School of Economics Working Paper 2023-04

Precipitation events and local corn prices: evidence from Brazil

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November 2023

Abstract

Weather variation plays a primary role in commodity price formation. In most contexts, the amount of rainfall is usually taken by farmers as an indicator of crop success or failure. However, the literature is still vague in defining when in the pre-harvest period weather information is more critical for price formation. In this sense, we investigate the impact of dryness on commodity price formation during the pre-harvest period and across phenological stages in the context of a major corn producing country. We build a database containing variables such as price and the number of days with no precipitation between January 2005 and December 2019. We use a panel data regression of corn spot prices on the number of days without rain, and its squares. We find a significant and nonlinear relationship between the number of dry days in a week and local corn price variations. Overall, prices start rising after 4 days with no precipitation. Disentangling this impact into phenological stages, we find that dryness events tend to impact prices during the vegetative and flowering stages but have no effect during the grain filling stage. We also find that abnormal precipitation events tend to increase corn prices, as they contribute to depressing farmers' expectations on future corn availability by harvest time. However, this result is led by water scarcity events, while, on the contrary, water overabundance events negatively affect prices.

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1. Introduction

Weather variation plays a primary role in commodity price formation. In most contexts, the amount of rainfall and the extent of temperature oscillation are usually taken by farmers as indicators of crop success or failure. A number of studies have demonstrated that weather and crop-related information is incorporated in prices even before harvest materializes through agents' expectations, both in futures markets (Adjemian, 2012) and in physical markets (Osborne et al., 2004; Letta et al., 2021).

However, the literature is still vague in defining when in the pre-harvest period weather information is more critical for price formation. Some studies relating crop yield to temperature and rainfall, such as Ortiz-Bobea (2011) and Ortiz-Bobea and Just (2012), have divided the pre-harvest period into phenological stages and investigated which stage has a bigger response to weather stress. The number of studies applying such an approach to price analysis is still quite limited though.

In this sense, we investigate the impact of weather variation on commodity price formation during the pre-harvest period and across phenological stages in the context of a major corn producing country. We build a database containing weekly variables such as price, temperature and precipitation between January 2005 and December 2019. We focus our analysis on the corn spot markets in the state of Mato Grosso, which has been consistently ranked as the top corn producer in Brazil, accounting for roughly one third of all corn in the country. Unlike other major corn producers, Brazil has two corn harvests per year. In this study, we analyze the second corn harvest, commonly known as *safrinha*, since it is the largest one and the most relevant to our study, due to the fact that it has been exposed to significant shortages of rainfall.

To the best of our knowledge, this is the first study to use a large dataset comprehending all key phenological stages related to corn crops. We use a panel data regression of corn spot prices on a variable that counts the weekly number of days with no precipitation and the square of the mentioned variable, using temperature as a control variable. In theory, the random nature of precipitation would allow us to identify the causal effect of the weather variation on corn prices in the pre-harvest period. However, estimations using variables based on fixed calendar periods may be subject to bias. Since we compute weekly averaged variables from daily data, we are able to precisely identify the key phenological stages of the corn plant - namely the vegetative, flowering and grain filling stages – significantly contribute to attenuate this bias (Ortiz-Bobea and Just, 2012).

We find a significant and nonlinear relationship between the number of dry days in a week (dryness) and local corn price variations. Overall, prices start rising after 4 days with no precipitation. Disentangling this impact into phenological stages, we find that dryness events tend to impact prices during the vegetative and flowering stages but has no effect during the grain filling stage. We also verify whether abnormal precipitation events – namely water scarcity or water overabundance – have an impact on prices. We find that such events contribute to increase corn prices as they contribute to depress farmers' expectations on future corn availability by harvest time. More specifically, water scarcity events strongly drive this result, while water overabundance events do not seem to overall impact prices. However, when phenological stages are considered, abnormal positive precipitation events tend to decrease prices in the grain-filling stage only, while the opposite is observed in the other two phenological stages. As extreme weather conditions are occurring more often (UNDRR, 2020), our findings imply that, if the extreme weather precipitation events increase in their frequency, corn prices will tend to become more volatile over time with a clear impact on farmers, investors, inflation and the whole society, especially on low-income families, potentially hitting food security. Moreover, water overabundance events contribute to increase prices during the vegetative stage (coefficient 0.013 at 5% significance level) and decrease prices during the grain filling stage (coefficient -0.030 at 5% significance level).

Building on the literature that seeks to identify the interplay between weather stress and commodity prices (Schaub and Finger, 2020; Letta et al., 2021), our main contribution to the literature is to show how rainfall variation impacts price formation across key phenological stages. This is made possible because of the high granularity of our database, which allows us to precisely identify the phenological stages. Since we shed light on the extent to which precipitation impact corn prices and on the exact stage when it happens, our findings also have broader implications for the animal feed, human consumption, fiber production, and biofuels industries, which in turn are composed of a wide range of agents such as farmers, investors, financial institutions, and policy makers.

Addressing these issues provides a way to better understand not only some specific properties of commodity price formation, but also how these markets respond to pressing issues such as climate change and food security worldwide. In fact, extreme weather events such as droughts, floods, cyclones, tropical storms, and heightened climate variability have been identified as major drivers of food insecurity and civil unrest in some countries and regions (World Bank, 2023). Regarding corn production specifically, potential future climate change scenarios tend to significantly reduce corn yields, having pronounced declines in rainfed crops, contributing to worsen the aforementioned issues (Irmak et al., 2022).

The reminder of this paper is organized as follows. Section 2 discusses the literature related to the weather stress and commodity prices. Section 3 describes the context of corn production in Mato Grosso, whereas section 4 explains the empirical approach and data. Section 5 discusses the main findings regarding the reaction of corn prices to dryness, section

6 investigates the impact of abnormal precipitation events on corn prices; and the final section provides a concluding summary.

2. Literature Review

Weather is one of the major sources of uncertainty and risk in agriculture, having impacts in all phases of crop development and consequences that go beyond harvest. There is a strand in the literature that investigates the impact of weather stress on crop yields (Ortiz-Bobea, 2011; Ortiz-Bobea and Just, 2012; D'Agostino and Schlenker, 2016; Cohen et al., 2020; Fu et al. 2021, Irmak et al., 2022). The general conclusion is that such events, in particular droughts and heat waves, have a significant impact on crop yields, above all when plants are exposed to stress during the reproductive stage (Cohen et al, 2020). It follows that reduced crop yields lead to smaller than expected harvests, which would ultimately entail higher prices. Nonetheless, the number of studies investigating the impact of weather stress events on commodity prices is still limited.

Some authors have considered the impact of well-known climatic events such El Niño and La Niña on commodity prices (Algieri, 2014; Ubilava, 2017; Ubilava 2018). Algieri (2014) emphasized that, among other factors, the La Niña phenomenon plays an important role in depressing wheat yields and consequently lifting wheat price in global markets. Ubilava (2017) further confirmed the impact of La Niña on wheat prices but argues that the price increase reaches the magnitude of about 6%. In a more comprehensive study with a wide range of commodity prices, Ubilava (2018) found that a group of commodity prices responds well to El Niño oscillations, however, the ability of this phenomenon to forecast commodity prices is rather limited.

A line of studies has investigated the impact of droughts and heat waves on commodity prices (Chung et a., 2014; Schaub and Finger, 2020; Letta et al., 2021; Rowley, 2023) and on cattle herds (Skidmore et al, 2022). Chung et al (2014) argue that the heat wave that impacted the US corn production in 2012 caused an increase of about 25% on international corn prices, raising food security concerns in many low-income in countries. Similar conclusions were reached by Sternberg (2012) when linking the 2011 winter drought in China's wheat growing region and to the sharp increase in international wheat prices and its effects on the Arab Spring protests.

In the United States, Rowley (2023) studied the impact of droughts on hay prices at the state and district level and found a positive relationship between hay prices and the occurrence of such events. Such studies, however, focus on the interplay between weather shocks and post-harvest commodity prices.

