AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

Wheat and maize futures reaction to weather shocks in Europe

Pierre, Guillaume[1]; Trueck, Stefan[2]; D'Ecclesia, Rita[1]; Montalbano, Pierluigi[1]

1: La Sapienza University of Rome;

2: Macquarie University

Paper prepared for presentation at the 172nd EAAE Seminar
'Agricultural policy for the environment or environmental policy for agriculture?'

May 28-29, 2019.

Brussels.

Copyright 2019 by Pierre G., Trueck S., D'Ecclesia R., Montalbano P. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Abstract

We build an index of abnormal weather conditions to study the short-run response of wheat and maize futures prices following a weather shock in Europe. As weather disruptions are not contemporaneous to the ensuing supply shock, there exist several price impact channels stemming from crop yield losses through which a climate anomaly can affect market prices. The formation and updating process of expectations of future spot prices is a key channel linking weather news and futures contract prices. Spot prices might not react contemporaneously due to contracts' rigidity and existing buffer stocks. However, advanced information on future availability can rapidly be priced in futures contracts. We estimate the average change in LIFFE wheat and maize futures contracts returns for a set of European weather events. Results suggest that later stages of the growing cycles of both wheat and maize are the most affected by abnormal weather and such impact is reflected with greater emphasis on contracts with maturities that are further away in time.

Keywords: Weather shocks, Europe, Futures Prices, Traders' anticipations, Rational expectations, Wheat, Maize
JEL : O13, Q13, Q56

1. Introduction

With the advent of electronic trading and evermore competitive global markets, public grain and supply reports are not market news anymore. Traders increasingly rely on their own crop models and weather forecasting tools to gain an edge. Weather conditions are among the main driving forces in models of agricultural price formation for they determine future supply shocks. The influence of weather patterns on crop yields is well documented by the scientific literature, through the impact of biophysical conditions on plant growth and labor productivity. Similarly, price reactions to supply shocks have been studied at large. The key causal link between weather and market prices is the impact on crop yields. However, financialised commodity markets function at a speed not comparable to relatively slow changing weather data and even slower materialisation of supply shocks. The sequential timing between observable weather events and their consequences on production, combined to market reactivity implies the existence of several price impact channels and the formation of future spot price expectations. Such expectations on forthcoming spot prices are embedded in the relationship between spot and futures prices. This paper studies the short-run response of wheat and maize futures prices on Euronext following a weather shock in Europe.

We develop a simple index of weather anomalies in Europe based on the number of regions undergoing abnormal rainfall or temperature conditions. This index is explored in a panel fixed effect with Euronext maize and wheat contracts from 2006 to 2017.

Section 2 discusses the literature on event studies and arrival of new information in agricultural commodities markets. Sections 3 formulates a simple futures contract pricing model to assess reactions to weather shocks. Section 4 presents the data empirical implementation. Results are discussed in section 5 and section 6 concludes.

2. Literature

2.1. Futures pricing and event studies

A commodity can be exchanged in a cash transaction, fetching a *spot* price. Alternatively, the right market infrastructure might allow a risk averse seller to enter in a forward or a futures contract with a counterpart in anticipation of a price change. Futures contract prices play an important role in price discovery as they embed all information known to market on cost of storage, future supply and expected future spot prices.

The spot price must equal the futures price, adjusted for some cost of storage and financing. The relationship is held by the no arbitrage equilibrium. If the futures were priced lower than the adjusted spot price, a market participant could earn a risk-less profit by purchasing futures contracts, short selling the cash commodity, and investing the proceeds. However, in the short run, the relationship is not perfect as high transaction costs can generate short lived deviations from the equilibrium, especially for grain commodities. The higher transaction costs faced by the spot market often lead its futures equivalent to react faster to new information and therefore lead the price discovery process. However, the causality might run in both directions and change over time (Garbade and Silber (1983); Silvapulle and Moosa (1999)).

While agricultural futures markets have been studied from numerous different perspectives,[1] We start by examining a strand of the literature exploring how new information is absorbed by futures markets. A key source of information for traders stems from various government agencies reports. For the US markets, USDA publications play a major role. Early papers examining the informational content of these reports for futures markets typically examine price behaviour in trading days preceding and immediately following announcements (Summer and Mueller (1989); Fortenbery and Sumner (1993); Garcia et al. (1997)). Carter and Galopin (1993) challenged the newsworthiness of USDA hogs reports through an estimation of the willingness to pay for early access to the reports. A conclusion later nuanced by Colino and Irwin (2010). Over time, the forecasting accuracy of public agencies have improved along with the availability of data and statistical techniques both in the US (Egelkraut et al. (2003)) and Europe (Van der Velde and Nisini (2018)). But so did private models.

