Weather shocks, food prices, and traders anticipations

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Abstract

We study the short run impact of weather shocks on local agro-food markets. Weather variations are accounted for in the formation of traders anticipations on harvest and future crop availability. We analyze the link between weather anomalies and market adjustments through standard rational expectations and commodity price formation theory. As weather disruptions are not contemporaneous to the ensuing supply shock, there exist several price impact channels for a climate anomaly to affect market prices. In the short run, the relevant channel is the update of anticipations regarding future supply. We present an empirical application on staple crops price variations in India. We exploit the time lag between a weather shock and the supply shock to identify and estimate price reactions that are solely due to changes in future price expectations.

Keywords: Weather Shocks, Food Prices, Competitive Storage Model, Anticipations
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1. Introduction

Weather-driven supply shocks have been among the main driving forces for models of agricultural prices. A large body of research has empirically established the influence of weather patterns on crop yields, through the impact of biophysical conditions on plant growth and labor productivity (Turvey (2001); Schlenker and Roberts (2006); Mainardi (2011); D'Agostino and Schlenker (2016); Heal and Park (2016)). 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, a weather disruption is not contemporaneous to the ensuing supply shock. This sequential timing implies the existence of several price impact channels. First, an immediate update of anticipations on the coming harvest might contemporaneously change market prices. Second, at the time of realization of harvest, prices will converge to their new equilibrium following the actual confrontation of supplied volumes to market demand. With well informed agents and adequate financial tools, the final price clearance might go unnoticed as the adjustment can gradually take place over the whole period between the initial weather shock and the harvest. This speculation reduces the annual variance of prices by spreading the effect of a disturbance over several time periods.

Furthermore, production systems react differently to marginal changes in climatic context, depending on the technology in use and whether conditions are normal or not at the time of change. Hence, one ought to see a non linear relationship between weather shocks and agricultural commodity prices, mirroring the non linear yield functions.

Knowing the most appropriate way to account for weather disruptions in price formation models is particularly useful for studying price shocks transmission at regional

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and global levels. Effective food security design and early warning systems require adequate modeling of repercussions of weather shocks on local prices. Consequently, impact channels of temperature and precipitation anomalies have been modeled and estimated in various manners. But modeling assumptions and data constraints often lead to simplify the way agents react to disruptions and update their beliefs on upcoming harvests. Few empirical exercises have built on economic theory to study how local market prices react to abnormal weather shocks. Yet, understanding how weather information is used by traders is essential to design efficient policy interventions.

In this paper, we explore the role of weather anomalies in the formations of traders anticipations on harvest and future availability, and the consequences for producer prices. As traders can observe present weather and biophysical developments and take immediate action, their weather based predictions on future availability have a direct impact on contemporaneous prices. Hence, while weather shocks can disrupt future supply, they can also shift the value of the remainder of past harvests. We draw on intra-annual competitive storage models, with a distinct treatment of news in the process of adapting expectations based on updated sets of weather information. We use the theory of competitive storage to inform the empirical observation of causality relations between weather anomalies and agricultural commodity prices.

Section 2 reviews previous literature on weather and food prices, section 3 discuss the competitive storage model and the role of weather news, section 4 presents an application to the case of Indian producer prices and section 5 concludes.

2. Literature on weather and food prices

Empirical studies. Fresh information on crop prospects is a known driver of market prices (Summer and Mueller (1989)). And as such, weather shocks generally act as local supply shifters in price formation models (Jia (2014); Götz et al. (2016)). Hence, the sensitivity of agricultural prices to weather fluctuation varies with transport costs and the ability to mitigate production deficits (Burgess and Donaldson (2010); Fox et al. (2011)). Using a fixed effect approach Deschenes and Greenstone (2007) showed that short-run variations in weather affect farm's profitability. The disruptive consequences of weather extremes on agriculture might also bear consequences on regional conflicts (Klomp and Bulte (2013); Maystadt and Ecker (2014)). El Nino and La Nina episodes of abnormal sea temperature and air pressure have been linked to price reactions on international markets (Algieri (2014)). At the global scale, repeated extreme weather events can have major adverse consequences across international markets (Piesse and Thirtle (2009); Headey and Fan (2008)).

Weather shocks can also be analyzed through the lens of futures price theory. Futures prices reflect agents' harvest-time price expectations and react to productions forecasts (McKenzie (2008); Adjemian (2012)). Observing adverse growing conditions, arbitrageurs with access to a futures market would sell the commodity in the spot market and buy futures contracts. Hence, spot prices might decline in the short run while futures prices raise to absorb rainfall or temperature exogenous shocks.(Goodwin and Schnepf (2000); Goodwin and Ker (2002); Bhanumurthy et al. (2013)).

Competitive storage model. News play an important role in commodity price formation. In the context we are concerned with, *news* is any new information carrying advance knowledge on future production or consumption[2], relevant to forward-looking

[2] Although demand has usual been considered inelastic in this literature, consumption related news also exert an influence on food prices, as demonstrated for the case of beef (Lloyd et al. (2001, 2006); Hassouneh et al. (2010)) and poultry (Hassouneh et al. (2012)) markets. Deaton and Laroque (2003) made an attempt to relax the inelasticity assumption in the long term.

agents. Access to information has a critical role in agro-food commodity price formation mechanisms (Jensen (2007); Aker (2010); Goyal (2010)).

In a variant of early competitive storage models, Wright and Williams (1982) introduce a crude representation of weather variation news and other exogenous shocks by using serially uncorrelated production disturbances, with no distinction between current and future excess supply or demand. Similarly, changes in the information at hand play a role in the formation of agents expectations in Deaton and Laroque (1992)'s confrontation of the storage model to historical price series. However the information was solely made of past availability combined to the future harvest's i.i.d. probability distribution. In a refinement of the formation of anticipations, Deaton and Laroque (1996) relaxed the i.i.d assumption and introduced serially correlated production information. Price expectations where then built by using current production as a source of information on future production. But weather news were still not explicitly modeled. Chambers and Bailey (1996)'s introduction of time dependent equilibrium prices functions allowed for anticipations to be constructed from periodic conditional expectations, more suited to model intra annual price variations. Building on this more flexible specification, Osborne (2004) modeled news and information on approaching harvest in the decision function of Ethiopian storers. The distinctive features of this iteration of the model are four equilibrium price functions, one per season, and conditional expectation of future price based on cumulative weather information and realized harvest.