A growing body of empirical research studies the pre-harvest dynamics of price formation. Letta et al. (2021) investigated the impact of weather anomalies on prices during the pre-harvest period in Indian commodity spot markets. They found that droughts significantly increased local prices while crops were still growing, as market agents immediately adjust their beliefs and expectations about future harvest shortfalls. Schaub and Finger (2020) using time series techniques studied the effect of droughts on hay, wheat and barley prices in Germany and found that regional and national droughts contribute to increase hay prices but have no impact on wheat and barley prices. One interesting feature of Schaub and Finger (2020) is that they divide the pre-harvest period into phenological stages.

3. Context

The state of Mato Grosso represents one of Brazil's most advanced agricultural frontiers. The increasing grain production puts Mato Grosso on top of Brazil's producing states, representing 27% of the soybeans and more than one third of domestic corn production. At the global level, Mato Grosso is responsible for 10% of the soybeans and approximately 3.7% of corn supplies (Victoria et al, 2012; Abrahao and Costa, 2018; Zhang et al, 2021, USDA, 2023).

From 2001 to 2011, the state increased its mechanized agriculture area from 3.3 million to 5.8 million hectares. The share of double cropping also increased from 15% in 2001 to 50% in 2011 (Spera et al., 2014). The results of such expansion translated in a significant increase in production. The participation of Mato Grosso relative to Brazil corn production went from around 6.6% in 2003 to over 35% in 2022, at around 38,3 million tons. Corn production in Mato Grosso occurs twice a year. The first corn crop is sown around October and harvested around March and benefits from the rainy season.

The second corn crop – also known as *safrinha* - is the most important one, and it is usually cultivated within the double cropping system. In this system, two different crops are combined, one after the other. In Mato Grosso, soybean crops start being sown by the beginning of the rainy season (around mid-September to October) and the corn crop is sown right after the soybean harvest, between February and March. As a result, the biggest part of the state's corn production is concentrated in the latter crop, whereas most of the soybean production happens in the first crop (Conab, 2017; Andrea et al, 2019).

Located in central Brazil, the state of Mato Grosso has a tropical climate agriculture, which implies that it is dependent on rainfall, and it experiences the upper limit of temperature tolerance (Rosenzweig et al., 2014; Zhang et al, 2021). In this sense, water scarcity and high temperatures pose the main threats for the second crop. For corn, it translates in potential damage in its most critical phenological phases: flowering and grain filling (Andrea et al., 2019). In addition, general global warming may increase concerns related to temperature impacts and climatic phenomena, such as El Niño and La Niña, may bring a higher degree of uncertainty regarding rainfall variability.

Our database is composed of the 17 existing corn spot markets[3] in the state of Mato Grosso between 2005 and 2019. Each spot market corresponds to a municipality, and they were added to our database in order of data availability, which results in an unbalanced panel data structure. In 2022, twelve of these municipalities ranked among the top 20 biggest corn producers in Brazil (IBGE, 2023). During the period of analysis, these municipalities combined accounted for up to 59.3% of corn production in Mato Grosso. In Brazil, a group of neighboring municipalities form a microregion. If then, we consider the combination of microregions in which these municipalities are inserted, this share goes up to 82,4%.

4. Empirical Approach and Data

In order to estimate the impact of weather variables on corn price formation we rely on a model in which weather regressors are matched with key stages of the corn production, namely vegetative, flowering, and grain filling (Ortiz-Bobea, 2011; Ortiz-Bobea and Just, 2012). In doing so, we avoid potential omitted bias that come from fixed calendar periods. Ortiz-Bobea and Just (2012) argue that crop yield models that use season-long weather variables, and therefore ignore the phenological stages, are subject to upward bias on the estimation of yield impacts. In addition, the authors emphasize that calendar weather variables, such as growing season average temperature (February-June) or harvest season average precipitation, are likely to be correlated with omitted factors. Building on Ortiz-Bobea and Just (2012) and Letta et al. (2021), we construct our model specification as in equation (1):

[3] Namely Campo Verde, Lucas do Rio Verde, Rondonópolis, Sapezal, Sorriso, and Tangará da Serra (from 2005 onwards); Canarana, Campo Novo do Parecis (from 2008 onwards); Nova Mutum, Primavera do Leste, and Diamantino (from 2009 onwards); Sinop, Alto Araguaia, Campos de Júlio, Ipiranga do Norte, Nova Ubiratã, Querênica (from 2015 onwards).

$$\log p_{it} = \sum_{n=1}^{2}\left(\beta_{1,s}DD_{i,t-n,s} + \beta_{2,s}DD_{i,t-n,s}^2 + \beta_{3,s}Temp_{i,t-n,s}\right) + \delta_i + \delta_t + \eta_{it} \quad (1)$$

$$\log p_{it} = \sum_{n=1}^{2}\left(\beta_{1,s}DD_{i,t-n,s} + \beta_{2,s}DD_{i,t-n,s}^2 + \beta_{3,s}Temp_{i,t-n,s}\right) + \delta_i + \delta_t + \delta_i x \delta_t + \eta_{it} \quad (2)$$

$$\log p_{it} = \sum_{n=1}^{2}\left(\beta_{1,s}DD_{i,t-n,s} + \beta_{2,s}DD_{i,t-n,s}^2 + \beta_{3,s}Temp_{i,t-n,s}\right) + \delta_i + \delta_w + \delta_m + \delta_y + \delta_i x \delta_w + \delta_i x \delta_m + \delta_i x \delta_y + \eta_{it} \quad (3)$$

where p_{it} is a set of weekly averaged corn prices at the municipal level i in week t of any given year y; n is the number of lags ($n = 1, 2$), s is the set of key phenological stages in corn production; DD is the variable that counts the number of days with no precipitation in seven consecutive days; $Temp$ is the temperature averaged in seven consecutive days. The term δ_i captures municipality fixed effects, and δ_t correspond to week fixed effects, δ_w, δ_m and δ_y capture week, month, and year fixed effects, respectively. The error term η_{it} is clustered at the municipal level to capture potential heteroskedasticity within municipalities.

The reader may wonder why we follow this order. If one started from the least saturated model, one would select model specifications (3), (1), (2). Unfortunately, as mentioned more in detailed below, regressions' estimates of (1) and (2) are affected by a sizable loss of observations, due to drops of singletons, which translates in a significant loss of information and potential unreliability of the estimations (Correia, 2015). For this reason, model specification (3) will be our benchmark one, and we produce several robustness checks to make sure that it turns out to be a solid model specification. Considering the high values of Adjusted-R^2, we are convinced that potential omitted variable issues are very limited.

We use a municipal-level unbalanced panel data (2005-2019) composed of weekly variables. We computed weekly averaged prices from daily corn prices registered by IMEA (Mato Grosso State Institute for Agricultural Economics). Prices are quoted in Brazilian Reais (R$). In the same fashion, we weekly averaged precipitation and temperature data from daily data provided by INPE (National Institute for Space Research). The weather variables are satellite-derived and have a 12,5km spatial resolution. Precipitation is measured in millimeters per day (mm/day) and Temperature in degrees Celsius (ºC). We considered several ways to compute the weekly average of our weather variables. The one that had the best fit in our estimations considered the average of the seven days starting from Friday of the current week back to the Saturday of the previous week.

Regarding alternative ways to measure temperature, we computed degree days above 29ºC (DD29) in the same fashion as Schlenker et al. (2009) and Tack et al. (2015)[4]. Using intraday temperature data, we proceeded a sinusoidal interpolation fitting a sine curve from the minimum temperature in day t to the maximum temperature in day t. We then fit another sine curve from the maximum temperature in day t to the minimum temperature in day $t + 1$. We finish by cumulatively summing our daily degree days across seven days to obtain the variable in the weekly format.

We defined the sowing and harvest dates for corn in Mato Grosso state inspired by the median sowing and harvest dates estimated by Zhang et al (2021) for soybeans in the same state. The authors estimated that the soybean cycle within the double crop (soybeans/corn) system finishes around February 17th and the corn second season (*safrinha*) starts immediately after. For the definition of the corn stages, we assume a cycle of 130 days. The vegetative stage comprehends the first 65 days, starting at planting and ending at flowering. The flowering stage occurs during four weeks around silking. And finally, the last stage is when the process of grain filling happens and at the end of this stage the corn plant is considered mature and ready for harvest. Based on this information, we consider the vegetative stage happens between the first week of February and the last week of March; the flowering stage between the first week of

[4] The same papers suggest that the threshold temperature of 29 ºC being the limit one, above which temperature becomes damaging for corn's crops.

