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ARTICLE

Weather shocks, traders' expectations, and food prices

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Abstract

The empirical literature on the impacts of weather shocks on agricultural prices typically explores post-harvest price dynamics rather than pre-harvest ones. Inspired by the intra-annual competitive storage theory, we empirically investigate the role of weather news in traders' anticipations on pre-harvest price fluctuations in India's local markets. Using a panel of district-level monthly wholesale food prices from 2004 to 2017, we leverage the time lag between a weather anomaly and the corresponding supply shock to isolate price reactions caused by changes in expectations. We find that drought conditions significantly increase food prices during the growing period, that is before any harvest failure has materialized. These results suggest that markets respond immediately to expected supply shortfalls by updating their beliefs and adapting accordingly and that the expectation channel accounts for a substantial share of supply-side food price shocks. A direct comparison with the effects of the same weather anomalies on the prices of the first harvest month reveals that expectations anticipate more than 80% of the total price impact.

KEYWORDS

competitive storage model, expectations, food prices, India, traders, weather

JEL CLASSIFICATION

C23, O13, Q02, Q56

Weather conditions affect agricultural production and, hence, prices. This assertion follows from the established influence of weather patterns on crop yields (Schlenker & Roberts, 2009). But can

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weather shocks also affect crop prices through expectations on future production, *before* the biophysical effect materializes? In this paper, we conduct an *ad hoc* empirical test to answer this question.

The impact of weather conditions on plant growth is well documented in the literature. However, as Osborne (2004) showed conceptually and Adjemian (2012) demonstrated empirically, advance information is important in agricultural commodity markets, more so in certain months of the crop year, when stocks are at their annual low and the market is thinner.

Our analysis is a further empirical attempt to grasp the subtle relationship between weather anomalies and food prices in one of the most important agricultural markets in the world, India. Indian agriculture is the backbone of the Indian economy, engaging more than 40% of the national workforce (ILO, 2021). However, it is still largely rain dependent, a lot of storage and distribution facilities are outdated, and markets are organized in a system of local Agricultural Produce Market Committees (APMCs) that supervise the functioning of the markets (called mandis), constraining the market choice of farmers to licensed traders. In this framework, a consistent narrative looks at Indian traders as being able to exploit farmers while promptly adjusting to external shocks, including weather ones. The Indian government implemented a recent set of measures to enhance competition in Indian agricultural markets through an extensive reform of the APMC mandi system with the aim to modernize and liberalize the regulatory environment of the Indian agricultural system.[1] These interventions are expected to accelerate changes (in terms of weather forecasting, storage facilities, market access, etc.) that will further emphasize the role of anticipatory news of pre-harvest weather in contemporaneous market prices.

By exploiting the time lag between weather shocks and supply shocks, we investigate the role of news in traders' expectations in primary wholesale Indian crop markets (the closest to producers). The intuition is that, as traders can observe present weather conditions and take immediate action, their weather-based predictions on future availability are likely to affect contemporaneous prices even before the new harvest can reach the market. We focus our attention on three crops: maize, rice and wheat. These are the three most important staple grain crops produced in India, and jointly account for more than 80% of foodgrain production in the country.[2] They are also highly storable commodities, which makes intertemporal arbitrage an essential feature of their price formation mechanism. We start by conceptually separating the expectation channel from other channels. Then we provide empirical evidence for its relevance in Indian crop wholesale market dynamics. To this end, in the spirit of the intra-annual competitive storage model (Osborne, 2004), we provide a separate treatment of news in the process of adapting expectations based on updated sets of weather information.

Our identification strategy relies on the presence of intra-annual time lags between weather shocks and supply shocks. We thus exploit time lags to identify current price reactions due to changes in traders' future price expectations that occur entirely outside the physical market channel. This exercise is done in a context where traders are key actors of the price formation process. Unlike smallholder farmers, traders are less likely to be credit constrained, they often own storage facilities, and thus can implement a full-market intertemporal arbitrage solution by setting current prices equal to discounted expected future prices, conditional on storage and available "news" to maximize expected Marshallian surplus.[3] The notion of "news" here extends to contemporaneous weather and biophysical conditions. To avoid potential confounders that might affect secondary and final markets, we focus on the wholesale markets closest to crop production. Finally, we focus on short-time (monthly) variations, assuming that demand is fully inelastic to intraseasonal price variations.