3. Theoretical framework : weather news in the Competitive Storage Model

To study the formation of traders anticipations, consider a simple model for commodity prices where risk-neutral inventory holders with access to a perfect capital market, charging an interest rate r, face a commodity spoilage rate δ, leading to the real cost of carrying positive cost across time: $\theta = (1-\delta)/(1+r) < 1$. Every period, traders also observe the realization of harvests, h_t. With the possibility to hold inventory, I_t, the available amount of grain in the market at time t is denoted $z_t = h_t + (1-\delta)I_{t-1}$, and the commodity price at period p_t, must satisfy :

$$p_t = \max\left[\theta E_t p_{t+1}, P(z_t)\right] \tag{1}$$

with E_t the expectation conditional on information available at t. This equilibrium is derived from maximizing profits of holding inventory, y_t from period t to $t+1$, given by:

$$[\theta E_t p_{t+1}]I_t \, ; \, I_t \geq 0 \tag{2}$$

This standard decision rule is at the core of the competitive storage model. When a rational trader expects prices to be high enough, i.e. $\theta E_t p_{t+1} \geq p_t$, there is a strictly positive profit from holding the entire stock until the next period. Hence, traders build up inventory and price would increase until marginal profit is zero. At this equilibrium, traders would stop purchasing and p_t equals exactly the expected future price, $\theta E_t p_{t+1} = p_t$. Deaton and Laroque (1992) prove the existence of a unique stationary rational expectation equilibrium (SREE), a function $f(z_t) = p_t$ that satisfies equation (1) for all z_t. The SREE implies the following:

$$p_t = \theta E_t p_{t+1} \quad if\ I_t > 0 \tag{3}$$

$$p_t > \theta E_t p_{t+1} \quad if\ I_t = 0 \tag{4}$$

And a threshold $p^\star$, the sock out price, can be identified by finding the minimum price such that carry over stock is zero. The equilibrium price is therefore shaped by expectations of the agent, $E_t p_{t+1}$.

In early standard storage models, anticipations of future price levels are established with the assumption that agents know the "amount on hand", this information is $h_t + (1-\delta)I_{t-1}$, the current harvest together with any inventories from the previous period net of costs, denoted by z_t. With harvest considered i.i.d, the only varying source of information is the result of previous storage decisions, such that expectations are of the form $E_t[p_{t+1}|I_{t-1}]$ and traders cannot any other type of news to infer future availability. To better accommodate observed price autocorrelation in the data, Deaton and Laroque (1996) refines the information available to agents at time t by relaxing the i.i.d assumption and modeling autocorrelated harvests. With the probability distribution of next period harvest disturbance depending on present disturbance, the amount produced each period carries information on future levels of supply. This form of news plays a role in calculating expected future prices and thus the demand for current inventories. With autocorrelated harvests, the expected price function becomes $E_t[p_{t+1}|I_{t-1}, h_t]$. Along these lines, Chambers and Bailey (1996) introduced a time dependent version of the equilibrium price with harvest probability distributions changing across production cycles. With $E_t[p_{t+1}|I_{t-1}, h_t, k]$ for $k = 1, .., K$, prices are modeled across a K parts seasonal cycle with a prices equilibrium function for each season. This significant extension of the model opened the possibility of accounting for intra-annual dynamics. The influence of new information on harvest and stocks could then vary across different times of the year. In their version of the model, Peterson and Tomek (2005) use a random walk to define the information set on expected crop supply used by traders to form anticipations during the months between planting and harvest.

The impact of weather related news is particularly important during the months of crop growth preceding harvest, when stocks are at their annual low and market is thinner. A quarterly version of the model would therefore feature four equilibrium price functions, each one supporting the formation of expectations with a different probability distribution of yields. With a seasonal distribution of harvest over 4 periods and conditional expectations augmented with weather information, Osborne (2004) shows that, in Ethiopia, a large proportion of the production information is known before the harvest itself, through the observation of rainfall. With one harvest cycle and four seasons s, this model of price expectation formation augmented with rainfall information takes the form of

$$E_t[p_{t+1}|I_{t-1}, h_t, s_t, V_t] \text{ with } s_t \in [1, .., 4] \tag{5}$$

where V_t is a vector denoting information on future harvest available in t. Considering that I_{t-1} and h_t might be retrieved from the news information set, the expected price function with weather news as a source of advance information can be written as

$$p_{t+1} = f_{t+1} = f(s_t, z_t(p_t, V_t(x, \tilde{\rho})), V_{t+1}(x, \tilde{\rho}); \tilde{\gamma}) \tag{6}$$

where x represents all relevant rainfall observations for the given production season and period. V are information states depending on rainfall and the standard deviations of news, $\tilde{\rho}$, which express the uncertainty of future harvest . $\tilde{\gamma}$ is a vector of structural parameters including demand elasticity, interest rate, storage cost and production cycle index. The key parts of anticipation formation mechanism are therefore the combinations of news in V and the treatment of the output of V in f. The specificity of these functions were not explored in depth in Osborne (2004), aside from the normality requirement for the distribution of news and the regularity and compactness of V.

To refine the modeling of the role of weather news in local traders' price expectation formation, we build on the specification of Osborne (2004). We introduce several points from the rational expectation theory as well as biophysical characteristics of production systems to inform how weather news enter the anticipation mechanism and uncover the

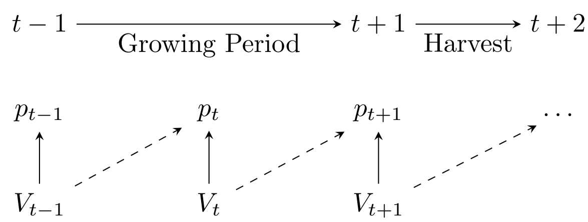

Figure 1: Timing of the price expectation updating process

short run sensitivity of local markets to various shocks.

Agents are forward looking, with a strategy selection based not on experience measured by relative past realized profits, but on a maximization of expected future profits. However their forward looking behavior is boundedly rational, as only past information on weather variability, specific to the agent's geographic localisation, is used to construct their expectation of future crop availability. Hence, for each period t, a weather anomaly from traders' perspective is defined based on a normal long term level obtained from weather realizations pre-dating t. As production and marketing systems evolve over time, expectations formation might adapt to new conditions and experience gathered by agents over their careers (Muth (1961); Böhm and Chiarella (2005)). A common approach is to construct anomalies with respect to a 10 years rolling window of average standard conditions prevailing in the concerned production area monitored by the agents. Meteorological information systems often disseminate real-time measurement together with long run normal conditions. The way expectations are formed specifically depends on the structure of the relevant systems. Traders use information to predict which distribution of yields will prevail at harvest time, based on their knowledge of the link between weather and growing conditions. When conducting this forecasting exercise, they know that the directions and amplitude of a weather variation bear different impact on crops. Quadratic functions can introduce non linearity in price reactions to mirror biophysical links. Yet the temperature and yield relationship is highly asymmetric. Temperatures above the optimal thresholds have roughly 10 times worse consequences on yields than a similar negative deviation (Schlenker and Roberts (2009)). The equilibrium price relation to weather would then feature non linear conditionality and asymmetric critical turning points. Furthermore, producers can accommodate to a certain extent early rains or a delayed start of the season. Therefore, cumulative level of weather parameters over a season might be more important that one specific week's conditions. Consequently, price expectations are gradually updated based on the strengthening of an incomplete information set made of weather observations, until the information is complete and the supply arrives on the market (a feature already introduced by Osborne (2004)).