More recently McKenzie (2008) implemented a finer identification of the impact on markets expectation generated by public provision of market information in USDA reports. They demonstrated that reports bring information, but futures prices adjust to the news quickly and efficiently. Looking further into this announcement effect, Adjemian (2012) estimates that, over the period 1980-2010, new information incorporated into futures prices within a single day. Bringing this estimate down to 10 minutes for more recent years, Lehecka et al. (2014) pointed out that the rise of electronic trading makes the market evermore rapid in absorbing new information. They found the impact of USDA corn production forecasts vanishes almost immediately in the futures market. And this efficiency level is partly explained by changes in beliefs due to privately informed traders significantly affecting trading volumes observed prior to USDA announcements, as estimated by Fernandez-Perez et al. (2018) who confirmed the asymmetric impact of such private news. Information asymmetry within increasingly globalised agricultural markets made some specific USDA announcements on international demand and supply

[1] See Garcia and Leuthold (2004) for a review.

more relevant as pointed out by Isengildina-Massa et al. (2008), providing a slightly different perspective on these public announcements. A last item to note in the section is the work of Mattos and Silveira (2016) who study the impact of crop reports from U.S. and Brazil on nearby US contracts of corn and soybean. To highlight that crop reports released in the months preceding the beginning of harvest are most impactful, they used a TARCH model with dummy variables. The times series approach developed later in this chapter follows a similar methodological approach.

This body of research generally concludes that institutional publications of production data brought significantly new information to US and European markets during the eighties. But even though their accuracy has improved over time, their informational value has gradually declined since then, especially for their respective domestic markets. Futures markets have significantly expanded and volumes have exploded with electronic trading taking over pit trading. Today's private production estimates are now quasi equivalent to their public counterparts and hence already priced in at release time. This literature is nonetheless particularly useful as it laid out the ground for so-called *event studies*. As traders have developed their own forecasting models able to rival the USDA reports, true market news must now be searched for among other types of events. Weather conditions are key drivers of production forecasts, embedded in all models. Recently, Van der Velde et al. (2018) highlighted that crop forecasting models are less accurate when coping with extreme weather events, especially if unprecedented. The next section discusses studies on weather events.

2.2. Weather events empirical applications

The literature specifically focused on the role of weather variations in food commodities futures pricing is particularly scarce. In a two step prediction workflow, futures prices forecasts typically rely on the output of yield forecasting models fed on weather data. Some studies have focused on connecting the El Nino variation to futures market Keppenne (1995); Liao et al. (2010). But the El Nino is a rather global phenomenon that in turn triggers local weather events.

In an earlier exploration of the impact of weather shocks on futures markets, Stevens (1991) attributed part of US cereal prices behaviour during the growing season to non random weather pattern. But he does not provide a quantification of this relationship. Later on, Hennessy and Wahl (1996) confirmed that rainfall and temperature have important influences on the variability of soybean, corn and wheat futures prices. More recently Goodwin and Schnepf (2000) analyse the determinants of price variability in US corn and wheat futures markets. They found a significant role for growing conditions, relying on an index derived from weekly reports of crop progress. Although they did not specifically used temperature or precipitation, an index of crop conditions is very similar to weather data in the type of information it carries. It informs the expectations of futures supply.

It is worth noting that even though non traded, weather processes are not ignored by financial markets which provide options to hedge against weather risk. Derivatives built on temperature features such as heating and cooling degree days deliver payoffs according to various contract settings (Benth and Benth (2007); Ritter et al. (2011)).

3. Price formation model with weather news

A conceptual framework is needed to examine futures market adjustments to new weather information. Consider a simple model where the inventory level, ΔN_t, is the difference between demand, $Q(.)$, and supply, $X(.)$:

$$\Delta N_t = X(P_t; z_{2t}, e_{2t}...) - Q(P_t; z_{1t}, e_{1t}...) \tag{1}$$

In the terminology used by Pindyck (2001), ΔN_t is the net demand, which must equal net supply, as expressed in equation 1. Aside from the price, demand shifting factors, z_1, typically include changes in consumer preferences, availability of a substitution good, demographics and growth. In the shorter run, sudden loss of consumer trust in a good might also reduce demand. In addition to the market price, supply is affected by factors such as cost of production, technology and weather conditions, represented by z_2. Finally, e_1 and e_1 are random shocks.

The cash price is thus a function of the drivers of supply and demand:

$$P_t = f(\Delta N_t; z_{1t}, z_{2t}, e_t) \tag{2}$$

The price of storage is the payment by inventory holders for the privilege of holding a unit of the good, usually referred to as the marginal convenience yield. It reflects the cost of storage, the depreciation and the opportunity cost of capital. The convenience yield reflects the increased utility associated with the immediate availability of the good.