April and the third week of May; and the grain filling stage between the fourth week of May and the third week of June.

[Table 1 around here]

Descriptive statistics reported in Table 2 show how corn price behaves as the plant develops, with greater variability in price in the last two stages, probably due to price expectations being formed during this time. Mean precipitation falls sharply as the corn plant grows. It happens because the sowing date coincides with the end of the rainy season in Mato Grosso, and the following months are usually drier than the previous ones. In this sense, while in the vegetative stage there is an average of 8.25 mm of average weekly precipitation and approximately 1.860 dry days per week, in the grain filling stage these averages are 0.607 mm and 6.370 dry days per week. In contrast, temperature varies little across the phenological stages, with an average that never drops below nor exceeds 24º C during the period of analysis. This fact reinforces that in this case precipitation is the key variable when analyzing the impact of weather-related events on prices.

[Table 2 around here]

Regarding abnormal precipitation events, we observe the most of them are related to water scarcity (abnormal negative precipitation). However, results may change if we consider the phenological stages. In the vegetative stage, 2.5% of the weeks went through water scarcity. In contrast, 37.1% of the weeks in the flowering season and 77.9% of the weeks in the grain filling season experienced some sort of water scarcity. On the other hand, in the vegetative stage, approximately 40% of the weeks registered water overabundance, whereas in the flowering and grain filling stages this figure drops to 8.2% and 0.5%, respectively.

In the following sections we proceed an in-depth analysis of how dryness impact local corn prices. We also consider the impact of abnormal precipitation – either water overabundance or water scarcity – on local prices during different stages of crop development.

5. Price reaction to dryness

Season-long analysis

Table 3 shows the regression outcomes related to the season long analysis, comprising all phenological stages. The first column shows the results of the regression with week-of-the-year and municipality fixed effects (equation (1)). Column (2) shows the regression outcomes of equation (2), as we add municipality linear week trends. Column (3) shows the estimates of equation (3) including municipality fixed effects and separate year, month, and week fixed effects, as well as municipality-week, municipality-month, and municipality-year linear trends. We observe that all explanatory variables are statistically significant across the three specifications, meaning that besides the linear relations, the effect of dryness on corn prices also has a quadratic component. As shown in Table 3, dryness – measured by the number of days with no precipitation in a week – initially provides a negative but diminishing, finally positive impact on prices. In this sense, as dryness increases, corn plants undergo water stress and farmers may depress the prospects of corn availability as harvest materializes, leading to a price increase.

The estimates depicted in column (1) and column (2) include the finest possible fixed effects, which allow us to obtain an Adjusted-R^2 of approximately 98%. However, in this way our sample loses 609 observations due to singleton groups, or a shrinkage of about 17.2%. The estimation of equation (1) in the presence of singletons may overstate statistical significance and lead to incorrect inference (Correia, 2015). For this reason, we rely on estimates reported in column (3). With an Adjusted-R^2 of roughly 90%, which is still very high, we are able to use all observations and control our estimation with multiple fixed effects. In addition, all coefficients in column (3) are significant at the 1% level.

Considering the results in column (3), the magnitude of the impact of dryness on prices slightly increases with the lags. Therefore, dryness occurred two weeks before the current price week has a slightly larger impact on prices than dryness occurred one week before.

Table 3A in the Appendix reports a robustness analysis for the estimation of equation (1). In fact, when year fixed effects are included, we observe a very strong increase in Adjusted-R^2 and the coefficient signals become consistent with the estimates shown in Table 3, meaning that week-of-the-year fixed effects are very well proxied by year fixed effects.

The implicit assumption of season-long regressions is that the effect of dryness is relatively similar across all crop stages (Ortiz-Bobea, 2011). The next session disaggregates the analysis to the phenological stage level.

Average marginal effects for the season-long analysis

Figure 1 shows the average marginal effects associated to equation (3). More specifically, it reports the plot of the average marginal effects of each lag of dryness on the log of corn price with respect to different percentiles of the correspondent lag of dryness' distribution. Regarding the marginal effects of the independent variable lagged in one and two weeks prior to the current week, shown in Figure 1 (a) and (b), we find that in the first case prices start increasing after 4 days with no precipitation. Regarding lag 2, it happens a bit earlier, between 3 and 4 days with no precipitation. In all cases, prices increase monotonically.

[Figure 1 around here]

Figure 1A in the Appendix show the average marginal effects for the estimation of equation (1), i.e., with municipality and week-of-the-year fixed effects. In fact, the marginal effects are quite similar to the ones depicted in Figure 1, confirming that our choice related to the final model specification does not affect the results in a significant manner.

Phenological stages analysis

The second, third and fourth columns in Table 4 report the regression outputs according to the key phenological stages. The estimates show how corn price reacts to variation in dryness during corn phenological stages. Column (2) shows the results for the vegetative stage, column (3) for the flowering stage and the column (4) for the grain filling and maturity stage.

[Table 4 around here]

The fit of all models slightly increases as we move from season-long to phenological stages analysis. However, we find no statistically significant coefficient for the grain filling stage regression. The vegetative stage regression shows a statistically significant relation between the number of dry days in a week and corn prices at lag 1 and lag 2, both for the linear and quadratic variables. In line with what has been found in the season-long results (column (1)), in the vegetative stage, dryness provides first a negative but diminishing, finally positive impact on prices. However, the magnitude of the coefficients, in particular the linear ones, are smaller if compared to the ones in column (1). This result shows that corn prices are sensitive to dryness during the vegetative stage, and dryness events occurred up to two weeks prior to the current week matter for price formation. It is during the vegetative stage that we observe the biggest amount of precipitation, around 8.001 mm on average per week (Table 2) – this also explains why coefficients are smaller in size if compared to column (1), whose precipitation's average is equal to around 4.316 mm per week. At this stage, rainfall shortages and may be perceived by farmers as a negative indicator for corn yield. Therefore, more dryness during the vegetative stage contributes to depress farmers' prospects of corn availability by harvest time, leading to a positive impact on prices.

The flowering regression outcomes show a significant relation between dryness and corn prices at lag 2 only. The linear variable has a negative signal whereas the quadratic variable exhibits a positive signal. This same pattern was observed in the season-long regression. It is during the flowering stage that rainfall becomes increasingly scarce, as shown in Table 2. However, recent dryness events (the ones that occurred one week before) seem to have no impact on prices, only to past ones affect prices (two weeks before). The magnitude of the statistically significant coefficients is similar to the ones found in the vegetative stage. Nonetheless, the literature states that stress during the flowering period can depress corn yields more than in any other phenological stage (Fageria et al., 2006; Ortiz-Bobea, 2011; Ortiz-Bobea, 2012).

Our results show that dryness events impact local corn prices (perhaps through agents' expectations, i.e., changes in expected corn supply), but this impact varies as crops develop. Dryness events both one week and two weeks before the current week may impact price formation during the vegetative stage. In the flowering stage, only dryness occurred two weeks before the current price impact corn prices. In the grain filling stage dryness events should have no impact on local corn prices, as expectations about harvest are already formed.

Average marginal effects for the phenological stages analysis

Figure 2 shows the average marginal effects for the vegetative stage. We observe the average marginal effects of the independent variable lagged in one week in the vegetative stage, when selecting different percentiles of the mentioned variable. Prices start increasing monotonically after about 5 days with no precipitation (Figure 2a). A similar result is found when the independent variable is lagged in two weeks, as seen in Figure 2b. As discussed earlier, the vegetative stage is the one with the biggest amount of rainfall. Therefore, it is natural that farmers will need a slightly larger number of dry days in a week to justify any concerns about water stress and future crop development.

[Figure 2 around here]

The average marginal effects with respect to the independent variable lagged in one and two weeks in the flowering stage are depicted Figures 3a and 3b. In this case, prices do not statistically change when lag 1 of the independent variable is considered, while they start rising monotonically after 2 days for lag 2. In the second case price rises earlier if compared to the results for the vegetative stage. Since the flowering stage has considerably less rainfall than the vegetative stage, a smaller number of dry days in a week is needed to raise farmers concerns about crop yields and future corn availability in the market.