Similar to Osborne (2004), the resulting reduced form price formation model may be written as :

$$p_{t+1} = F(p_t, s_t, x; \rho, \gamma) + \varepsilon_{t+1} \tag{7}$$

4. Empirical application: Rice and Wheat prices in India

In this section we examine the role of weather shocks in Indian local spot price formation process by estimating the contemporaneous impact of weather anomalies in local market prices. We use a reduced form of the price formation model laid out in section 3, estimated for primary wholesale prices of key crops.

4.1. Context and data

The Indian climate is particularly heterogeneous throughout the country. Annual rainfall vary from a few centimeters in dry states, like Rajasthan, to several hundred centimeters in the northeastern states. The temperature distribution also features considerable regional differences. However, a seasonal cycle drives agricultural activities across the whole the country. India knows two main harvest seasons Rabi (Winter) and Kharif (Autumn, after the summer monsoon). Some States benefit from Rabi rainfalls while others have dry winters (see figure 9). Northern states make intense use of irrigation, especially during the Rabi months, whereas Rain-fed agriculture is more prevalent in the south. Monsoon typically starts in June and reaches its peak in August, but the rainfall might last longer in some States, especially the ones on the east coast (see figure 8). Kharif season crops include rice, millet, sorghum, maize, gram (chickpea) and pigeonpea, grown between June and September and harvested in OctoberNovember. Rabi production typically includes wheat, barley and masur lentils, planted after the summer monsoon and harvested at the end of the spring, but chickpea can also be grown during the wet winter of some southern states.

Both inter-annual and long-term climate variability affect food production in India (Guiteras (2009); Preethi and Revadekar (2013)). The relationship between weather and crop yields has been studied, among others, by Guhathakurta and Rajeevan (2008); Barnwal and Kotani (2013); Birthal et al. (2014b,a, 2015); Pattanayak and Kumar (2014); Dkhar et al. (2017); Mishra et al. (2017). Climatic variables significantly drives the yield distribution and features considerable non linearity. The resulting impact of a weather anomaly depends on the type of soils, on agroclimatic zones and on seasonality. Kharif crops are more sensitive to temperature and precipitation, whereas Rabi crops remain more resilient to changes in precipitation levels. Temperature is most important to winter crops which rely on irrigation (Mondal et al. (2015)). Extreme heat affects cereal crops growth and might trigger senescence onsets, leading to lower yields Lobell et al. (2012) . While crop production is strongly influenced by the summer monsoon rainfall, event the post post-monsoon winter cropping season depends on summer rains through replenishment of on ground water stocks needed for irrigation (Kumar and Parikh (2001); Krishna Kumar et al. (2004); Das et al. (2014)).

Auffhammer et al. (2012) found non linear relationship between weather and Indian yields as the negative impact of reduced rainfall is amplified when rainfall is very low (drought), and the positive of impact of higher rainfall reversed sign and becomes negative when the increase generates extreme rainfall. They found that nonlinearity related to drought was much more important than the one related to extreme rainfall.

The Indian marketing system is built on a physical and legal framework facilitating trade, storage and processing of a large share of the agricultural produce. Wholesale markets might be labeled as primary, secondary or terminal, according to the volumes of trade and the type of participants. We focus on primary wholesale market yards, which are closest to producers. These market yards (*mandis*) are designated and operated under the supervisions of market committees, made of members of producer's cooperatives and civil servants. Producers and aggregators are matched with bidders in organized auctions. Bidders are traders, processors, and during a few month per year, public procurement agencies.

Every day, market operators record the minimum, maximum, and modal transaction prices and send the data to the AgMarkNet price information portal. We construct monthly district averages of daily market modal prices of maize rice and wheat during their respective growing seasons. In some *mandis* from remote area or low producing districts trade only takes place after harvest, during a few months of the year. In other *mandis* trade might happen all year long. We focus on markets which trade during the growing season of each respective crop, to study their price reaction to a weather anomaly.

Table 1: Data sources

Item	Temporal resolution	Spatial Resolution	Source
Precipitation & temperature	Monthly 1980-2017	0.5x0.625	NASA/MERRA2
SPEI	Monthly 1980-2016	0.5x0.5	University of East Anglia (Beguería et al. (2014)).
Producer prices	Daily 2003-2017	Market	AgMarkNet, primary wholesale markets for medium to large producers, and aggregators.

4.2. Empirical implementation

To estimate the relationship between weather variations and prices, we follow two different approaches. *First* we estimate the contemporaneous and lagged impact of specific anomalies in climatic variables and events susceptible to affect yields and therefore be monitored by traders. *Second*, we attempt to estimate the full price reaction functions to temperature and rainfall by regressing discrete intervals of weather variables realizations on prices. Binning the data provides a simple way to uncover the asymmetry and non linearity of weather variations in the price expectation mechanism. In both approaches, we exploit the time lag between a weather shock and the ensuing supply shock to identify and estimate price reactions that are solely due to a change in future price expectations.

In our *first approach*, a set of estimations are obtained be regressing price levels, p_t, on specific weather anomalies:

$$p_{d,t} = \beta_0 + \beta_1' \bar{\mathbf{W}}_{d,t} + \phi_d + \psi_{m,s} + \tau_{y,s} + \eta_{d,t} \tag{8}$$

where $\bar{W}_{d,t}$ is a series of i weather variables for district d. The equation is estimated for the vector of weather conditions constituted of monthly district rainfalls and temperatures. Another sets of estimations is obtained with different measures of weather anomalies captured by the SPEI or deviations from long term averages. Each equations include fixed effect for districts (ϕ_d), year-states($\tau_{y,s}$), a state specific monthly seasonal cycle ($\psi_{m,s}$) with m$= 1, .., 11$, and an error term, $\eta_{d,t}$. The interest rate and storage loss parameters from our structural model described in section 3 are absorbed by the time and district fixed effects. Similarly, idiosyncratic local shocks and government interventions such as the recommended Minimum Support Price and related procurement decisions are captured by state-year fixed effects. District characteristics that do not change every month such as irrigation technology, storage facilities, infrastructures and soil quality fixed effects, thus offsetting potential sources of omitted variable bias.

Measures of deviation are based on the information available to market players at time t. Anomalies are calculated for each t based solely on long term mean or reference values pre-dating t, as that is what traders base their knowledge on. To construct district specific monthly time series from 1990 to 2018, we sum pixels within the spatial boundaries of each district, for all weather variables. Cumulative rainfall from and tally of degrees are also calculated for every year. Then, for each weather variable i, we construct 10 years moving averages to establish benchmark levels, $\bar{X}_{i,t}$, weighted with exponentially decreasing weights such that recent years have stronger weights. The anomalies variables are defined as the percentage deviation from the 10 years rolling benchmarks: $\frac{x_{i,t}-\bar{X}_{i,t}}{\bar{X}_{i,t}}$.

For our *second approach*, rainfall and temperature deviations from long term averages are allocated to bins of fixed width with respect to their distribution. In other words the realized outcome distribution of each variable is divided in 40 sections of 2.5% length.