Futures prices also must equal the expected future spot prices net of the storage cost, the risk free interest rate and the convenience yield. Denoting the convenience yield by Ψ_t, in the presence of futures contracts priced as $F_{t,t+1}$ for a delivery in $t+1$, the no arbitrage condition implies that:

$$\Psi_t = (1 + r_{t+1})P_t - F_{t,t+1} + k_{t+1} \tag{3}$$

where r_{t+1} is the risk-free interest rate and k_{t+1} is the physical cost of storage. When making decision regarding arbitrage, the expected return on investment of stock holding is the difference between the price at time of purchase and the expected future spot price. Denoting the expected future spot price $E_t(P_{t+1})$ and the resulting discount rate ρ_{t+1} , we have that :

$$E_t(P_{t+1}) - P_t + \Psi_t - k_t = \rho_{t+1} P_t \tag{4}$$

Consider that the futures and spot prices are bound by the no arbitrage condition (equation 3) and that the expected return of storage in t depends on the expectations of spot price changes. With discount and interest rates known for the upcoming period, equations 3 and 4 might be combined to obtain a relationship between futures prices and expected futures spot prices:

$$F_{t,t+1} = E_t(P_{t+1}) + (r_{t,t+1} - \rho_{t,t+1})P_t \tag{5}$$

This specifications puts the formation of traders' expectations at the centre of the futures price formation process. Advance information on the upcoming harvest, I_t, can be used to form early estimates of future supply which will in turn determine future spot prices (equations 1 and 2). By shifting the expected future supply, and therefore modifying the expected future spot price, weather plays a determinant role in futures contract prices. Combining the interest and discount rates into $\beta_{t,t+1}$, a reduced form model emerges, centred around expectations :

$$F_{t,t+1} = E_t(P_{t+1}|I_t) + \beta_{t,t+1} P_t \tag{6}$$

$$
\begin{tikzcd}
WeatherAnomaly \arrow[dr, "\text{Expectations Update}"] & \\
F_{t,t+1} & E_t(P_{t+1}) \arrow[l, "\text{Arbitrage Optimization}"]
\end{tikzcd}
$$

Figure 1: Weather impact channel on futures market

4. Empirical model and data

To examine market reactions to a weather anomaly in Europe, we start from equation 5 which states that futures prices are moved by the drivers of expectations on future spot prices. Weather data carries advance information regarding future supply, especially during the growing months, and therefore shapes these expectations. We examine abnormal weather days through the estimation of a panel fixed effect model, in the spirit of the event study approaches reviewed in section 2. A set of interacting variables identifies to what extent weather anomalies influence the price of different contract maturities.

4.1. European temperature and precipitation data: indices of abnormal conditions

This section presents an index of marginal weather changes to measures abnormal weather conditions. Reconciling the relatively slow changing weather data with higher frequency market data is not straightforward. Traders typically react instantly but a weather event that matters for future production might unfold over a period of several weeks. As a first step to tackle this problem, we start by using the cumulative rainfall and cumulative temperature in a moving window of 40 days. We also examine the deviation from the average conditions calculated across windows of 20 years. Finally we look at abnormal days, i.e. days during which the temperature was outside the range of two standard deviations around the 20 year moving average.

We use the E-OBS 17.0 daily gridded observational dataset for precipitation, temperature and sea level pressure provided at a 0.25 degree pixel resolution by the European Climate Assessment & Dataset project (Van den Besselaar et al. (2011)). We mask the rasters with the global land cover[2] so as to keep only cells predominantly covered by croplands and non forest vegetation. Then, we sum precipitation and temperature data from cells within the NUTS 1 administrative borders to derive local level indicators. To account for the fact that weather during a specific day cannot influence the outcome of the overall season while markets adjust on a daily basis, we compute a set of daily weather indicators for each region:

- *Hot day*: Day during which the 40-day rolling average temperature stood **above** 2 standard deviations of the rolling long term average (20 years).
- *Cold day*: Day during which the 40-day rolling average temperature stood **below** 2 standard deviations of the rolling long term average (20 years).
- *Rain deficit day*: Day during which the 40-day rolling average rainfall stood **below** 2 standard deviations of the rolling long term average (20 years).
- *High precipitation day*: Day during which the 40-day rolling average rainfall stood **above** 2 standard deviations of the rolling long term average (20 years).

[2] https://www.eea.europa.eu/data-and-maps/data/global-land-cover-250m (EEA).

Based on the above definitions, European wide information is obtained by summing the number of regions facing an abnormal weather day.

The maps in figure 5 provide example of daily rasters used to construct weather variables. These variables are plotted in figures 3 and 4. Abnormal episodes such as the warm spell of 2007 are apparent. Up to 70% of regions might experience the same type of event at once. A particularity and a limitation of this approach is that Europe might experience at the same time abnormal hot and cold or dry and wet days, across different regions. However these types of event are generally highly negatively correlated.

	Number of NUTS 1 regions experiencing days of:			
	High temperature	Low temperature	Rainfall deficit	High rainfall
Min.	0.000	0.00	0.00	0.00
1st Qu.	0.00	0.00	0.00	1.00
Median	1.00	1.00	10.00	4.00
Mean	5.55	2.70	15.40	6.05
3rd Qu.	5.00	2.00	10.00	9.00
Max.	71.00	69.00	49.00	4.00

Table 1: Descriptive statistics (1990-2017)

4.2. Financial data: wheat and maize futures contracts from Euronext

4.2.1. Contracts panel data

For wheat, we consider Euronext Paris milling wheat futures contracts (trading code 'EBM') exchanged on the London International Financial Futures and Options Exchange (LIFFE)[3]. These contracts are traded for delivery months November, January, March and May until May 2015 and then September, December, March and May from September 2015 onward, such that 12 delivery months are available for trading and quoted in euro per tonne of wheat delivered in an approved silo in Rouen, France.