[Figure 3 around here]

The average marginal effects with respect to lags 1 and 2 of the grain filling stage can be found in Figure 4. As mentioned previously and reported in Table 4, none of the coefficients in the grain filling regression are statistically significant. This drives Figure 4's results. We observe, however, that the marginal effect becomes slightly significant in lag 2 after 2 days with no precipitation, as shown in Figure 4b.

[Figure 4 around here]

Tables 3B and 4B in the Appendix bring additional robustness analysis for this section. In these tables we repeat the estimations of Table 3 and Table 4. However, instead of using lags 1 and 2 of Temperature (in ºC) as controls, we use the lags 1 and 2 of the Degree Days above 29ºC. We observe that the coefficients of both tables remain approximately the same.

6. The impact of abnormal precipitation events on prices

In this section we extend our analysis to incorporate the occurrence of abnormal precipitation events. For this purpose, we follow Rocha and Soares (2015) and define E_{it}^{-} as an abnormal negative precipitation event (water scarcity) and E_{it}^{+} as an abnormal positive precipitation event (water overabundance). Further, compute E_{it} as a composite dummy variable to account for abnormal precipitation events, either positive or negative, as demonstrated in equations (2), (3) and (4):

$$E_{it}^{-} = 1 \; if \; r_{it} < (\bar{r}_i - r_i^{SD}) \, , \qquad and \; 0 \; otherwise \tag{4}$$

$$E_{it}^{+} = 1 \; if \; r_{it} \; > (\bar{r}_i + r_i^{SD}), \qquad and \; 0 \; otherwise \tag{5}$$

$$E_{it} = 1 \; if \; E_{it}^{-} = 1 \; or \; E_{it}^{+} = 1, \qquad and \; 0 \; otherwise \tag{6}$$

where r_{it} is precipitation in municipality i in week t, $\bar{r}_i$ is the average historical (2005-2019) precipitation for municipality i, and r_i^{SD} is the historical (2005-2019) standard deviation in precipitation for municipality i.

In order to verify whether abnormal precipitation events have any impact on corn prices, we use our panel data structure and regress the weekly averaged corn prices on lagged composite dummy variable E_{it}, as shown in equation (5). In order to see potential heterogenous impacts within the realm of abnormal precipitation events, we then regress corn prices on abnormal positive and negative precipitation events for both season-long and phenological stages, as shown in equation (6):

$$\log p_{it} = \sum_{n=1}^{2} \beta_{1,s} E_{i,t-n,s} + \beta_{2,s} Temp_{i,t-n,s} + \delta_i + \delta_t + \eta_{it} \quad (7)$$

$$\log p_{it} = \sum_{n=1}^{2} \beta_{1,s} E_{i,t-n,s} + \beta_{2,s} Temp_{i,t-n,s} + \delta_i + \delta_t + \delta_i x \delta_t + \eta_{it} \quad (8)$$

$$\log p_{it} = \sum_{n=1}^{2} \beta_{1,s} E_{i,t-n,s} + \beta_{2,s} Temp_{i,t-n,s} + \delta_i + \delta_w + \delta_m + \delta_y + \delta_i x \delta_w + \delta_i x \delta_m + \delta_i x \delta_y + \eta_{it} \quad (9)$$

$$\log p_{it} = \sum_{n=1}^{2} \left(\beta_{1,s} E_{i,t-n,s}^{+} + \beta_{2,s} E_{i,t-n,s}^{-} + \beta_{3,s} Temp_{i,t-n,s}\right) + \delta_i + \delta_t + \eta_{it} \quad (10)$$

$$\log p_{it} = \sum_{n=1}^{2} \left(\beta_{1,s} E_{i,t-n,s}^{+} + \beta_{2,s} E_{i,t-n,s}^{-} + \beta_{3,s} Temp_{i,t-n,s}\right) + \delta_i + \delta_t + \delta_i x \delta_t + \eta_{it} \quad (11)$$

$$\log p_{it} = \sum_{n=1}^{2} \left(\beta_{1,s} E_{i,t-n,s}^{+} + \beta_{2,s} E_{i,t-n,s}^{-} + \beta_{3,s} Temp_{i,t-n,s}\right) + \delta_i + \delta_w + \delta_m + \delta_y + \delta_i x \delta_w + \delta_i x \delta_m + \delta_i x \delta_y + \eta_{it} \quad (12)$$

where p_{it} is a set of weekly averaged corn prices at the municipal level i in week t of any given year y; n is the number of lags ($n = 1, 2$), s is the set of key phenological stages in corn production; $E_{it}^{-}$and E_{it}^{+} are abnormal negative and positive precipitation events, respectively in seven consecutive days. $Temp$ is the temperature averaged in seven consecutive days. The term δ_i captures municipality fixed effects, and δ_t correspond to week fixed effects,

δ_w, δ_m and δ_y capture week, month, and year fixed effects, respectively. The error term η_{it} is clustered at the municipal level to capture potential heteroskedasticity within municipalities.

Abnormal precipitation events

Regression outcomes for equation (7-9) are shown in Table 5. Column (1) reports the outcomes of the estimation of equation (7) with municipality and week-of-the-year fixed effects and column (2) shows the outcomes of this same estimation plus municipal trends (equation (8)). Column (3) provides the reader with the outcomes of the estimation of equation (9). As previously discussed, we rely on the latter in order to use the most observations and to circumvent the singleton issue.

[Table 5 around here]

We observe statistically significant coefficients for the two lagged variables. Hence, we find a positive relationship between the occurrence of abnormal precipitation events – either positive or negative – and corn prices. In this sense, such events contribute to depress farmers 'expectations about the future corn harvest as they negatively impact corn crops. In addition, the magnitude of these impacts increases with week lags. Thus, abnormal precipitation events that occurred two weeks before the current week price have a larger impact on prices than events one week before the current week price. With the next tables, we will try to dissect the drivers of these findings.

Table 6 reports the regression outcomes of equation (9) for the season-long and phenological stages analysis.

[Table 6 around here]

Abnormal precipitation events impact local corn prices across all three phenological stages, and we find statistically significant coefficients at the 5% level in all stages for the second lag of our variable of interest. However, the magnitude of the impact differs as crop develops, so that an abnormal precipitation event during the grain filling stage has a slightly bigger impact than an abnormal event during the vegetative stage.

Abnormal positive and abnormal negative precipitation events

We disentangle the abnormal precipitation events into abnormal negative precipitation events (water scarcity) and abnormal positive precipitation events (water overabundance) as specified in equations (10-12). Table 7 reports the outcomes.

[Table 7 around here]

Column (1) in Table 7 reports the regression outcomes for equation (10), column (2) the outcomes for equation (11) e column (3) the outcomes for equation (12). As discussed previously, we rely on the estimates shown in column (3) because its correspondent model specification allows us to use all observations and avoid the singletons issue. These results clarify the drivers of Table 5's findings by disentangling the impact of water scarcity (abnormal negative precipitation) from the one arising from water overabundance (abnormal positive precipitation). We find a statistically significant relationship between abnormal negative precipitation and corn prices in the season-long analysis across all reported model specifications. Overall, water scarcity contributes to increase corn prices. However, the impact of such events differs across lags, as abnormal negative precipitation events occurred two weeks before the current week have an impact on corn prices more than twice as big if compared to events occurred one week before the current week (column (3)). In fact, water scarcity is the main factor to reduce corn yields in Brazil (de Araujo Rufino et al., 2018). When the corn plant water demands are not met, plants undergo water stress and consequences may include reduced plant height and metabolic activity, decreases in photosynthetic rate and ultimately an unsatisfactory corn yield.

We do not find any statistical significance of the coefficients related to the two lags of abnormal positive precipitation events (-0.005 and -0.005, respectively): they, ultimately, exert a confounding effect on their correspondent aggregate variables' coefficients, as seen in Table 5 (0.004 and 0.015**, respectively), with respect to the previously mentioned coefficients of abnormal negative precipitation events (0.018*** and 0.040***, respectively), both in terms of size and significance. In other words, at this stage, it seems that our results are purely led by water scarcity events.

Nonetheless, it is possible that Table 7's findings may vary across phenological stages, although Table 6, where the aggregate variable of abnormal precipitation events was used, did not seem to suggest so. In order words, we estimate the impact of positive and negative abnormal precipitation events on corn price across season-long and phenological stages, whose estimates are depicted in Table 8.