With regard to the empirical strategy, we construct a panel dataset of monthly food prices and weather variables at the district level for the period between 2004 and 2017. Crop prices for maize,

[1]The reform includes the promotion of barrier-free interstate and intrastate trade in agricultural produce, and allows farmers to engage directly with processors, aggregators, wholesalers, large retailers, and exporters in the form of contract farming (Beriya, 2021).

[2]http://agricoop.gov.in/sites/default/files/agristatglance2018.pdf

[3]There is a consensus in the literature that the "buy low" and "sell high" guiding principles, at the core of the competitive storage model, are unattainable for farmers whose liquidity comes from grain sales (Stephens & Barrett, 2011). This is because farmers' decisions to sell or store grain are subject to liquidity constraints and heterogeneous price expectations. For an adaptation of the competitive storage model to analyze the role of farm storage on price volatility see Maître d'Hôtel and Le Cotty (2018).

rice, and wheat are obtained from the *AgMarkNet* price information platform. Results from district-level pooled regressions show that weather shocks affect market prices via traders' expectations in addition to the supply shock channel. Specifically, we find a significant and non-linear effect of cumulative weather anomalies on food prices. A back-of-the-envelope test based on the discontinuity between the growing and harvest seasons reveals that the expectation mechanism we have isolated accounts for about 85% of the total price impact of growing-season droughts.

We contribute to the theoretical and empirical literature on weather and crop prices, and the substantive literature on Indian commodity markets. First and foremost, the existence of an intra-seasonal short-run connection between weather and food markets, channeled by economic agents' expectations, extends the range of determinants of crop price fluctuations driven by climatic factors and paves the way for a better and more timely design of early warning systems in food security policies. In this respect, the paper also highlights the opportunity to promote further research on the drivers of food market resilience to weather shocks during the pre-harvest season.

Second, the finding that weather anomalies enter the expectation function of traders emphasizes the need to account for appropriate short-run modeling of weather ex-ante/pre-harvest effects on intraseasonal changes in agricultural prices by drawing on the well-established strand of the theoretical literature on competitive storage markets.

Third, we contribute to the study of price dynamics in Indian wholesale commodity markets by shedding light on the often neglected role played by traders' expectations in the current mandi system and on the relevance of the anticipatory channels, which has been further enhanced by the new set of reforms implemented by the Indian government. Uncovering the empirical aspects of pre-harvest dynamics is of particular importance for policymaking, especially in countries and developing contexts where large subpopulations are employed in the agricultural sector, and many poor households remain vulnerable to price fluctuations stemming from agricultural dynamics (Stephens et al., 2012).

Finally, we show that market forces take into account not only the risk represented by slow, distant, or gradual changes in climate but also readily respond to immediate disruptions caused by unusual weather events, thus complementing the recent literature on market anticipations of possible future losses brought about by climate change (Schlenker & Taylor, 2019; Severen et al., 2018).

1 | LITERATURE ON WEATHER AND FOOD PRICES

The extreme sensitivity of agricultural commodity prices to weather anomalies and fluctuations is well known. A substantive strand of empirical research has investigated this linkage and has shown that the causal chain can act either indirectly via the role played by crop yields and production volumes or through consumption choices (D'Agostino & Schlenker, 2016; Dercon, 2004; Hirvonen, 2016; Parker & Meretsky, 2004; Schlenker & Roberts, 2006; Schlenker & Roberts, 2009) or directly through spatial price transmission induced by factors such as market integration, networking, and trade arbitrage (Baffes et al., 2017; Brown & Kshirsagar, 2015; Gilbert et al., 2017; Haile et al., 2015; Hatzenbuehler et al., 2019; Mawejje, 2016; Minot, 2010; Stephens et al., 2012). The disruptive consequences of weather extremes on international prices (Algieri, 2014; Chatzopoulos et al., 2019; Headey & Fan, 2008; Piesse & Thirtle, 2009) and regional conflicts (Klomp & Bulte, 2013; Maystadt & Ecker, 2014) have also been studied extensively.