With the assumption that the short run price formation process is a combination of non linear functions of observed weather, $g(RAIN)$ and $m(TMP)$, we re-write equation 7 for district d at time t as:

$$p_{d,t} = \int g(RAIN)\Theta(RAIN) + \int m(TMP)\Theta(TMP) + \phi_d + \psi_m + \tau_{y,s} + \eta_{d,t} \quad (9)$$

where $\Theta(RAIN)$ and $\Theta(TMP)$ are the distribution of anomalies within our dataset. In order to estimate the form of $g()$ and $m()$, we discretize the price interval over rainfall and temperature anomalies with fixed width bins, each of which the relationship to prices will be jointly estimated:

$$p_{t,d} = \beta_0 + \sum_{q=1}^{B_{rain}} \beta_q^1 RAIN_{q,d,t} + \sum_{q=1}^{B_{tmp}} \beta_q^2 TMP_{q,d,t} + \phi_d + \psi_m + \tau_{y,s} + \eta_{d,t} \quad (10)$$

For each set of bins, the bin that includes zero, the no-deviation interval, is treated as the omitted reference category.

4.3. Results

We start our empirical exploration by examining short run price reactions to weather anomalies as captured by the SPEI and deviations from long term rainfall and temperature levels.

Table 2: Regression results: SPEI

	Log(Wheat Prices)		Log(Rice Prices)		Log(Maize Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)
$SPEI_t$	.007***	.008***	.004**	.005**	.009***	.010***
	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
$SPEI_t^2$	−.002**	−.003**	−.001	−.002	−.003*	−.004**
	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
$SPEI_{t-1}$		−.001		−.001		.003
		(.001)		(.002)		(.002)
$SPEI_{t-1}^2$		−.007***		.003*		−.006***
		(.001)		(.002)		(.002)
Month-State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,519	8,970	8,278	7,815	6,921	6,564
R^2	.878	.844	.857	.850	.829	.810
Adjusted R^2	.872	.836	.846	.838	.814	.793
Note:						*p<0.1; **p<0.05; ***p<0.01

Regression results suggest that prices of wheat, rice and maize react positively and contemporaneously to a precipitation anomaly captured by the SPEI (table 2). The reaction also shows signs of non linearity, as quadratic terms indicate that after a certain level of disruption, price reactions will falter.

In our second set of results (table 3) we study the impact of marginal changes contemporaneous and lagged rainfall and temperature levels on prices, after having controlled for seasonality and time invariant characteristics. This second sets of results indicate an immediate but modest price reaction to marginal changes and short run anomalies in climatic conditions. For each time frames and commodities, the signs of level and quadratic coefficients suggest a reaction functions that looses momentum when marginal changes reach high proportions.

Marginal changes in precipitations matter for all commodities but are seen positively only for rice as wetter growing conditions seem to have a price reduction effect, with a one month lag.

The direction of reactions to temperature deviations for rice and maize suggest a price reduction through anticipations of better growth but not for wheat, grown in colder conditions and more dependent on irrigation.

The negative coefficients of positive rainfall deviations for rice hint that wetter growing conditions would been seen by the market as beneficial for future yields. Whereas it is the opposite for the two other crops.

Table 3: Regression Results - Rainfall and temperature

	Log(Wheat Prices)		Log(Rice Prices)		Log(Maize Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall variables						
$RAIN_t$	.0001***	.0001***	−.00001	−.00001	.00003**	.00002
	(.00001)	(.00001)	(.00001)	(.00001)	(.00001)	(.00001)
$RAIN_t^2$	−.00000***	−.00000***	.000	.000	−.000	−.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
$RAIN_{t-1}$	−.00002	−.00001	−.00002***	−.00003***	−.00000	−.00000
	(.00001)	(.00002)	(.00001)	(.00001)	(.00001)	(.00001)
$RAIN_{t-1}^2$	.00000	.000	.000***	.000***	−.000	−.000
	(.00000)	(.00000)	(.000)	(.000)	(.000)	(.000)
Temperature variables						
TMP_t	.006**	.013***	−.043***	−.043**	−.053***	−.049***
	(.003)	(.003)	(.016)	(.018)	(.018)	(.019)
TMP_t^2	−.0001***	−.0003***	.001**	.001**	.001***	.001***
	(.0001)	(.0001)	(.0003)	(.0003)	(.0003)	(.0003)
TMP_{t-1}	.009***	.006*	.025	.028	−.092***	−.096***
	(.003)	(.003)	(.016)	(.017)	(.016)	(.017)
TMP_{t-1}^2	−.0001**	−.0001	−.0005*	−.001*	.001***	.001***
	(.0001)	(.0001)	(.0002)	(.0003)	(.0003)	(.0003)
Standardized precipitation and evapotranspiration index						
$SPEI_t$		.004***		.004*		.007***
		(.001)		(.002)		(.002)
$SPEI_t^2$		−.001		−.001		−.003*
		(.001)		(.002)		(.002)
Observations	10,391	9,465	9,630	8,151	7,534	6,824
R^2	.887	.876	.875	.854	.844	.827
Adjusted R^2	.882	.869	.866	.843	.831	.811

Note: *p<0.1; **p<0.05; ***p<0.01 - Year and seasonal cycles state specific fixed effects included in all regressions.

For the second part of our analysis we plot the regression results of equation (10). In figures 2 to 5, price reactions associated to each interval of weather anomaly are presented with a 95% confidence interval (black lines passing through each point; clustered at district level). To facilitate reading and reconstitute the full price function, we connect the different levels of reaction with a local polynomial regression. The upper panel always features reactions to rainfall anomalies and the lower panel plots the temperature impacts. For each figure, all coefficients are jointly estimated to account for the interaction between precipitation and temperature as well as the time dimension. Blue panels present regressions of anomalies in cumulative parameters while yellow ones assemble coefficients of anomalies realized temperature or precipitation in a given month.

For rice, we find that a rainfall deficit of 80% below long term levels in a given month increases prices of about 5%. Cumulative temperature deficits can be much more disruptive as episodes colder than 7% below normal conditions can lead to a 40% price increase. Very warm episodes, at the other tail of the anomaly distribution, might reduce prices by 20%.

Small rainfall deficits over time slightly increase wheat prices, as captured by coefficients of deviations from long term cumulative precipitations. Price do not exhibit a strong reaction to cumulative precipitations higher than the long term average, except during extreme episodes during which prices immediately increase by up to 2%. However, cumulative temperatures warmer than usual lead to lower wheat prices, counterbalanced by adjustment in the following period, while extreme cold episodes lead to a price increase in the same month.

Results for maize are less pronounced. Coefficients indicate with that small anomalies do not trigger price movements but reactions to stronger anomalies are much more uncertain, as indicated by wider confidence intervals.

A common feature of the estimations for all crops is an absence of immediate price reaction to small anomalies close to 0. And long term average of climate variables, the 0, is an inflection point for most of the price reaction functions.

