigma_{ct} = \frac{1}{M-1} \sum_m (p_{cm} - \overline{p_{cm}}), \quad (4)$$

with $\overline{p_{cm}}$ denoting the average price for c in year t .

We calculate a farm-specific price volatility for each period as the sum of crop price volatilities for C ($c = 1, \dots, C$) crops weighted by the farm's corresponding crop share, $share_{itc}$, such that:

$$\sigma_{it} = \sum_c \sigma_{ct} \times share_{itc} \quad (5)$$

We consider the main crops cultivated by the sampled farms, i.e., wheat, rape, oats, barley, and potatoes. Other crops—corresponding to around 20% of the arable land use in our sample—form a residual category. For the residual category, we use the average price of rye and triticale, for which our sample contains no detailed land use information.

In the empirical modelling, we indicate economics risks using the lagged volatility of farms' output prices, σ_{it-1} and the lagged price volatility of potatoes $\sigma_{c=Potatoes,t-1}$. To capture market risks, we additionally rely on farm-specific variances of the per-hectare income from cropping calculated over the periods without irrigation.

Descriptive statistics for the respective variables (Table 3) indicate some differences between the two farm types. In particular, observations taking up irrigation in period t show notably higher potato price volatility in the year before the uptake.

Table 3: Descriptive statistics of output price volatility by farm type

Variable	Never irrigating ($N_{nirr} = 1,006$)		Irrigation uptake ($N_{irr} = 98$)	
	Mean	SD	Mean	SD
Crop price vol. σ_{it-1}	0.013	0.011	0.018	0.016
Potato price vol. $\sigma_{Pot,it-1}$	0.007	0.038	0.035	0.069

Empirical Model

We estimate farm-level inefficiency using a stochastic frontier approach. We estimate technical efficiency using a 4-component stochastic model (Colombi *et al.*, 2014; Kumbhakar, Lien and Hardaker, 2014),

$$y_{it} = \alpha_0 + f(x_{it}, \beta) + \epsilon_{it} = \alpha_0 + f(x_{it}, \beta) + \tau_i - a_i - v_{it} + \varepsilon_{it}, \quad (6)$$

with y_{it} denoting farm i 's output in period t . $f(x)$ denotes the production function with inputs x_{it} . The composed error term ϵ_{it} summarizes all deviations from the production function due to: unobserved farm heterogeneity, τ_i ; farm i 's persistent time-invariant inefficiency, a_i ; farm i 's transient inefficiency for period t , v_{it} ; and random shocks to the production, ε_{it} .

To estimate farms' productive inefficiency prior to the technology change by irrigation uptake, we use only farms' observations without observed irrigation (i.e., periods of adoption are excluded). We employ a Cobb-Douglas functional form with total crop output in monetary terms as a measure of crop farm output y_{it} . As inputs, we use total arable and grassland of the farm (land input, x_1), the total agricultural work units (labor input, x_2), average annual farm capital (capital input, x_3), and the sum of expenditures for crop protection, fertilizer, seeds, and energy (material input, x_4). We differentiate farm types using the FADN classification (TF14, see DG Agriculture and Rural Development, 2020 for details) differentiating between specialist COP farms, general crop farms, and mixed crop farms. Monetary variables are deflated to 2015 values using the agricultural producer price index for Denmark (Eurostat, 2022).

We add a linear-quadratic time trend variable, t and t^2 , to accommodate technical change as shifts in the production function in our study period. We assume that all four error components are random and homoscedastic, independent of each other, and independent of the input choices. We further assume that $\tau_i \sim iid N(0, \sigma_\tau^2)$, $a_i \sim iid N^+(0, \sigma_a^2)$, $v_{it} \sim iid N^+(0, \sigma_v^2)$, and $\varepsilon_i \sim iid N(0, \sigma_\varepsilon^2)$ (Colombi *et al.*, 2014).

To estimate the determinants of irrigation uptake, $P[d_{it}^{irr} = 1 | Z_{it}]$, we use a random effects logit model (Pieralli, Hüttel and Odening, 2017). Estimates of the farms' persistent productive inefficiency \hat{a}_i enter Z_{it} in this binary model. The model is:

$$P[d_{it}^{irr} = 1|Z_{it}] = \frac{1}{1 + \exp(-Z_{it}'\xi - \mu_i)} \quad (7)$$

where ξ is a vector of parameters associated with explanatory variables Z_{it} ; μ_i is a vector of unobserved farm-specific intercepts assumed to be random (Chamberlain, 1980).

In the empirical model, Z_{it} contains the variables reflecting our theoretical considerations for the real options approach and additional contextual variables: approximated investment cost C_t^1 , lagged input and output price volatility σ_{it-1} and $\sigma_{c=Potatoes,t-1}$, and the productive inefficiency of the farms' production system without irrigation, \hat{a}_t . We model weather and climate influence through the de Martonne drought index as average annual \overline{dMI} and the minimum dMI_{\min} of the lagged period.