Maize prices come from Euronext Paris corn futures contracts (trading code 'EMA') issued with delivery in January, March, June, August and November such that ten delivery months are available for trading. Approved silos for delivery can be found in French cities of Bayonne, Blaye, Bordeaux, La Rochelle Pallice, and Nantes

For both commodities, these contracts are linked to produce from EU origin only (see Figure 5 for a distribution of production across EU). The price data is obtained from Quandl/CHRIS and all price observations are brought into a panel in which the unit of observation is the contract-day. Some contract data is reported for more than a year before delivery. All observations are dropped for contracts trading at a time earlier than 1.5 year from maturity.[4]

[3]The LIFFE was acquired by the New York Stock Exchange in 2007, to form NYSE Euronext. It is now part of the Intercontinental Commodity Exchange (ICE).

[4]A change in reporting occurred in 2013, when the Intercontinental Exchange (NYSE: ICE), completed acquisition of NYSE Euronext. This applies for the case of wheat for which, in addition, two contracts with delivery in F and X, traded exceptionally in 2013-2014 and 2014-2015 respectively, were omitted.

4.3. Empirical application: A panel fixed effect approach

Consider an estimation of the weather news contribution to futures prices in equation 5 through a panel fixed effect model. For this exercise, each individual contract is a unit of observation, throughout its trading lifespan. In the spirit of event studies reviewed in section 2, the informational nature of abnormal weather days is assessed with a set of markers in the dataset for these particular events.

Estimates are obtained by regressing the return of settle prices at day t for delivery in month j of year i, $F_{t,i,j}$, on specific weather parameters:

$$F_{t,i,j} = \beta_0 + \boldsymbol{\beta}_1' \bar{\mathbf{W}}_t + r_t + \tau_{i,j} + y_i + s + \eta_{t,j} \tag{7}$$

where $\bar{W}_t$ is a vector of European level abnormal weather indices derived from the number of NUTS 1 regions experiencing abnormal conditions, for each day, t. The estimated model includes year fixed effects (y_t) and contract fixed effects (τ_i). A monthly seasonal cycle is also included, (s_t). Finally, $\eta_{t,i}$ is an error term, clustered at the contract level to capture heteroskedasticity. The interest rate is represented by r_t the risk free interest rate (German Government 10 years bond) and the storage loss parameters from our structural model in equation 5 are absorbed by the time and contract fixed effects.

In Europe, winter wheat is planted from September to December and harvested from June to August, whereas spring wheat might be planted from February to March and harvested during July-August. We explore the different impacts of abnormal days in each month preceding harvest with a set of interactions.

5. Results and discussion

This section presents an assessment of the marginal effect of regions experiencing days above or below normal weather conditions (increments of 10 regions). Tables 2 and 3 present results of the panel fixed effect estimates for wheat and maize respectively and where the unit of observation is the contract-day, between 2006 and 2017. Weather indices coefficients give the change in percentage points associated to each increase of 10 regions/day undergoing a weather anomaly. Both result tables feature a first specification with the four weather variables interacted with quarters. The second specification focus on the last few months of the growing cycle and interacts weather variables with months to map the impact of weather across this part of the seasonal cycle. Finally, the last two specification explore the impact on prices for near deliveries (within the next 6 months) and far deliveries (more than 6 months, up to 1.5 years). All models have a set of year and monthly dummies to control for seasonality in prices returns. Year fixed effects capture the overall price return trend.

Coefficients from specifications with monthly or quarterly interactions are to be interpreted differently than a basic specification. The first coefficient represents the impact for the base period. Coefficients associated to months or quarters are the additional impacts. The total impact of an additional 10 regions undergoing a particular anomaly in a given month can therefore be obtained by summing the base term and the specific month's interaction.

For *wheat*, a high temperature anomaly throughout the continent is significantly associated with higher prices returns across all specifications (table 2). Interactions reveal that high temperatures can have the strongest impact on wheat prices in the second and third quarters, which coincide with the latest stages of the growing cycle. Monthly interactions also suggest that hot weather can have a slightly negative impact on returns in June. High rainfall anomalies are significantly associated to higher price returns across all quarters except the second. Results also suggest that cold spells push price returns up in the second quarter (specification 1) or the month of June (specification 2). Period of drought have a significant and positive impact across the seasonal cycle except during the second quarter.

Differences between specification 3 and 4 suggest that weather has a stronger impact on contracts with deliveries further away in time. This implies that grain stocks might buffer the short run adverse impact of supply shocks, but are less effective over a longer time horizon.

For *maize*, the results present a similar picture, with drought events significantly increasing price returns, except in the second quarter (table 3). Abundant rainfall seems to be perceived as beneficial for crop prospects until June, after which the price returns will increase with the anomaly. Hot anomalies also seem to reduce price returns across specifications. Dry spells increase maize price returns (base coefficient of the first specification), except during the second quarter).