In effect, while in Table 7 abnormal positive precipitation events do not significantly impact corn's prices, ewe observe that water overabundance may cause price hikes during the vegetative and flowering stages, particularly if it occurs two weeks before the current week (lag 2) – coefficient equal to 0.012 at 1% of significant level for the vegetative stage, and coefficient equal to 0.011 at 10% of significance level for the flowering stage. In fact, such events can potentially impact corn crops negatively posing hurdles in the usage of tractors and machinery, hindering pollination, decreasing the exposure of corn plants to sunlight and radiation, which are essential to the proper development of the plant. Besides, it may also positively impact leaching and the growth of weed and fungi, which are harmful to the corn plant (Resende et al., 2019). All these factors tend to decrease crops yields, depressing the prospects of corn availability by harvest time, which tend to increase prices.

[Table 8 around here]

On the other hand, water scarcity events impact corn prices during the flowering and grain filling stages. Coefficients are larger in the former though. In effect, the agronomic literature states that stress during the flowering period can depress corn yields more than in any other phenological stage (Fageria et al., 2006). Our novel findings are most likely due to correspondent opposite impacts on corn's production, which would be in line with Ortiz-Bobea (2012)'s findings on crop's yields. Overall, water scarcity events have a larger impact than water overabundance events. The impact of water scarcity is well documented in the literature (Schaub and Finger, 2020; Irmak et al, 2022; Rowley, 2023; World Bank, 2023).

We also find a statistically significant causal relationship between corn prices in the grain-filling stage and water overabundance events. Interestingly, the coefficient is the biggest for this stage and has a negative signal, meaning that such events contribute to decrease prices. It is worth noting that this is the driest of all stages (as depicted in Table 2) and excessive rainfall could be perceived by farmers as an alleviation to the typical rainfall shortage and therefore a positive indicator to corn yields at harvest time. In fact, it is during this stage that kernel development occurs and more water at this point translates into better formed kernels, better yields, and therefore more corn availability and lower prices.

In conclusion, abnormal precipitation events do not exert the same impact on crop's prices: abnormal negative precipitation events positively affect prices, while abnormal positive precipitation events may have a heterogeneous impact. When rainfall is more frequent and the observed levels of precipitation are higher, as in the vegetative and flowering stages (Table 2), abnormal positive precipitation events have a positive effect on prices. On the contrary, when observed precipitation levels are low, as in the grain filling stage (Table 2), the impact is negative.

Tables 5A and 7A in the Appendix explore the estimation of equations (9) and (12) with different combinations of week, month, and year fixed effects as a robustness check exercise. As noted previously, the addition of year fixed effects greatly improves the fit as Adjusted-R^2 increases. In both cases we are able to obtain significantly stronger estimates when we include municipality fixed effects and all separate time fixed effects combined, that is, week, month, and year fixed effects, as shown in Tables 5 and 7.

Finally, we complete our robustness analysis with Tables 5B to 8B in the Appendix. In these tables, we proceed the same estimations as in Tables 5 to 8, substituting only lags 1 and 2 of Temperature (in ºC) with the same lags of Degree Days above 29ºC. After implementing Degree Days as controls, we observe that the coefficients of our variables of interest remain overall stable. In the few cases when we verify changes, they are marginal and do not affect our results.

7. Conclusion

Brazil has been consistently ranked among the top corn producing countries, having two major harvests during the year. The second corn harvest – known as *safrinha* – is the largest one and the most vulnerable to the effect of dry weather, leading to losses in production and potentially higher prices. Our analysis investigates the impact of dryness, as measured by the number of days in a week with no precipitation, on local corn price variation both during the whole pre-harvest season (season-long) and across the phenological stages.

Many studies regarding pre-harvest crop developments have relied on fixed calendar weather variables as *proxies* for the crop's phenological stages (Schlenker and Roberts, 2009). However, this approach may be subject to calendar bias that come from fixed calendar periods. The availability of corn spot prices and precipitation data in higher frequencies has allowed us to correctly match price variations to the phenological stages of the corn crop, and therefore circumvent such potential bias.

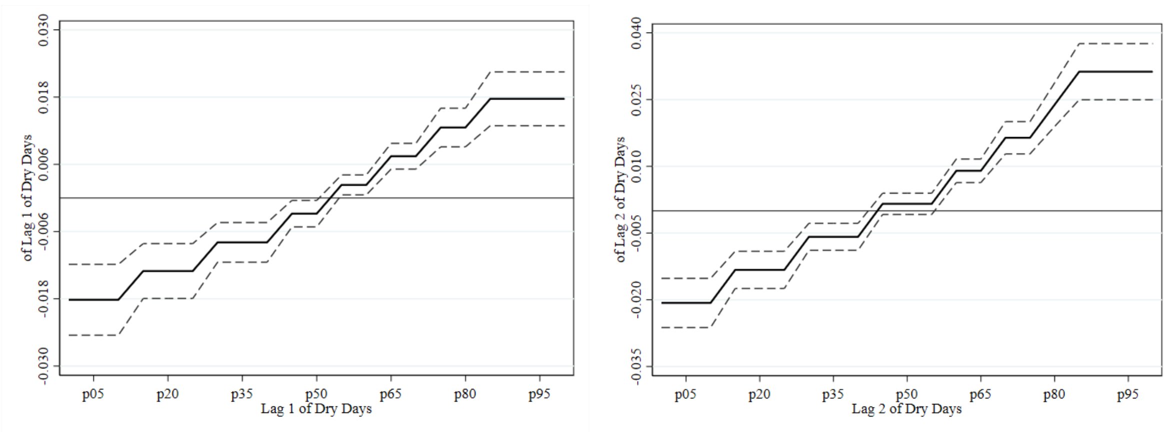
The preliminary findings show that local corn prices may indeed increase due to the lack of precipitation. When the whole pre-harvest period is considered, prices are subject to increases when there is roughly 4 days with no rainfall. However, the impact of dry days on corn prices may differ across the phenological stages. During the vegetative stage, the one that receives most precipitation, the impact of dry days on corn prices is always present and varies in sign: until 4 days with no precipitation within a week, it shows a negative impact on local prices, while the sign swaps after 5 days with no precipitation within a week. On the other hand, during the flowering stage, 2 days of no precipitation seems to be enough to have an impact on local prices. In all cases, local prices rise likely due to farmer's depressed expectations about the materialization of the crop by harvest time.

We also assess the impact of water overabundance and water scarcity abnormal precipitation events on prices and find that overall, these events positively affect local corn prices, albeit the two cases show a dissimilar impact. More specifically, water scarcity has a bigger weight in farmer's expectations than water overabundance, affecting positively corn's prices, above all during the flowering stage. Water overabundance, on the other hand, may cause prices hikes during the vegetative and flowering stages, and price decreases during the grain filling stage. If the current trend of observing more frequently extreme weather conditions is maintained (UNDRR, 2020), our findings suggest that corn prices may become more volatile over time, having clear implications for farmers, investors, inflation rates and the whole society, especially on low-income families.

This paper provides insights on the behavior of commodity prices in the presence of weather stress. The correct understanding of how prices change under such circumstances is useful for improving the decision-making process of a wide range of agents that go beyond the agricultural sector, including farmers, traders, investors, financial institutions, the food industry, governments, and many others. Current events have shown that incorporating climatic and weather-related information to business is of upmost importance and more studies of this kind are needed.