We run all calculations in R 4.2.3. Equation (6) is estimated with the R-package npsf (Badunenko, Mozharovskyi and Kolomiyetseva, 2020) using maximum simulated likelihood (Filippini and Greene, 2016) due to advantages in statistical efficiency compared to multi-step procedures (Lien, Kumbhakar and Alem, 2018). Point estimates of farms' persistent efficiency scores are obtained using the JMLS estimator (Jondrow et al., 1982) such that $\hat{a}_t = \exp(-E[a_i | \epsilon_i])$ with ϵ_i denoting the composed error term. We estimate equation (7) using the random effects logit estimator by Bates *et al.* (2015).

Results and Discussion

The stochastic frontier analysis shows parameter estimates for the production function in line with the expectations (see Table 4, top): we find positive marginal effects for labor, capital, land, and materials. Standard errors are generally small; as indicated by one-sided confidence intervals, most coefficient estimates are statistically significant at the 95% level based on a z-test assuming random sampling. Coefficients for labor and capital show large standard errors, which could be explained by the high correlation between land, capital and labor inputs (Pearson correlation >0.65 in all cases). We observe positive technical change for the whole observation period with a slow down towards the end of the observation period. At identical input levels, we find higher output potentials for mixed crop farms and general crop farms compared to specialist COP farms.

The positive estimate of $\log(\sqrt{\sigma_u/\sigma_v})$ indicates that inefficiency is present in the model, i.e., $\sigma_u^2 > \sigma_v^2$. Descriptive statistics of persistent and transient efficiency scores (see Table 4, bottom) underline notable efficiency differences between farms with average persistent efficiency scores of around 70%, ranging between 18% and 87%. Transient inefficiency averages at similar levels. We note that a translog specification leads to qualitatively identical results with Pearson correlations coefficients above 0.9 for estimates of the transient and the persistent inefficiency, respectively.

Table 4: Parameter estimates, standard errors (SE) and 95% confidence intervals of the Stochastic Frontier Analysis (N=4,307)

	Estimate	SE	95% CI
(Intercept)	4.1536	0.1205	[3.6774,4.2564]
log(Labor)	0.0145	0.0169	[-0.1055,-0.0035]
log(Capital)	0.0001	0.0105	[0.0339,0.0821]
log(Land)	0.5497	0.0183	[0.5104,0.6448]
log(Materials)	0.4902	0.0138	[0.4555,0.5245]
Trend	0.0774	0.0038	[0.0107,0.0393]
Trend ²	-0.0035	0.0002	[-0.0014,-0.0002]
TF14: General crop farm	0.1029	0.0131	[0.0663,0.1337]
TF14: Mixed crop farm	0.3310	0.0315	[0.1873,0.3519]
$\log(\sqrt{\sigma_u/\sigma_v})$	0.6983	0.0205	[0.6581,0.7385]
$\log(\sigma)$	-1.0874	0.0171	[-1.1209,-1.0539]
$\log(\sigma_v^2)$	-1.8161	0.1374	[-2.0854,-1.5468]
$\log(\sigma_u^2)$	-0.8270	0.0785	[-0.9809,-0.6731]
<i>Persistent inefficiency</i>		<i>Transient inefficiency</i>	<i>Overall</i>
Min	0.180	0.170	0.031
Q25	0.698	0.684	0.483
Q50	0.736	0.717	0.524
Q75	0.764	0.743	0.555
Max	0.868	0.892	0.701

The results for the logit model are summarized in Table 5. We find that farms with higher persistent efficiency have a lower probability for irrigation adoption, which is in line with the theoretical considerations and empirical evidence (e.g., Pieralli, Hüttel and Odening, 2017).

We find farms with higher expenditures on energy and water per hectare have a higher probability to invest into irrigation. Conversely, we find that higher output price volatility reduces the likelihood of irrigation investment. However, higher price volatility specifically for potatoes in the previous year increases the probability of investment. Farms may potentially anticipate higher gains from the investment and from potato productions specifically. Our model specification may not fully capture this interplay, and the anticipated production volatility reducing effect of irrigation may correlate with potato price volatility. No meaningful effect size is found for the volatility measure in per-hectare crop income.

In the periods after the strong droughts in 2011 and 2018, we find positive effects on our dependent variable, suggesting that extreme events may trigger adaptation. We note that the estimated effect for 2018 is small and shows high statistical uncertainty. For the drought related measures, minimum DMI and average DMI, results are mixed: Less severe droughts in the previous period, indicated by higher values of $dMI_{\min,t-1}$, decrease the probability of adoption. This effect is, however, outweighed to some extent by the estimates for the average DMI in the previous period, \overline{dMI}_{t-1} .