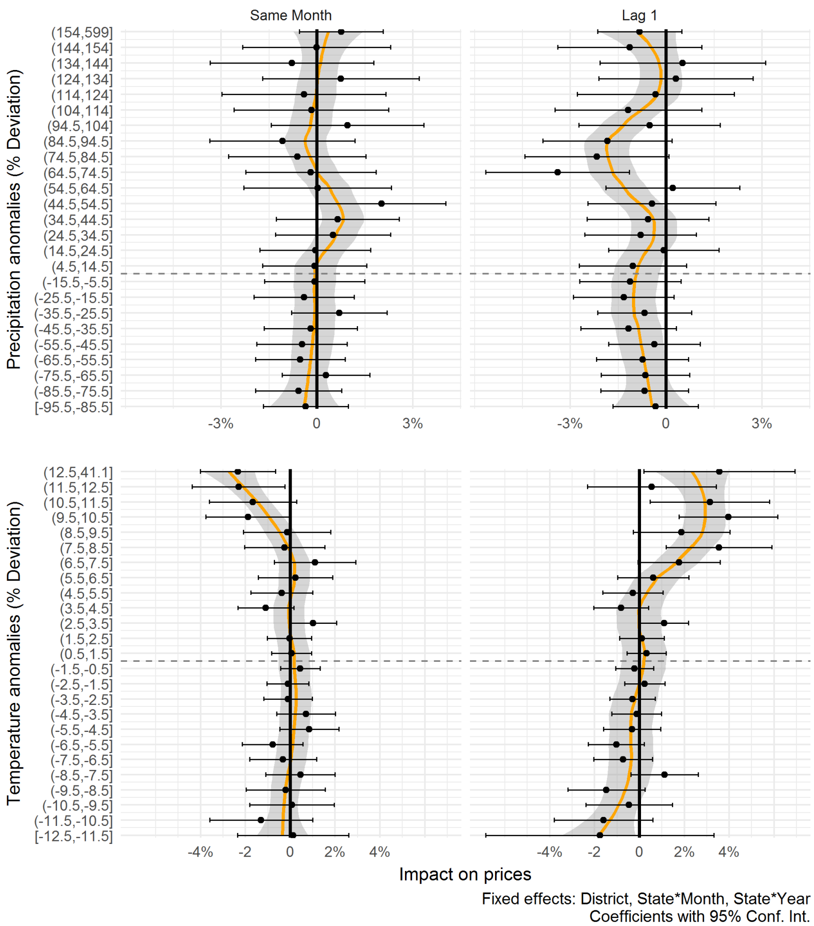

Figure 2: **Wheat price reactions to rainfall and temperature anomalies:** Wheat price do not seem to strongly react to abnormal precipitation levels. Although a 50% rainfall increase might reduce price by about 3% after one month. Only temperature anomalies above 7% lead to a significant price increase, also after one month.

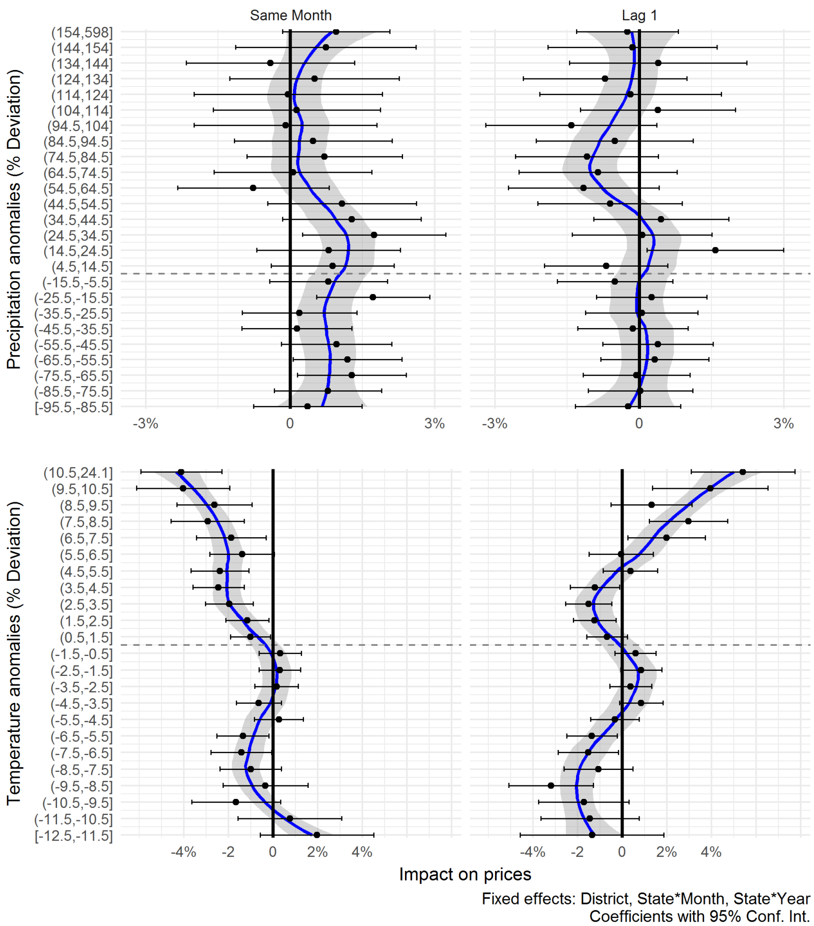

Figure 3: **Wheat price reactions to anomalies in cumulative rainfall and cumulative temperature:** *Rainfall deficit* increase prices (upper panel). Price do no exhibit a strong reaction to cumulative precipitations deviations from the long term average. During extreme temperature episodes prices immediately decrease by up to 2%, but only to be compensated by the opposit moment the next month.