Such literature pointed out the presence of different price elasticities as a function of the specific crop-country combination, the sensitivity of the local food system to domestic production, and the degree of openness to international markets. Much less investigated, yet, is the crucial role of information flows in influencing spatial price adjustment across seasons, with the only exceptions of Stephens et al. (2012) and Hatzenbuehler et al. (2019). Furthermore, this body of empirical research on the weather-price relationship typically explores post-harvest price dynamics rather than pre-harvest ones. Our choice to investigate price responsiveness to weather information and study the role of pre-harvest dynamics in agricultural commodity markets thus enables a departure from previous work and fills a gap in this large but still incomplete literature.

Unpredictable news leads to similarly unpredictable price changes, as already argued by Working (1958) in his anticipatory market model. If that is the case, then weather-related news matters most during the sowing and growing period preceding harvest, when stocks are at their annual low. After the harvest period, in fact, their influence diminishes progressively and the price becomes more affected by variations in consumption demand. Such seasonality (i.e., "normal" fluctuation) drives a wedge between prices before and after the harvest, as highlighted by Gilbert et al. (2017). Furthermore, price seasonality depends not only on storage costs and intertemporal arbitrage, but also on the sell-low and buy-high behavior of liquidity- and credit-constrained farmers (Burke et al., 2019; Stephens & Barrett, 2011). Our empirical analysis is informed from the insights provided by these studies on price seasonality in that we choose to focus solely on the pre-harvest period and sheds more light on traders' behavior regarding inter-temporal arbitrage.

News plays an important role in commodity price formation. In the context of this paper, *news* is any new information advancing knowledge on future production or consumption, relevant to forward-looking agents.[4] Several studies have underlined that news and access to information play a critical role in engendering agri-food commodity price formation mechanisms (Aker, 2010; Goyal, 2010; Jensen, 2007). As a consequence, information lies at the core of competitive storage models and has been progressively incorporated in this strand of the literature on the theoretical modeling of price formation. Wright and Williams (1982) introduced a crude representation of weather variation news and other exogenous shocks by using serially uncorrelated production disturbances, but they made no distinction between current and future excess supply or demand. Subsequently, Deaton and Laroque (1992), Deaton and Laroque (1996), and Chambers and Bailey (1996) enhanced the model by introducing time-dependent equilibrium price functions. In turn, this led to anticipations constructed from periodic conditional expectations, more suited to model intra-annual price variations. Building on this more flexible specification, a seminal paper by Osborne (2004) modeled news and information on the approaching harvest in the decision function of Ethiopian storers. The distinctive features of this iteration of the model are the importance of seasonal equilibrium price functions, and the presence of conditional expectation of future price based on cumulative weather information and realized harvest. In this paper, we draw on Osborne's seasonal competitive storage model with cumulative news to set up a reduced empirical form and analyze short-run price reactions to weather disruptions in Indian wholesale markets.

2 | WEATHER NEWS IN THE COMPETITIVE STORAGE MODEL

To investigate the formation of traders' anticipations, we consider a simple version of the competitive storage model where risk-neutral inventory holders, facing an interest rate[5] r and a commodity depreciation rate $\delta > 0$, leading to the real cost of carrying a positive inventory across time equal to: $\theta = (1 - \delta)/(1+r) < 1$.[6] At the start of every period, traders observe current availability and any accumulated information about the coming harvests, h_t, including the current period's *cumulative news*.

[4]Consumer demand is usually considered inelastic with respect to prices in the competitive storage model literature. For an attempt to relax the inelasticity assumption of demand in the long run, see Deaton and Laroque (2003).

[5]The standard assumption of the neoclassical competitive storage model is the presence of a perfect capital market to ensure an efficient outcome. Depreciation rate and interest rate are assumed to be fixed for simplicity (Osborne, 2004; Wright & Williams, 1982). All prices and costs are expressed in real terms.