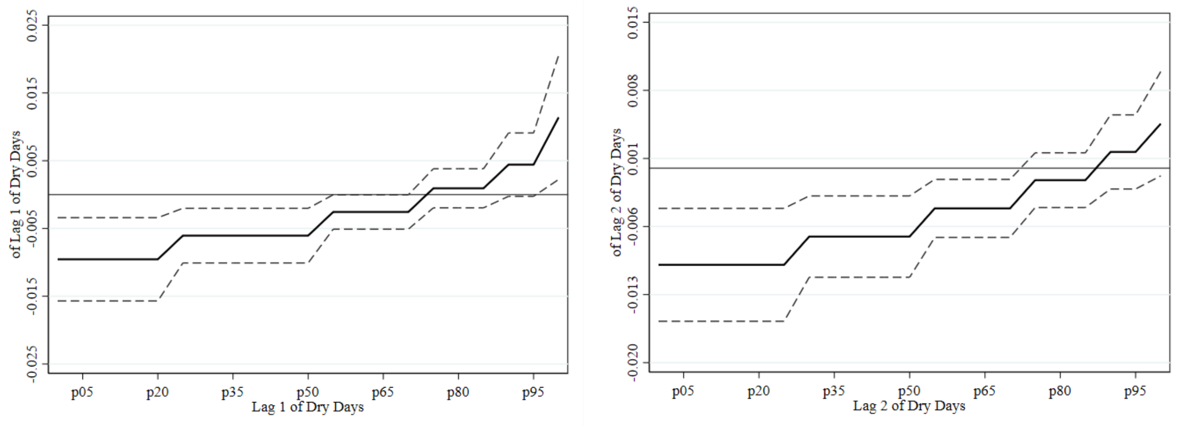
Tables and Figures

Figure 1 – Average marginal effects on log price for the season-long analysis



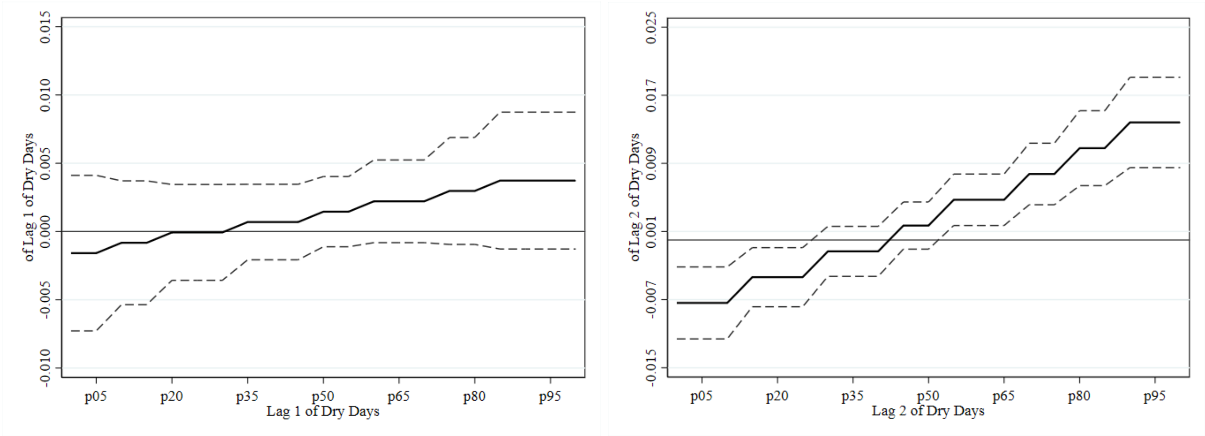
(a) Marginal effects of Dry days$_{t-1}$; (b) Marginal effects of Dry days$_{t-2}$

Figure 2 – Average marginal effects on log price for the vegetative stage analysis



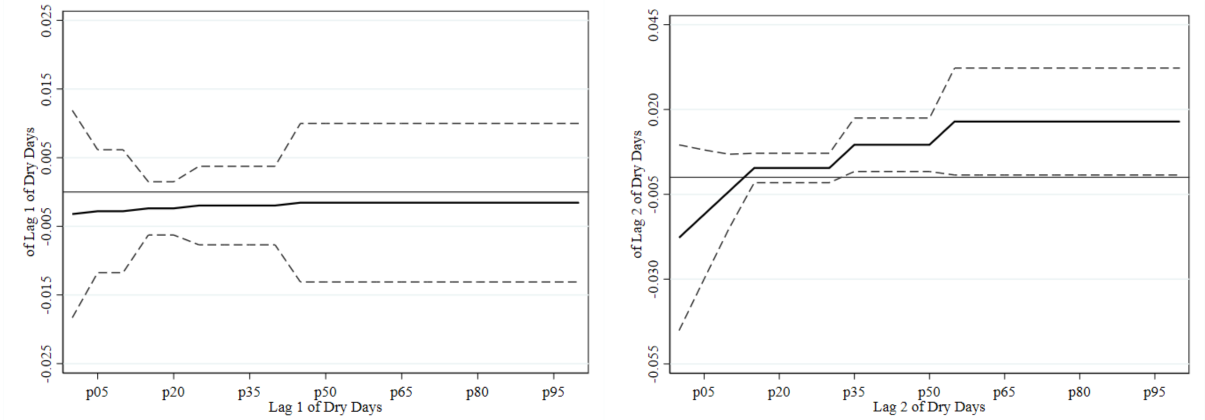
(a) Marginal effects of Dry days$_{t-1}$; (b) Marginal effects of Dry days$_{t-2}$

Figure 3 – Average marginal effects on log price for the flowering stage analysis



(a) Marginal effects of Dry $days_{t-1}$; (b) Marginal effects of Dry $days_{t-2}$

Figure 4 – Average marginal effects on log price for the grain filling stage analysis



(a) Marginal effects of Dry $days_{t-1}$; (b) Marginal effects of Dry $days_{t-2}$

Table 1 – Data Sources

Variable	**Frequency**	**Spatial Resolution**	**Source**
Prices (R$)	weekly averaged	Market; municipal level	IMEA
Precipitation (mm/day)	weekly averaged	0.125 x 0.125	INPE
Temperature (ºC)	weekly averaged	0.125 x 0.125	INPE

Table 2 – Descriptive Statistics according to season-long and phenological stages

	Obs	Mean	Std. Dev.	Min	Max
Vegetative Stage					
Price (R$)	1,347	18.456	5.381	6	32.583
Precipitation (mm/day)	1,399	8.001	5.180	0	32.857
Temperature (ºC)	1,399	24.921	1.009	22.289	29.732
Number of dry days	1,399	1.767	1.488	0	7
Abnormal precip. (%)	1,399	42.173	49.401	0	1
Positive	1,399	39.457	48.893	0	1
Negative	1,399	2.716	16.261	0	1
DD29	1,399	1.261	1.878	0	16.842
Flowering Stage					
Price (R$)	1,364	18.708	6.616	6.3	40.340
Precipitation (mm/day)	1,400	2.901	3.577	0	24.286
Temperature (ºC)	1,400	24.819	1.300	18.867	28.600
Number of dry days	1,400	4.226	2.163	0	7
Abnormal precip. (%)	1,400	46.857	49.919	0	1
Positive	1,400	8.286	27.576	0	1
Negative	1,400	38.571	48.694	0	1
DD29	1,400	2.227	2.501	0	14.067
Grain Filling Stage					
Price (R$)	831	17.165	6.934	6.6	38.475
Precipitation (mm/day)	841	0.547	1.327	0	12.429
Temperature (ºC)	841	23.932	1.379	18.575	27.621
Number of dry days	841	6.432	0.997	1	7
Abnormal precip. (%)	841	81.332	38.989	0	1
Positive	841	0.476	6.884	0	1
Negative	841	80.856	39.367	0	1
DD29	841	2.763	2.141	0	11.851
Season-long					
Price (R$)	3,542	18.250	6.285	6	40.340
Precipitation (mm/day)	3,640	4.316	4.991	0	32.857
Temperature (ºC)	3,640	24.653	1.280	18.575	29.732
Number of dry days	3,640	3.791	2.477	0	7
Abnormal precip. (%)	3,640	53.022	49.992	0	1
Positive	3,640	18.462	38.804	0	1
Negative	3,640	34.560	47.563	0	1
DD29	3,640	1.979	2.276	0	16.842

Table 3 – Regression Results – Season-long – across model specifications

	(1)	(2)	(3)
	ln corn price	*ln corn price*	*ln corn price*
Dry days$_{t-1}$	-0.008***	-0.008**	-0.018***
	(0.003)	(0.003)	(0.004)
Dry days$^2_{t-1}$	0.001**	0.001**	0.003***
	(0.000)	(0.000)	(0.000)
Dry days$_{t-2}$	-0.008***	-0.008**	-0.021***
	(0.002)	(0.003)	(0.003)
Dry days$^2_{t-2}$	0.001***	0.001***	0.004***
	(0.000)	(0.000)	(0.000)
Temperature Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Week-of-the-Year FE	Yes	Yes	No
Municipality trend FE	No	Yes	No
Week FE	No	No	Yes
Month FE	No	No	Yes
Year FE	No	No	Yes
Municipality-week trend FE	No	No	Yes
Municipality-month trend FE	No	No	Yes
Municipality-year trend FE	No	No	Yes
Adjusted-R^2	0.979	0.982	0.908
Observations	2,931	2,931	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 4 – Regression Results – Season-long and Phenological Stages