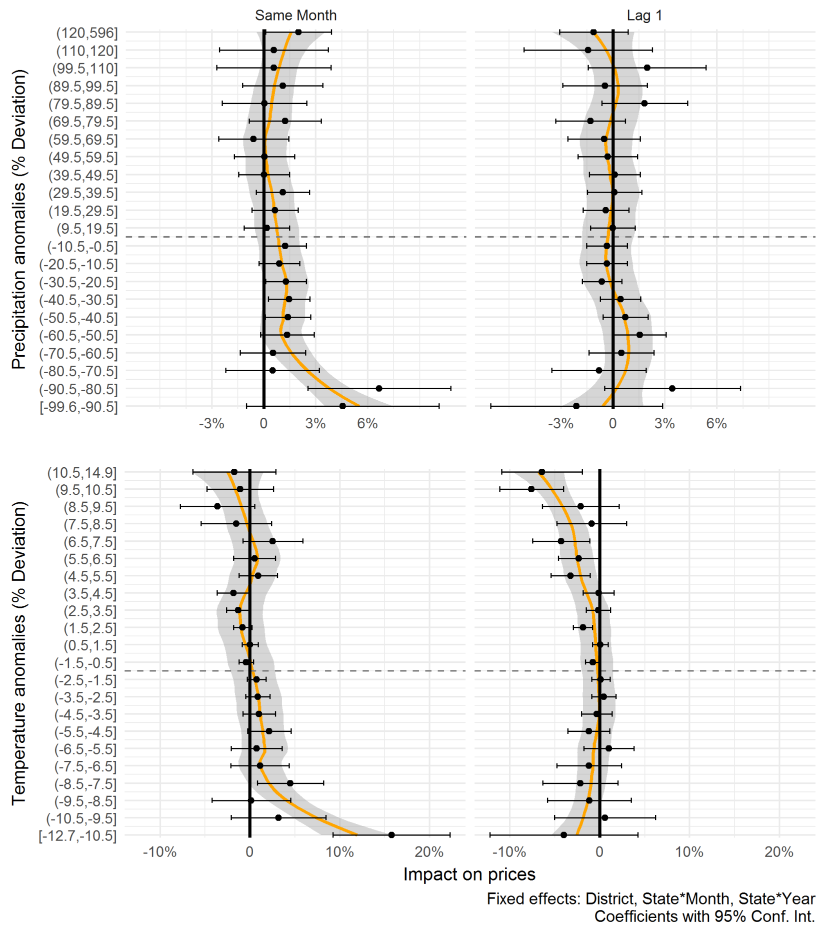

Figure 4: **Rice price reactions to rainfall and temperature anomalies:** Rice prices do not exhibit a significant immediate price reaction to small precipitation or temperature anomalies. However, extreme rainfal deficit lead to a immediate 6% price increase and cold spells of 10% and more below average can increase prices between 10 and 15%.

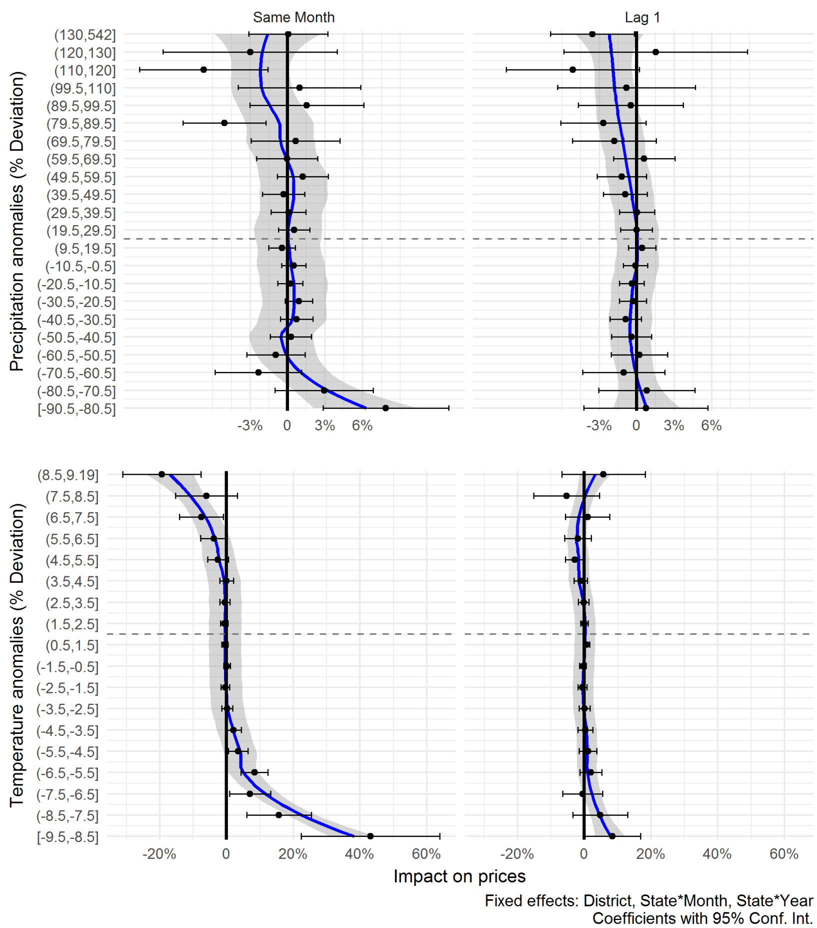

Figure 5: **Rice price reactions to cumulative rainfall and cumulative temperature anomalies:** *Rainfall deficit* of 80% below long term levels increase prices of about 5% (upper panel). Cumulative temperature deficits can be much more disruptive as episodes colder than 7% below normal conditions can lead to a 40% price increase. Very warm episodes at the other tail of the anomaly distribution might reduce prices by 20% (lower panel).

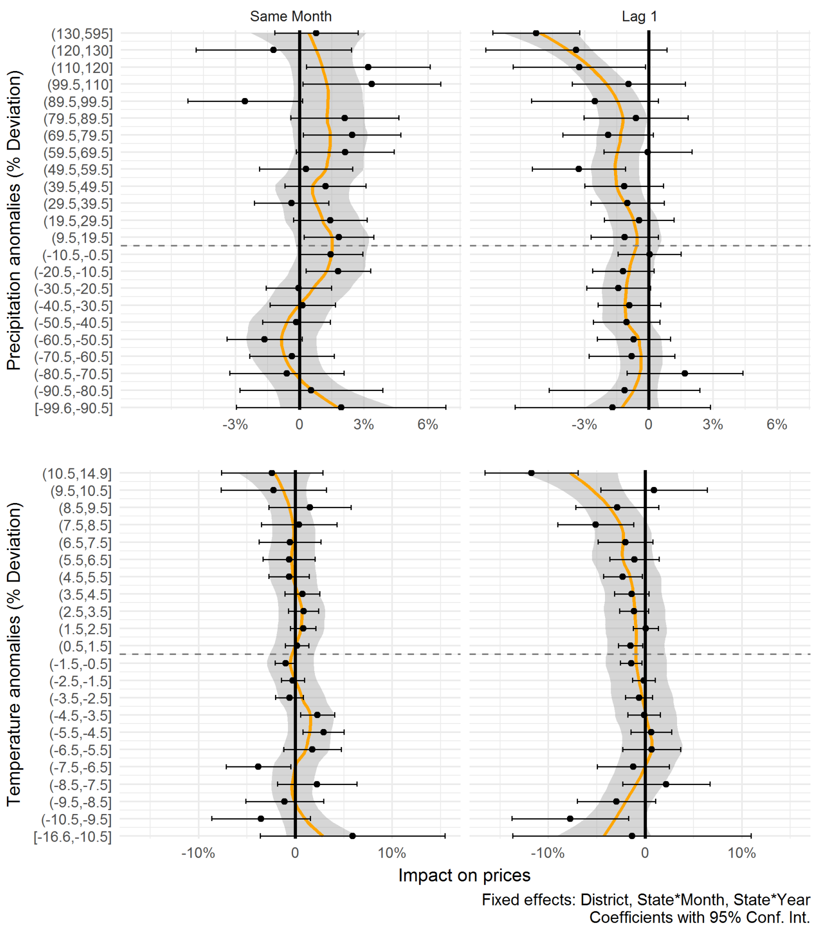

Figure 6: **Maize price reactions to rainfall and temperature anomalies:** Results do not suggest conclusive evidence of maize price reaction to anomalies