Price returns for far deliveries are slightly more affected than short run ones, but to a lesser extent than for wheat.

Table 2: Impact of weather anomalies on daily Euronext **wheat** returns

	All year	Growing period	Near (< 180 days)	Far (>180 days)
	(1)	(2)	(3)	(4)
Constant	−.459 (.419)	−.507*** (.174)	2.011* (1.151)	−1.073* (.593)
Interest Rate	−.078** (.035)	.290*** (.085)	−.209*** (.079)	−.060 (.043)
hot anomaly	−.016 (.017)	.103*** (.026)	.009 (.045)	−.020 (.020)
cold anomaly	−.009 (.021)	−.003 (.037)	−.007 (.036)	−.006 (.028)
dry anomaly	.099** (.048)	−.191 (.239)	−.035 (.114)	.127** (.055)
wet anomaly	.113*** (.026)	.119 (.106)	.061 (.063)	.130*** (.029)
Quarterly interactions with high temperature days				
hot:Q02	.042** (.021)		.010 (.052)	.055** (.025)
hot:Q03	.047** (.023)		−.003 (.053)	.050* (.027)
hot:Q04	−.011 (.022)		−.034 (.050)	−.007 (.026)
Quarterly interactions with cold temperature days				
Q02:cold	.084*** (.030)		.065 (.053)	.120*** (.039)
Q03:cold	−.092 (.087)		.119 (.178)	−.116 (.105)
Q04:cold	.026 (.055)		.089 (.102)	.004 (.083)
Quarterly interactions with rain deficit days				
Q02:dry	−.186*** (.061)		−.007 (.128)	−.228*** (.074)
Q03:dry	−.159 (.102)		−.138 (.232)	−.154 (.118)
Q04:dry	−.033 (.063)		.091 (.126)	−.038 (.081)
Quarterly interactions with rain deficit days				
Q02:wet	−.310*** (.036)		−.200** (.078)	−.362*** (.043)
Q03:wet	−.071** (.031)		−.049 (.071)	−.083** (.037)
Q04:wet	−.039 (.043)		.017 (.091)	−.069 (.051)
Monthly interactions with high temperature days				
m05:hot		−.096*** (.035)		
m06:hot		−.113*** (.037)		
m07:hot		−.038 (.037)		
Monthly interactions with cold temperature days				
m05:cold		.058 (.081)		
m06:cold		.201** (.078)		
m07:cold		−.169 (.130)		
Monthly interactions with rain deficit days				
m05:dry		.204 (.246)		
m06:dry		−.259 (.264)		
m07:dry		−.129 (.295)		
Monthly interactions with high rainfall days				
m05:wet		−.229** (.116)		
m06:wet		−.434*** (.115)		
m07:wet		−.104 (.110)		
Observations	11,172	3,506	2,908	8,264
R^2	.024	.045	.050	.027
Adjusted R^2	.015	.025	.018	.016

Note: Year, month and contract fixed effect included in all specifications.
Dep. var. :Log returns of settle prices: $log(P_1/P_{t-1}) * 100$
Significance: * $p < .10$, ** $p < .05$, *** $p < .010$. Standard errors in parentheses.

Table 3: Impact of weather anomalies on daily Euronext **maize** returns

	All year	Growing period	Near (< 180 days)	Far (>180 days)
	(1)	(2)	(3)	(4)
ir	.187** (.075)	.785*** (.147)	.382 (.355)	.185** (.082)
Constant	−.663*** (.230)	−1.621*** (.233)	−1.396 (1.359)	−.673*** (.246)
hot anomaly	−.098*** (.029)	.192*** (.062)	−.072 (.092)	−.102*** (.031)
cold anomaly	−.025 (.125)	1.700** (.701)	.099 (.425)	−.067 (.135)
dry anomaly	.169*** (.063)	.119 (.797)	.211 (.153)	.145** (.071)
wet anomaly	.048 (.044)	.489** (.238)	.208 (.148)	.043 (.047)
Quarterly interactions with high temperature days				
hot:Q02	.047 (.041)		−.054 (.131)	.059 (.043)
hot:Q03	.107*** (.041)		.113 (.116)	.110** (.046)
hot:Q04	.029 (.040)		.032 (.122)	.033 (.043)
Quarterly interactions with cold temperature days				
Q02:cold	−.011 (.154)		−.172 (.570)	.014 (.163)
Q03:cold	−.206 (.239)		−1.137* (.655)	−.004 (.268)
Q04:cold	−1.039*** (.396)		−.918 (1.249)	−1.062** (.435)
Quarterly interactions with rain deficit days				
Q02:dry	−.619*** (.185)		−1.309** (.538)	−.504** (.199)
Q03:dry	.062 (.164)		.403 (.401)	−.029 (.183)
Q04:dry	−.087 (.106)		−.291 (.269)	−.052 (.119)
Quarterly interactions with high rainfall days				
Q02:wet	−.348*** (.069)		−.446** (.212)	−.340*** (.074)
Q03:wet	.023 (.060)		−.087 (.178)	.015 (.066)
Q04:wet	−.093 (.072)		−.112 (.219)	−.105 (.077)
Monthly interactions with high temperature days				
m05:hot		−.620** (.246)		
m06:hot		−.291*** (.073)		
m07:hot		−.201** (.095)		
m08:hot		−.711*** (.117)		
Monthly interactions with cold temperature days				
m05:cold		−1.732** (.694)		
m06:cold		−1.827** (.759)		
m07:cold		−3.147*** (.809)		
m08:cold		−.140 (.828)		
Monthly interactions with rain deficit days				
m05:dry		.028 (.925)		
m06:dry		−1.284 (.816)		
m07:dry		−.081 (.889)		
m08:dry		.609 (.832)		
Monthly interactions with high rainfall days				
m05:wet		−.539** (.257)		
m06:wet		−.914*** (.255)		
m07:wet		−.382 (.250)		
m08:wet		−.439* (.249)		
Observations	6,182	2,243	1,029	5,153
R^2	.025	.098	.067	.026
Adjusted R^2	.016	.079	.020	.016