	(1)	(2)	(3)	(4)
	ln corn prices	*ln corn prices*	*ln corn prices*	*ln corn prices*
Dry days$_{t-1}$	-0.018***	-0.010**	-0.002	-0.004
	(0.004)	(0.004)	(0.003)	(0.021)
Dry days$^2_{t-1}$	0.003***	0.002**	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.002)
Dry days$_{t-2}$	-0.021***	-0.010**	-0.007**	-0.031
	(0.003)	(0.004)	(0.003)	(0.027)
Dry days$^2_{t-2}$	0.004***	0.001**	0.002***	0.003
	(0.000)	(0.001)	(0.000)	(0.003)
Temperature Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Municipality-week trend FE	Yes	Yes	Yes	Yes
Municipality-month trend FE	Yes	Yes	Yes	Yes
Municipality-year trend FE	Yes	Yes	Yes	Yes
Adjusted-R^2	0.908	0.962	0.955	0.967
Observations	3,540	1,346	1,364	829

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 5 – Regression Results – Abnormal Precipitation Events – Season-long – across model specifications

	(1)	(2)	(3)
	ln corn price	*ln corn price*	*ln corn price*
E_{t-1}	0.003	0.004	0.007**
	(0.002)	(0.003)	(0.003)
E_{t-2}	0.004	0.004	0.015***
	(0.003)	(0.003)	(0.004)
Temperature Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Week-of-the-Year FE	Yes	Yes	No
Municipality trend	No	Yes	No
Week FE	No	No	Yes
Month FE	No	No	Yes
Year FE	No	No	Yes
Municipality-week trend FE	No	No	Yes
Municipality-month trend FE	No	No	Yes
Municipality-year trend FE	No	No	Yes
Adjusted-R^2	0.978	0.982	0.905
Observations	2,931	2,931	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 6 – Regression Results – Abnormal precipitation events – Season-long and phenological stages

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*	(4) *ln corn price*
E_{t-1}	0.007**	0.001	0.006	0.004
	(0.003)	(0.004)	(0.005)	(0.006)
E_{t-2}	0.015***	0.010**	0.016**	0.015**
	(0.004)	(0.004)	(0.006)	(0.005)
Temperature Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Municipality-week trend FE	Yes	Yes	Yes	Yes
Municipality-month trend FE	Yes	Yes	Yes	Yes
Municipality-year trend FE	Yes	Yes	Yes	Yes
Adjusted-R^2	0.905	0.962	0.955	0.967
Observations	3,540	1,346	1,364	829

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 7 – Regression Results – Abnormal positive and negative precipitation events – Season-long

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*
E^{-}_{t-1}	0.006	0.012***	**0.018*** **
	(0.004)	(0.004)	(0.006)
E^{-}_{t-2}	0.009*	0.014***	0.040***
	(0.005)	(0.004)	(0.006)
E^{+}_{t-1}	0.000	-0.003	**-0.005**
	(0.003)	(0.004)	(0.004)
E^{+}_{t-2}	-0.000	-0.003	-0.005
	(0.003)	(0.003)	(0.005)
Temperature Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Week-of-the-Year FE	Yes	Yes	No
Municipality trend FE	No	Yes	No
Week FE	No	No	Yes
Month FE	No	No	Yes
Year FE	No	No	Yes
Municipality-week trend FE	No	No	Yes
Municipality-month trend FE	No	No	Yes
Municipality-year trend FE	No	No	Yes
Adjusted-R^2	0.978	0.982	0.906
Observations	2,931	2,931	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 8 – Regression Results – Abnormal positive and negative precipitation events – Season-long and phenological stages

	(1)	(2)	(3)	(4)
	ln corn price	*ln corn price*	*ln corn price*	*ln corn price*
E^{-}_{t-1}	0.018***	0.014	0.011	0.004
	(0.006)	(0.014)	(0.007)	(0.006)
E^{-}_{t-2}	0.040***	-0.012	0.021**	**0.018*** **
	(0.006)	(0.013)	(0.008)	(0.006)
E^{+}_{t-1}	-0.005	-0.001	-0.002	**-0.036** **
	(0.004)	(0.004)	(0.006)	(0.017)
E^{+}_{t-2}	-0.005	**0.012*** **	**0.011* **	**-0.039** **
	(0.005)	(0.004)	(0.005)	(0.018)
Temperature Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Municipality-week trend FE	Yes	Yes	Yes	Yes
Municipality-month trend FE	Yes	Yes	Yes	Yes
Municipality-year trend FE	Yes	Yes	Yes	Yes
Adjusted-R^2	0.906	0.962	0.955	0.967
Observations	3,540	1,346	1,364	829

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

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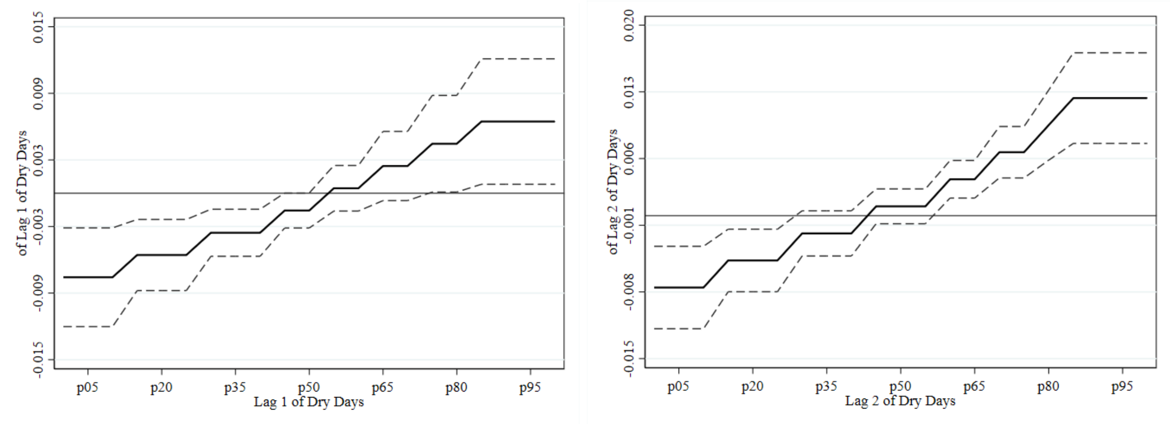
APPENDIX

Figure 1A – Marginal effects for the estimation of equation (1) with municipality and week-of-the-year fixed effects



(a) Marginal effects of Dry days$_{t-1}$;   (b) Marginal effects of Dry days$_{t-2}$

Table 3A – Robustness checks for the estimation of equation (1)

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*	(4) *ln corn price*	(5) *ln corn price*
Dry days$_{t-1}$	0.012	0.004	0.002**	0.01	-0.014***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.003)
Dry days$^2_{t-1}$	-0.002*	-0.001	0.000	0.000	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Dry days$_{t-2}$	-0.006*	-0.015*	-0.016*	-0.013	-0.020***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.003)
Dry days$^2_{t-2}$	-0.000	0.001	0.002*	0.002	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Temp. Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	Yes
Week FE	No	No	Yes	No	No
Month FE	No	No	No	Yes	No
Year FE	No	No	No	No	Yes
Adjusted-R^2	**0.007**	**0.110**	**0.116**	**0.123**	**0.892**
Observations	3,540	3,540	3,540	3,540	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 5A – Robustness checks for the estimation of equation (9)

	(1)	(2)	(3)	(4)	(5)
	ln corn price	*ln corn price*	*ln corn price*	*ln corn price*	*ln corn price*
E_{t-1}	-0.037***	-0.039***	-0.015*	-0.015*	-0.014***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.005)
E_{t-2}	-0.019**	-0.021*	-0.000	-0.002	-0.003
	(0.008)	(0.008)	(0.009)	(0.009)	(0.004)
Temperature Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	Yes
Week FE	No	No	Yes	No	No
Month FE	No	No	No	Yes	No
Year FE	No	No	No	No	Yes
Adjusted-R^2	0.003	0.103	0.116	0.123	0.885
Observations	3,540	3,540	3,540	3,540	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 7A – Robustness checks for the estimation of equation (12)