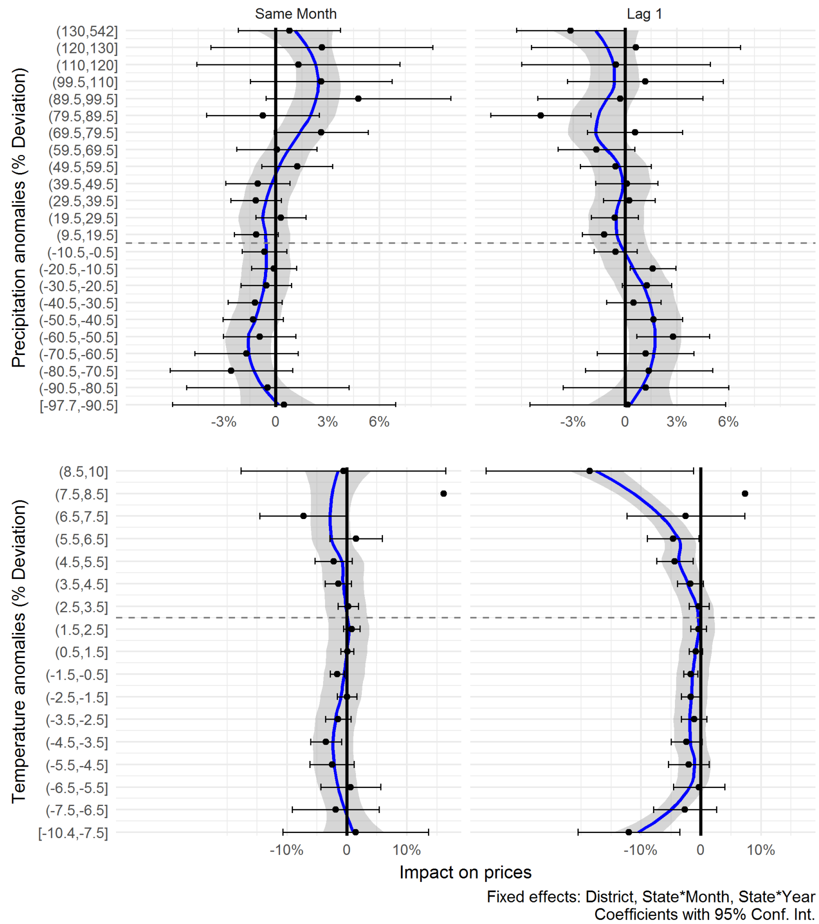

Figure 7: **Maize price reactions to anomalies in cumulative rainfall and cumulative temperatures :** Results do not suggest conclusive evidence of maize price reaction to anomalies. Note: one confidence interval for a temperature bin is omitted for exposition purpose due to its wide size.

5. Conclusion

This papers presents an approach to model the impact of weather anomalies on agricultural markets. We propose a theoretical framework drawing from the competitive storage model to analyze short run price reaction to weather disruptions. Results from the empirical application confirms that market prices react to weather shocks in a non linear fashion. The main source of non linearity is the non linear and asymmetric impact of climate on yields. This complex process is reflected in the way agents update their anticipations on future harvest and affects their decisions trading decisions.

A weather disruption is often not contemporaneous to the ensuing supply shock. Consequently, there exist several interlinked channels for impact on prices. First, the update of anticipations on future harvest causes the market valuation of the remained of past harvest to change. Second the market clearance, when harvest confronts demand. The first channel is important and deserves detailed analysis of the beliefs and anticipations of market players. Further, the timing dimension matters as results suggest that, after an initial reaction, prices follow a gradual update process during the growing season.

A defining characteristic of the binned regressions is that all price expectations reaction functions feature a turning point in zero. Reaction differs in adverse/favorable conditions and the intensity of the shock matters. Shocks in the tail of the distribution of weather conditions have a stronger impact on expectations than those in the center, closer to long term averages.

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Annex

In February and March 2002, a precipitation anomaly watered the State of Uttar Pradesh up to an average of 117% more than the long term average rainfall (see figure 11).

In July and August of 2002, northern Indian States such as Rajasthan, Punjab and Haryana received significantly less rainfall that usual. In August 2005, such an anomaly took place also in Uttar Pradesh with a 48% precipitation deficit that month (see figure **??**).

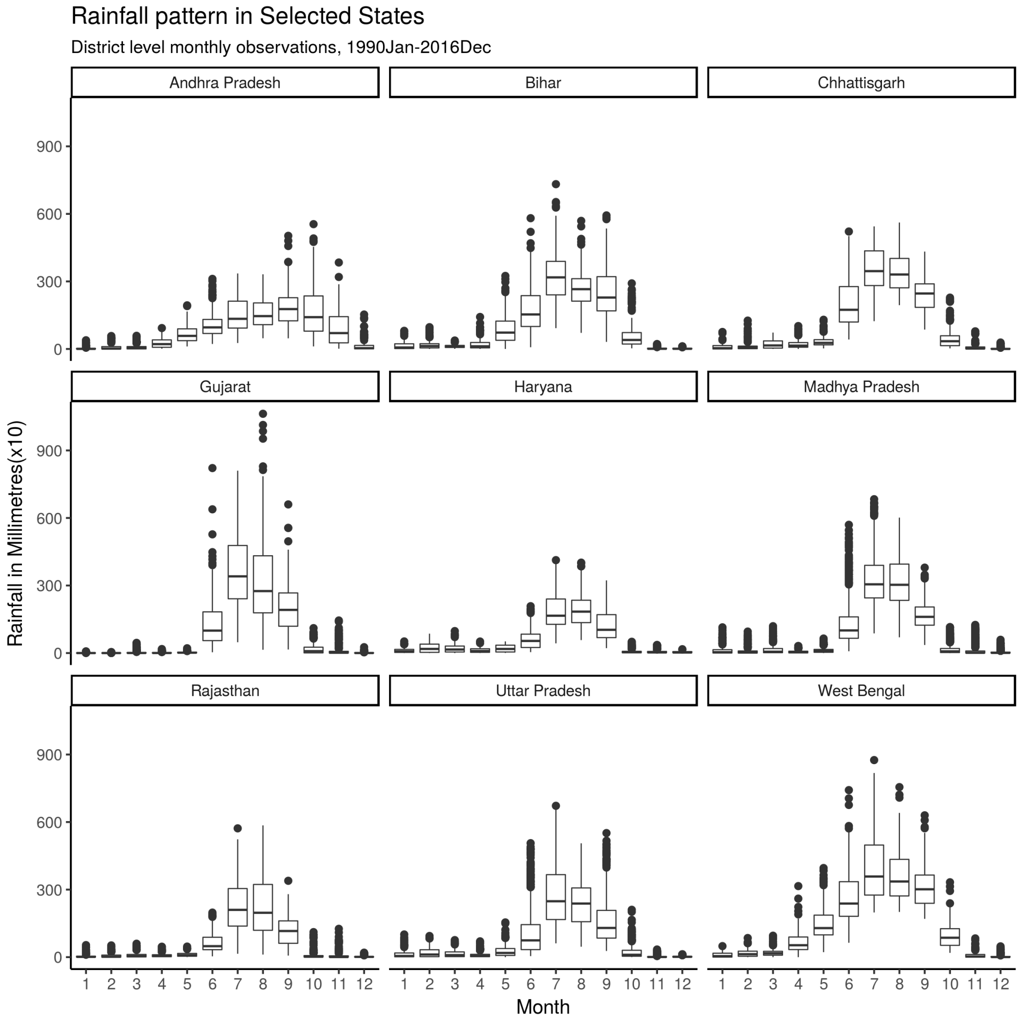

Figure 8: Monsoon timing in selected States.