Note: Year, month and contract fixed effect included in all specifications.
Dep. var. :Log returns of settle prices: $log(P_1/P_{t-1}) * 100$
Significance: * $p < .10$, ** $p < .05$, *** $p < .010$. Standard errors in parentheses.

6. Conclusion

Alongside the increased market orientation of the last iterations of the European Common Agricultural Policy (CAP), futures markets have gradually taken more importance among risk management options for European producers, especially for the grain sector. Although few farmers are directly trading futures contracts, commercialisation intermediaries routinely offer fixed or differed price forward contracts, informed by futures market pricing.

Weather conditions are among the main forces driving pricing models, for they determine future supply shocks. The influence of weather patterns on crop yields is well documented by the scientific literature. Similarly, price reactions to supply shocks have been studied at large. However agri-commodities' futures behaviour in the face of weather anomalies deserves better scrutiny within the literature and the policy making community. Enhanced understanding of agri-food markets reaction to climatic anomalies is relevant to the undergoing effort of improving risk management strategies in a market oriented CAP confronted to climate change, and in an evermore financialised context. Hence, this paper presents insights on how such a financialised type of agricultural commodity market is affected by climate disruptions, as measured by abnormal weather days. An estimation of the impact of weather anomalies on European wheat and maize futures markets is provided to explore how weather information moves the futures contract prices. Building from basic theoretical elements of futures pricing, we show that weather developments affect futures prices through impacting drivers of spot prices in the next period, which are mediated to current prices by expectations. We use this framework to set up a panel fixed effects for wheat and maize European futures contracts.

The panel fixed effect estimations indicate that abnormal weather events raise futures prices more often than the opposite, through a positive impact on returns. It also confirms that price sensitivity to weather shocks varies along the seasonal cycle. Results suggest that later stages of the growing cycles of both wheat and maize are the most affected by abnormal weather and such impact is reflected with greater emphasis on contracts with maturities that are further away in time.

This analysis has several limitations. First, the ECAD weather data has the advantage of being of a higher spatial resolution than most publicly available alternatives and makes a finer analysis possible. But the dataset has several missing periods for different pixels (e.g. Sicilia, Northern Italy, Poland). Second, the empirical identification of a meaningful weather event for agriculture is still insufficient. Options to improve on this area are the use of growing degree days, a recourse to a country specific crop calendar to focus on important weeks of the crop cycles, a better land use mask to better map wheat and maize producing regions, and definition of events combining rainfall and temperature. These options should be considered in an improved version of this work. Furthermore, the contract fixed effect approach has the advantage to increase the available number of observations, but the term structure is lost, thereby obscuring useful information. Finally, an interesting additional option for future research would be to inform the empirical implementation by an analysis of standard trading strategies.

References

Adjemian, M.K., 2012. Quantifying the wasde announcement effect. American Journal of Agricultural Economics 94, 238–256.

Benth, F.E., Benth, J.š., 2007. The volatility of temperature and pricing of weather derivatives. Quantitative Finance 7, 553–561.

Van den Besselaar, E., Haylock, M., Van der Schrier, G., Klein Tank, A., 2011. A european daily high-resolution observational gridded data set of sea level pressure. Journal of Geophysical Research: Atmospheres 116.

Carter, C.A., Galopin, C.A., 1993. Informational content of government hogs and pigs reports. American Journal of Agricultural Economics 75, 711–718.

Colino, E.V., Irwin, S.H., 2010. Outlook vs. futures: Three decades of evidence in hog and cattle markets. American Journal of Agricultural Economics 92, 1–15.

Egelkraut, T.M., Garcia, P., Irwin, S.H., Good, D.L., 2003. An evaluation of crop forecast accuracy for corn and soybeans: Usda and private information agencies. Journal of Agricultural and Applied Economics 35, 79–95.

Fernandez-Perez, A., Frijns, B., Indriawan, I., Tourani-Rad, A., 2018. Surprise and dispersion: informational impact of usda announcements. Agricultural Economics 0.