Table 5: Regression results of the random effects logit regression, dependent variable d_{it}^{irr}

	Estimate	SE	
Constant	-1.051	1.773	[-4.526, 2.424]
Persistent efficiency without irrigation ($\hat{\alpha}_i$)	-6.023	1.568	[-9.096, -2.950]
Lagged farms size (UAA_{t-1})	0.001	0.0004	[0.001, 0.002]
Lagged irrigation investment costs (I_{t-1}) $\times 10^{-2}$	0.002	0.001	[-0.002, 0.002]
Lagged crop price volatility (σ_{it})	-146.282	37.832	[-220.433, -72.131]
Lagged potato price volatility ($\sigma_{c=Potatoes,t-1}$)	40.765	9.208	[22.717, 58.813]
Variance of crop income without irrigation	-0.295	0.33	[-0.942, 0.352]
Energy costs per hectare without irrigation	0.016	0.003	[0.010, 0.022]
\overline{dMI}_{t-1}	0.922	0.325	[0.285, 1.559]
$dMI_{\min,t-1}$	-0.935	0.355	[-1.631, -0.239]
2012 dummy (post 2011 drought dummy)	1.801	0.391	[1.035, 2.567]
2019 dummy (post 2018 drought dummy)	0.188	0.657	[-1.100, 1.476]
2014-2020 dummy (post fertilization reform)	-0.219	0.742	[-1.673, 1.235]
Observations		4,170	
Log Likelihood		348.422	
Akaike Inf. Crit.		722.844	
Bayesian Inf. Crit.		805.208	

Concluding Remarks

Our results lend some support for the presence of a real option in the adoption of irrigation. Our results suggest that increasing market uncertainties, indicated by higher price volatilities, reduce the likelihood to invest into adaptation. The variability of agronomic weather conditions, indicated by the de Martonne drought index, may likewise foster the adaptation investment, since weather shocks related to climate extremes seem to play a role (Lee and Zhao, 2021). In line with previous empirical evidence (e.g., Pieralli, Hüttel and Odening, 2017; Lambarraa, Stefanou and Gil, 2016), we also find later adaptation under high productive efficiency of the non-adapted system.

Our results suggest that the increasing uncertainty under an uncertain future climate can discourage farmer adaptation investments into irrigation. In line with the real option theory, our results underscore that uncertainty in the economic dimension (e.g., output price variation) may cause reluctance to adapt due to the beneficial value of waiting for additional market signals to learn about future operational profit under an uncertain future climate. Reluctance to adapt jeopardizes, however, farms resilience by causing avoidable losses due to climate change.

For policymakers, our results underscore the need to further incentivize adaptation and strengthen farms' climate resilience. Potential policy measures may not only address the investment into irrigation itself, but focus on a combination of measures to reduce farms' vulnerability to risks associated with climate change. For instance, policies supporting investments into water storage to enable irrigation, also after consecutive drought periods (Ebers *et al.*, 2023), may increase the attractiveness of irrigation investments. Drought-resistant varieties may likewise lower drought risk exposure while reducing the operating expenditures of irrigating (Foulkes, Scott and Sylvester-Bradley, 2002). Ultimately, weather insurances may reduce farms' financial risk exposure by offsetting risks at the farm level; however, without physical compensation for output losses (Bucheli, Dalhaus and Finger, 2021).

We recognize that our results might be preliminary as they are most likely affected by several shortcomings to be addressed. First, the spatial resolution of farm locations at the NUTS-2 level hinders

a direct assignment of local weather and climate conditions at farm locations. We plan to increase the precision of this assignment using a probabilistic spatial downscaling approach aiming for information at the NUTS-3 municipality level (Kempen *et al.*, 2011; Hartig *et al.*, 2023). Second, while the de Martonne drought index provides a traceable measure for drought occurrence, it is sensitive to precipitation relative to temperature, and ignores soil and hydrological properties (Paltineanu C. *et al.*, 2007). Based on more precise farm locations, additional measures for weather, climate, and drought, such as soil moisture indices, are thus considered (Zeri *et al.*, 2022). Surface soil moisture and the soil water index, provided by Copernicus for our spatial and temporal scale, are considered for this end (e.g., Bauer-Marschallinger *et al.*, 2019). Third, and relatedly, our inefficiency estimation omits the role of weather realizations for farm-level efficiency estimates. Our estimates may be improved by accounting for weather realizations in the variance terms for the transient inefficiency. Fourth, our current model specification disregards expectations about future price development of farms' output and relies on a noisy measure of irrigation investment costs. Adding price trend variables obtained through fitting stochastic processes to observed price data may address this issue. For the investment costs, more sophisticated models analyzing farm capital development as well as information for irrigation investments outside of FADN should be considered. And fifth, our model disregards strategic interactions of adaptation investment decisions (e.g., Narita and Quaas, 2014). To better account for local determinants of irrigation, such as the depletion of underground water, one should account for local shares of irrigation, and to acquire locally-specific information on irrigation water availability and respective prices.

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