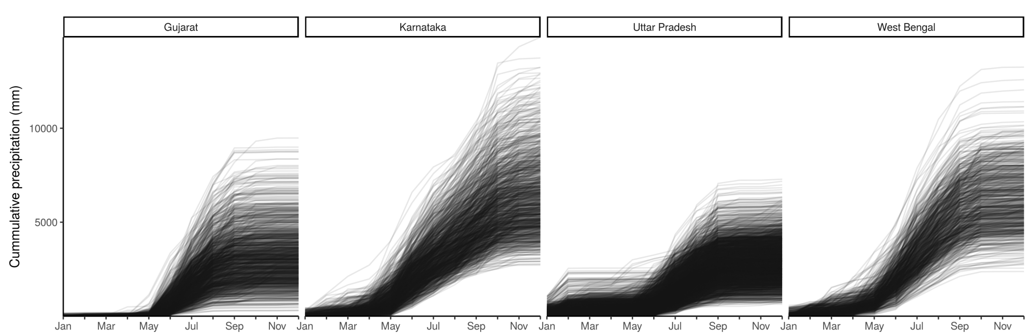

Figure 9: District level cumulative rainfall patterns in selected States (1990-2017)

In the third set of regressions, (see table 4), we focus on the non linear and asymmetric features of the reaction function to rainfall and temperature anomalies. Rainfall anomalies have a non linear impact on prices as indicated by the opposite coefficient of quadratic

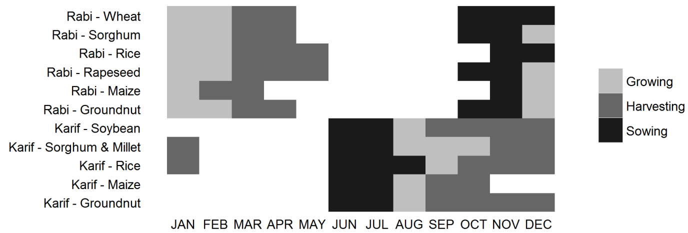

Figure 10: Crop calendar (FAO)

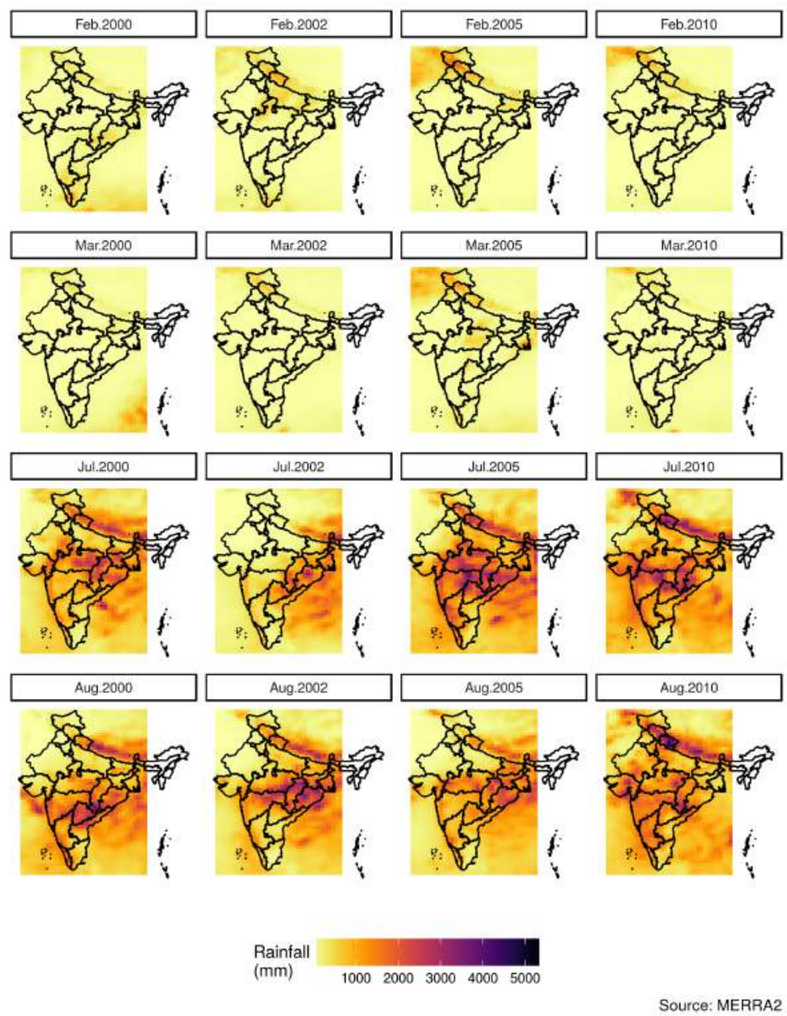

Figure 11: February - March & July - August rainfall in selected years.

terms. But the effect of rainfall deficits (negative shocks) and surplus (positive shocks) is heterogeneous across the three commodities.

Table 4: Regression Results- Anomalies

	Log(Wheat Prices)		Log(Rice Prices)		Log(Maize Prices)	
	(1)	(2)	(3)	(4)	(5)	(6)
$+RAINdev_t$	.00001		.0001**		.00001	
	(.00001)		(.00004)		(.00004)	
$-RAINdev_t$	.0001***		−.0002***		.0003***	
	(.00003)		(.0001)		(.0001)	
$+TMPdev_t$	−.001**		.0001		.001	
	(.0003)		(.001)		(.001)	
$-TMPdev_t$	.001***		−.004***		−.001	
	(.0003)		(.001)		(.001)	
$RAINdev_t$		.0001***		−.0001**		.0001***
		(.00001)		(.00004)		(.00004)
$RAINdev_t^2$		−0.00000***		0.00000***		−0.00000**
		(0.00000)		(0.00000)		(0.00000)
$TMPdev_t$		.0002		−.002***		.0001
		(.0002)		(.001)		(.001)
$TMPdev_t^2$		−.00001		.0003***		−0.00000
		(.00001)		(.0001)		(.0001)
Month-State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,628	11,628	9,757	9,757	7,631	7,631
R^2	.890	.890	.878	.878	.846	.846
Adjusted R^2	.885	.885	.869	.869	.833	.833
Note:						*p<0.1; **p<0.05; ***p<0.01