Fortenbery, T.R., Sumner, D.A., 1993. The effects of usda reports in futures and options markets. Journal of Futures Markets 13, 157–173.

Garbade, K.D., Silber, W.L., 1983. Price movements and price discovery in futures and cash markets. The Review of Economics and Statistics , 289–297.

Garcia, P., Irwin, S.H., Leuthold, R.M., Yang, L., 1997. The value of public information in commodity futures markets. Journal of Economic Behavior & Organization 32, 559–570.

Garcia, P., Leuthold, R.M., 2004. A selected review of agricultural commodity futures and options markets. European Review of Agricultural Economics 31, 235–272.

Goodwin, B.K., Schnepf, R., 2000. Determinants of endogenous price risk in corn and wheat futures markets. Journal of Futures Markets: Futures, Options, and Other Derivative Products 20, 753–774.

Hennessy, D.A., Wahl, T.I., 1996. The effects of decision making on futures price volatility. American Journal of Agricultural Economics 78, 591–603.

Isengildina-Massa, O., Irwin, S.H., Good, D.L., Gomez, J.K., 2008. The impact of situation and outlook information in corn and soybean futures markets: Evidence from wasde reports. Journal of Agricultural and Applied Economics 40, 89–103.

Keppenne, C.L., 1995. An enso signal in soybean futures prices. Journal of Climate 8, 1685–1689.

Lehecka, G.V., Wang, X., Garcia, P., 2014. Gone in ten minutes: Intraday evidence of announcement effects in the electronic corn futures market. Applied Economic Perspectives and Policy 36, 504–526.

Liao, S.Y., Chen, S.T., Chen, C.C., 2010. Modelling the enso forecast on soybean spot and future prices. Journal of Agriculture and Forestry 59, 91–103.

Mattos, F.L., Silveira, R.L., 2016. Futures price response to crop reports in grain markets. Journal of Futures Markets 36, 923–942.

McKenzie, A.M., 2008. Pre-harvest price expectations for corn: The information content of usda reports and new crop futures. American Journal of Agricultural Economics 90, 351–366.

Pindyck, R.S., 2001. The dynamics of commodity spot and futures markets: a primer. The energy journal , 1–29.

Ritter, M., Musshoff, O., Odening, M., 2011. Meteorological forecasts and the pricing of temperature futures. Journal of Derivatives 19, 45.

Silvapulle, P., Moosa, I.A., 1999. The relationship between spot and futures prices: evidence from the crude oil market. Journal of Futures Markets: Futures, Options, and Other Derivative Products 19, 175–193.

Stevens, S.C., 1991. Evidence for a weather persistence effect on the corn, wheat, and soybean growing season price dynamics. Journal of Futures Markets 11, 81–88.

Summer, D.A., Mueller, R.A., 1989. Are harvest forecasts news? usda announcements and futures market reactions. American Journal of Agricultural Economics 71, 1–8.

Van der Velde, M., Baruth, B., Bussay, A., Ceglar, A., Garcia Condado, S., Karetsos, S., Lecerf, R., Lopez, R., Maiorano, A., Nisini, L., Seguini, L., van den Berg, M., 2018. In-season performance of european union wheat forecasts during extreme impacts. Scientific Reports 8.

Van der Velde, M., Nisini, L., 2018. Performance of the mars-crop yield forecasting system for the european union: Assessing accuracy, in-season, and year-to-year improvements from 1993 to 2015. Agricultural Systems .

Annex: Figures

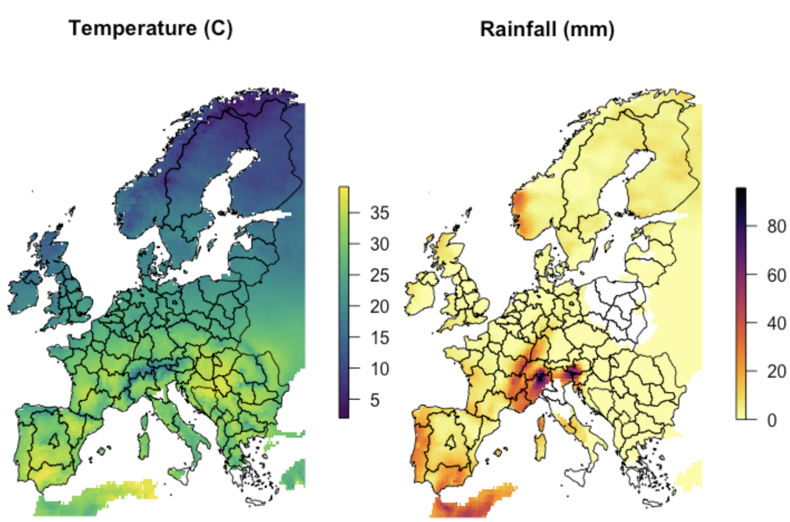

Figure 2: **Temperature and rainfall across NUTS 1 regions** on the 27th of August 2017 and 25th of December 2013 respectively. Source: Author based on ECAD data.