	(1)	(2)	(3)	(4)	(5)
	ln corn price	*ln corn price*	*ln corn price*	*ln corn price*	*ln corn price*
E^{-}_{t-1}	-0.031***	-0.037***	0.037***	0.031***	-0.026***
	(0.010)	(0.008)	(0.012)	(0.010)	(0.005)
E^{-}_{t-2}	-0.028**	-0.031***	0.047***	0.035***	-0.014***
	(0.010)	(0.008)	(0.012)	(0.011)	(0.005)
E^{+}_{t-1}	-0.040***	-0.035***	-0.066***	-0.063***	0.012**
	(0.010)	(0.009)	(0.012)	(0.012)	(0.004)
E^{+}_{t-2}	-0.011	-0.009	-0.041**	-0.037**	0.018***
	(0.011)	(0.011)	(0.015)	(0.014)	(0.005)
Temperature Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	Yes
Week FE	No	No	Yes	No	No
Month FE	No	No	No	Yes	No
Year FE	No	No	No	No	Yes
Adjusted-R^2	0.002	0.103	0.125	0.131	0.888
Observations	3,540	3,540	3,540	3,540	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 3B – Robustness check: Replication of Table 3 using the first two lags of DD29 as temperature controls.

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*
Dry days$_{t-1}$	-0.008**	-0.007**	-0.019***
	(0.003)	(0.003)	(0.004)
Dry days$^2_{t-1}$	0.001**	0.001**	0.003***
	(0.000)	(0.000)	(0.000)
Dry days$_{t-2}$	-0.008***	-0.007**	-0.023***
	(0.002)	(0.003)	(0.003)
Dry days$^2_{t-2}$	0.001***	0.001***	0.004***
	(0.000)	(0.000)	(0.000)
DD29$_{t-1}$	-0.002**	-0.002**	-0.003**
	(0.001)	(0.001)	(0.001)
DD29$_{t-2}$	0.002	0.001	-0.002
	(0.002)	(0.002)	(0.001)
Municipality FE	Yes	Yes	Yes
Week-of-the-Year FE	Yes	Yes	No
Municipality trend FE	No	Yes	No
Week FE	No	No	Yes
Month FE	No	No	Yes
Year FE	No	No	Yes
Municipality-week trend FE	No	No	Yes
Municipality-month trend FE	No	No	Yes
Municipality-year trend FE	No	No	Yes
Adjusted-R^2	0.979	0.982	0.907
Observations	2,931	2,931	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4B – Robustness check: Replication of Table 4 using the first two lags of DD29 as temperature controls.

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*	(4) *ln corn price*
Dry days_{t-1}	-0.019***	-0.008*	-0.002	-0.006
	(0.004)	(0.004)	(0.004)	(0.020)
Dry days^2_{t-1}	0.003***	0.002**	0.001	0.000
	(0.000)	(0.001)	(0.000)	(0.002)
Dry days_{t-2}	-0.023***	-0.009**	-0.007**	-0.030
	(0.003)	(0.004)	(0.003)	(0.026)
Dry days^2_{t-2}	0.004***	0.001**	0.001***	0.003
	(0.000)	(0.001)	(0.000)	(0.003)
$DD29_{t-1}$	-0.003**	-0.002**	-0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
$DD29_{t-2}$	-0.002	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Municipality-week trend FE	Yes	Yes	Yes	Yes
Municipality-month trend FE	Yes	Yes	Yes	Yes
Municipality-year trend FE	Yes	Yes	Yes	Yes
Adjusted-R^2	0.907	0.962	0.955	0.967
Observations	3,540	1,346	1,364	829

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 5B – Robustness check: Replication of Table 5 using the first two lags of DD29 as temperature controls.

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*
E_{t-1}	0.003	0.004	0.009***
	(0.002)	(0.003)	(0.003)
E_{t-2}	0.004	0.004	0.016***
	(0.003)	(0.003)	(0.004)
$DD29_{t-1}$	-0.002**	-0.002**	-0.003**
	(0.001)	(0.001)	(0.001)
$DD29_{t-2}$	0.002	0.002	-0.001
	(0.002)	(0.002)	(0.001)
Municipality FE	Yes	Yes	Yes
Week-of-the-Year FE	Yes	Yes	No
Municipality trend	No	Yes	No
Week FE	No	No	Yes
Month FE	No	No	Yes
Year FE	No	No	Yes
Municipality-week trend FE	No	No	Yes
Municipality-month trend FE	No	No	Yes
Municipality-year trend FE	No	No	Yes
Adjusted-R^2	0.978	0.982	0.904
Observations	2,931	2,931	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 6B – Robustness check: Replication of Table 6 using the lags of DD29 as temperature controls.

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*	(4) *ln corn price*
E_{t-1}	0.009***	-0.002	0.007	0.004
	(0.003)	(0.003)	(0.005)	(0.006)
E_{t-2}	0.016***	0.010**	0.016**	0.015**
	(0.004)	(0.004)	(0.006)	(0.006)
$DD29_{t-1}$	-0.003**	-0.003**	-0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
$DD29_{t-2}$	-0.001	-0.002***	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Municipality FE	No	Yes	Yes	Yes
Week FE	No	No	Yes	No
Month FE	No	No	No	Yes
Year FE	No	No	No	No
Adjusted-R^2	0.904	0.962	0.955	0.967
Observations	3,540	1,346	1,364	829

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 7B – Robustness check: Replication of Table 7 using the first two lags of DD29 as temperature controls.

VARIABLES	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*
E^{-}_{t-1}	0.006	0.012**	0.022***
	(0.004)	(0.004)	(0.006)
E^{-}_{t-2}	0.010**	0.015***	0.036***
	(0.005)	(0.004)	(0.007)
E^{+}_{t-1}	0.001	-0.002	-0.003
	(0.003)	(0.004)	(0.004)
E^{+}_{t-2}	-0.001	-0.003	-0.000
	(0.003)	(0.003)	(0.004)
$DD29_{t-1}$	-0.002**	-0.002**	-0.004***
	(0.001)	(0.001)	(0.001)
$DD29_{t-2}$	0.002	0.002	-0.002*
	(0.002)	(0.002)	(0.001)
Municipality FE	Yes	Yes	Yes
Week-of-the-Year FE	Yes	Yes	No
Municipality trend FE	No	Yes	No
Week FE	No	No	Yes
Month FE	No	No	Yes
Year FE	No	No	Yes
Municipality-week trend FE	No	No	Yes
Municipality-month trend FE	No	No	Yes
Municipality-year trend FE	No	No	Yes
Adjusted-R^2	0.978	0.982	0.905
Observations	2,931	2,931	3,540

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1

Table 8B – Robustness check: Replication of Table 8 using the first two lags of DD29 as temperature controls.

	(1) *ln corn price*	(2) *ln corn price*	(3) *ln corn price*	(4) *ln corn price*
E_{t-1}^{-}	0.022***	0.018	0.012	0.004
	(0.006)	(0.015)	(0.007)	(0.006)
E_{t-2}^{-}	0.036***	-0.007	0.021**	0.018***
	(0.007)	(0.016)	(0.008)	(0.006)
E_{t-1}^{+}	-0.003	-0.003	-0.002	-0.035*
	(0.004)	(0.004)	(0.006)	(0.017)
E_{t-2}^{+}	-0.000	0.011**	0.011**	-0.040**
	(0.004)	(0.004)	(0.005)	(0.017)
$DD29_{t-1}$	-0.004***	-0.003**	-0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
$DD29_{t-2}$	-0.002*	-0.002**	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Municipality-week trend FE	Yes	Yes	Yes	Yes
Municipality-month trend FE	Yes	Yes	Yes	Yes
Municipality-year trend FE	Yes	Yes	Yes	Yes
Adjusted-R^2	0.905	0.962	0.955	0.967
Observations	3,540	1,346	1,364	829

Standard errors clustered at municipality level are shown in parentheses. Significance levels are reported as follows: *** p<0.01, ** p<0.05, * p<0.1