[6]As in Osborne (2004), we use here a simplified analysis of storage that does not include financial carrying costs. This is a widespread assumption when examining aggregate market behavior, because it avoids a more complicated cost structure (Deaton & Laroque, 1992). Furthermore, as standard in the competitive storage models, we assume perfect information on aggregate stock availability and no liquidity constraints across traders. These assumptions are generally relaxed in storage models that take the point of view of farmers (see—*inter alia*—Maître d'Hôtel & Le Cotty, 2018).

With the possibility to hold inventories, I_t, they adjust them accordingly so that the overall amount of crop available in the market at time t (denoted z_t) is given by: $z_t = h_t + \theta\, I_{t-1}$.

The commodity price at any period [$p_t = P(z_t)$] must satisfy:

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

where P () is the inverse demand function, and E_t *is* the expectation conditional on information available at t. This equilibrium is derived from a standard no-arbitrage condition that equates current period price with expected price in the next period, minus the marginal cost of storage (including depreciation and interest of capital invested). Thus, traders maximize profits for holding inventory from period t to $t+1$, as follows:

$$\left[\theta E_t p_{t+1} - p_t\right] I_t; I_t \geq 0 \tag{2}$$

This standard decision rule is at the core of the competitive storage model. When a rational trader expects prices to be high enough, that is $\theta E_t p_{t+1} > p_t$, there is a strictly positive profit from holding the entire stock until the next period. Hence, traders build up inventory and the price increases until marginal profit is zero. At this equilibrium, traders stop purchasing, and p_t aligns on the expected future price, $\theta E_t p_{t+1} = p_t$. Conversely, when $p_t > \theta E_t p_{t+1}$, traders sell until the current price goes down to the discounted expected future price. Traders' expectations thus shape the equilibrium price.

According to the competitive storage model depicted above, weather could enter Equation 2 via two main channels: (i) changes in current supply (harvest and/or in commodity inventory, infrastructure damage, etc.); (ii) changes in $E_t p_{t+1}$, via changes in *expectations on future prices*, through anticipatory effects on future supply.[7]

We focus below on the second channel. In this respect, we rely mainly on Osborne's (2004) modeling of the role played by *cumulative weather news* in affecting seasonal equilibrium prices in an intra-annual competitive storage model. With a seasonal distribution of harvest 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. In this theoretical framework, expectations regarding future prices p_{t+1} in pre-harvest seasons (when $h_t = 0$), are formed on the basis of current inventories I_t, and V_t, that is the information set for the future harvest (or supply), based on a vector of observable weather information. Assuming that demand for consumption is constant at the monthly frequency, we can model expectations on future prices as follows:

$$E_t\left[p_{t+1} | I_t, V_t\right] \tag{3}$$

Following Osborne (2004) and Adjemian (2012), we assume that weather-related news matters the most during the sowing and growing period preceding harvest, when stocks are at their annual low and the market is thinner. That is the time when weather events can have a material impact on yields and/or cultivation areas. During the other seasons, weather can still have an impact on crop prices, albeit to a lesser extent and mostly through the first impact channel, directly affecting supply,

[7]Consistently with most of the literature in the field, the implication is that farmers, unlike traders, do not adjust their behavior throughout the season in response to weather news. This is due to our focus on anticipatory effects of traders when farmers have already taken their planting decisions. More generally, we acknowledge that farmers in developing countries often face information and physical storage constraints. If we assume that they could change their behavior in response to informative weather forecasts (e.g., planting mainly on their most productive lands), there may be no yield effects, and the effects on future prices would consequently depend on changes in aggregate output. In both cases, it would not have direct implications on our identification and empirical strategies, because we would register the same anticipatory effects on off-market contemporaneous prices.

such as inventory destruction, infrastructural damage, and lower labor productivity. These direct weather-induced supply variations are much weaker, if not absent, during the growing months.[8] From the assumptions and intertemporal arbitrage mechanics of the competitive storage model, it follows that current prices must equal expected future prices. Therefore, during the sowing and growing season, prices are driven by:

$$p_t = \theta E_t \left[p_{t+1} | I_t, V(x_t) \right] \tag{4}$$

where x_t represents all relevant weather *news*, and θ is the cost of carrying a positive inventory across time. When weather news signal a potential lower future supply, they anticipate future prices to increase and therefore align current prices through the intertemporal arbitrage condition.