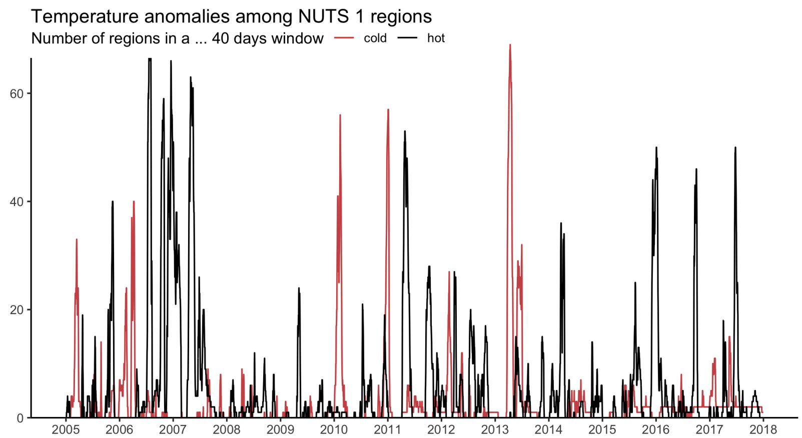

Figure 3: **Abnormal precipitation levels in Europe.** Days at the right end of a moving window of 40 days whose average temperature is above or below 2 standard deviations of the local long term average. Source: Author based on ECAD data.

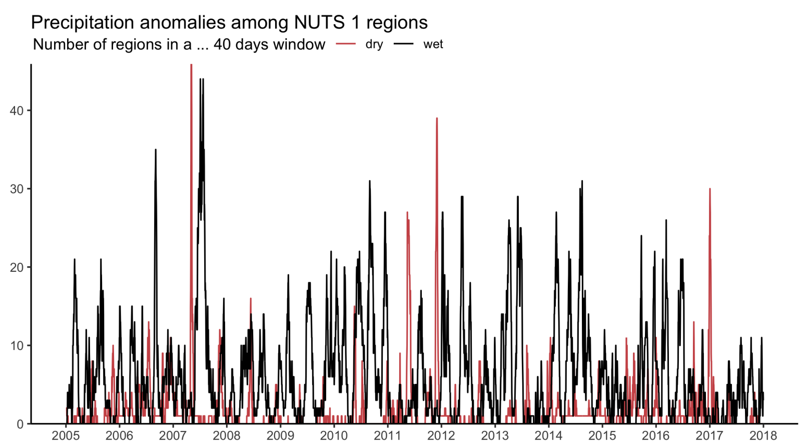

Figure 4: **Abnormal precipitation levels in Europe.** Days at the right end of a moving window of 40 days whose average precipitation is above or below 2 standard deviations of the local long term average. Source: Author based on ECAD data.

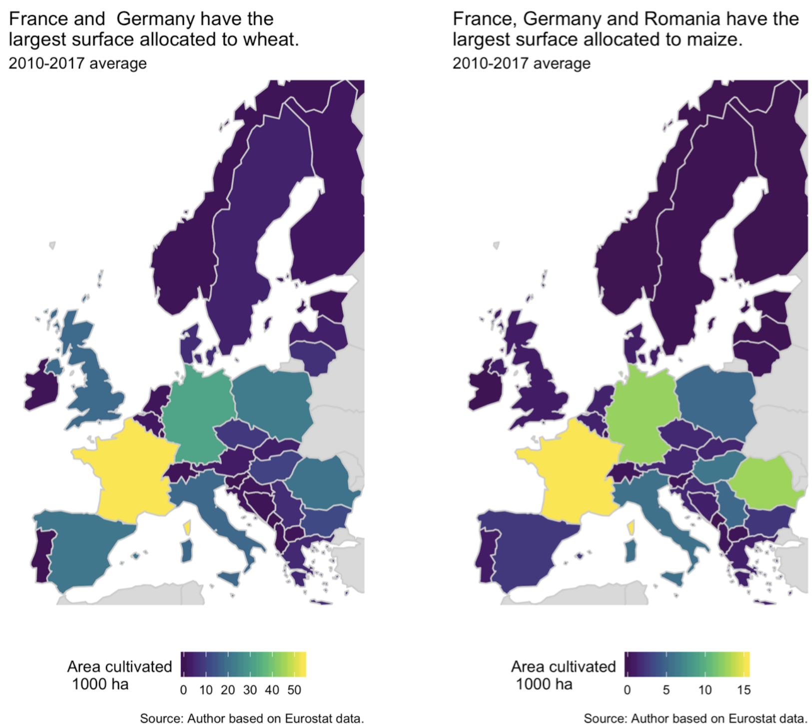

Figure 5: **Wheat and maize production area** across EU countries. For wheat, France and Germany have the largest total surface under cultivation, followed by a cluster of four countries, namely Poland, Romania, Spain and the United Kingdom. Surfaces for maize are the largest in the group made of France, Germany and Romania, followed by the cluster of Poland, Italy, Slovakia and Bulgaria. Source: Author based on Eurostat data.