Starting from Equation 4, in the subsequent empirical test we exploit the time lag between weather shocks and supply shocks to investigate the role of news in pre-harvest season wholesale market prices in India.

3 | CONTEXT AND DATA

The Indian climate is particularly heterogeneous throughout the country. Annual rainfall varies from a few centimeters in dry states, like Rajasthan, to several hundred centimeters in the north-eastern states (Das et al., 2014; Guhathakurta & Rajeevan, 2008). Temperature distribution also features considerable regional differences. Nevertheless, a seasonal cycle drives agricultural activities across the whole country. India has two main harvest seasons, rabi (winter) and kharif (autumn, after the summer monsoon). Some states benefit from rabi rainfalls, whereas others have dry winters. Northern states make intense use of irrigation, especially during the rabi months, whereas rain-fed agriculture is more prevalent in the south. The monsoon season typically starts in June and reaches its peak in August, but the rainfall might last longer in some states, especially those on the east coast. Kharif season crops include rice, millet, sorghum, maize, gram (chickpea), and pigeon pea, grown between June and September and harvested in October–November. 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 in some southern states.

Both inter-annual and long-run climate variability affect food production in India (Guiteras, 2009; Pre & Revadekar, 2013). The relationship between weather and crop yields has been studied in India, among others, by Auff et al. (2012); Barnwal and Kotani (2013); Birth et al. (2014); Birthal et al. (2014, 2015); Pat and Kumar (2014); Dkhar et al. (2017); and Mishra et al. (2017). Weather variables significantly drive the yield/production distribution and feature considerable nonlinearity. Although crop yields are strongly influenced by summer monsoon rainfall, even the post-monsoon winter cropping season depends on summer rains through the replenishment of groundwater stocks needed for irrigation (Kris et al., 2004; Kumar & Parikh, 2001). Auff et al. (2012) found a non-linear relationship between weather and rice yields in India during the period 1966–2002. Specifically, their results suggest that droughts and heavy rains negatively affected rice yields, but that the impact of droughts 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 percentage of agricultural produce (Chand, 2016). Wholesale markets might be labeled as primary, secondary, or terminal, according to the volumes of trade and type of participants. This analysis is focused on primary wholesale market yards, which are closest to producers. These market yards (*mandis*) are designated and operated under the supervision of market committees, made up of members of producers' cooperatives and civil servants. Producers and

[8]Most long-distance transport takes place after harvest. A risky form of open-air storage happens mainly on farms and at the early stage of commercialization, right after the harvest months.

aggregators are matched with bidders in organized auctions. Bidders are traders, processors, and, for a few months in the year, public procurement agencies. Bids are placed at specific times of the day, and the highest bid wins the lot. Every day, market operators record the minimum, maximum, and modal transaction prices, and send the data to the *AgMarkNet* price information portal. Notably, Indian grain markets are generally protected from imports, and this implies the predominance of local production condition effects on market dynamics. Another important feature of primary agricultural markets in India is the Minimum Support Price (MSP) recommendation, issued annually by the Ministry of Agriculture.[9] This policy intervention has an impact on markets but is not observable with a monthly frequency during the sowing and growing period. MSPs are announced to producers before sowing, and procurements at the recommended price take place after the harvest. Hence, in our empirical analysis, the effect of this policy during the growing season across the years is filtered out by the use of state-specific time trends. However, it should be noted that, given that the policy goal of the MSP is to prevent low prices, and because seasonally low prices are most commonly observed during the post-harvest period, the MSP is less relevant during the growing period (on which we focus), when prices are most commonly at their seasonal peak.

For the purpose of our empirical analysis, we construct a panel dataset of monthly crop prices and weather variables at the district level (see Tables 1 and 2 for data sources, definitions, and basic descriptive statistics). Monthly district averages are constructed from daily market crop prices registered by *AgMarkNet* during the sowing and growing season. See Figure 1 for district coverage of the price data. Wholesale prices have been deflated using the national-level annual World Bank Wholesale Price Index for India.[10] We use the *Global Monthly Irrigated and Rainfed Crop Areas around the year 2000* (MIRCA 2000), prepared by the Physical Geography Department of the Goethe Universitat Frankfurt am Main (Portmann et al., 2010), as our source for state-level crop-specific calendars. MIRCA 2000 provides state-level information on growing seasons. We focus on the primary cropping period for each crop (maize, rice, wheat) to select the sowing and growing season months in which we can isolate the crop-specific expectation channel in the price formation mechanism.

Our indicator of abnormal weather is the one-month Standardized Evapotranspiration Index (SPEI), a multiscalar drought index developed by Beguería et al. (2014), which jointly considers precipitation, potential evaporation, and temperature, and is commonly used to capture weather shocks (Harari & La Ferrara, 2018) and combines the temperature and precipitation information that has been seen to affect crop yields. The SPEI is obtained by taking the difference between precipitation (P) and potential evapotranspiration (PET): $D_i = P_i - PET_i$. Then D_i is standardized such that the index represents the deviation from the normal water balance. In other words, an SPEI of 0 indicates a value corresponding to 50% of the cumulative probability of D, according to a log-logistic distribution. The SPEI is interpreted as follows: A negative SPEI value is associated with dry events, that is

TABLE 1 Data sources

Item	Frequency	Spatial resolution	Source
SPEI	Monthly 2004–2017	0.5 x 0.5	University of East Anglia (Beguería et al., 2014).
Prices (Rupees)	Daily 2004–2017	Market	*AgMarkNet*, wholesale markets for medium to large producers, and aggregators.
Crop calendar	Monthly	State (crop specific)	*Global Monthly Irrigated and Rainfed Crop Areas around the year 2000* - MIRCA 2000 (Portmann et al., 2010)

[9]Note that the MSP reaches less than 7% of farmers in the country, whereas the share of officially procured crop output is close to 11% in total crop output and 7% in total agricultural output. For an overview of MSP recommendations, see the annual reports of the Commission for Costs and Agricultural Prices, available at: https://cacp.dacnet.nic.in.

[10]Available at the following link: https://data.worldbank.org/indicator/FP.WPI.TOTL?locations=IN .

TABLE 2 District-level variables—sowing and growing season descriptive statistics

Variable	Symbol	Description	Mean	*SD*	Obs
SPEI	$SPEI_{t,av.}$	Cumulative average	−0.083	0.828	28,524
Positive SPEI	$+SPEI_{t,av.}$	Cumulative average	0.287	0.434	28,524
Negative SPEI (absolute value)	$\|-SPEI_{t,av.}\|$	Cumulative average	0.370	0.534	28,524
Crop price (INR per tonne)	p_{t_maize}	Monthly average of modal maize prices	980.7	246.3	7330
	p_{t_rice}	Monthly average of modal rice prices	1055.3	295.9	9306
	p_{t_wheat}	Monthly average of modal wheat prices	1232.1	202.7	11,888

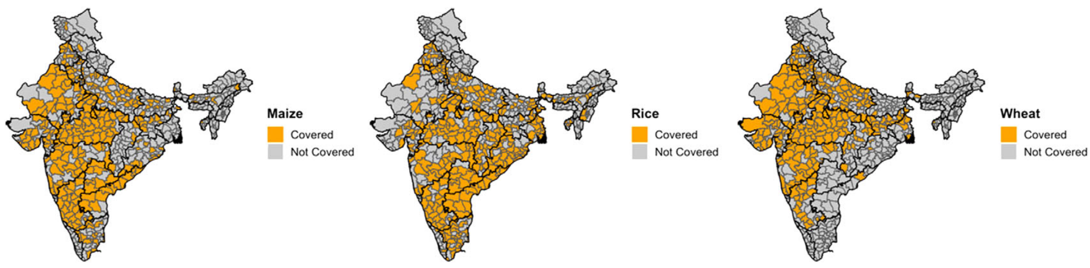

FIGURE 1 District price coverage in our dataset. *Note:* Districts with at least one price observation in the sample

lower rainfall; positive SPEI values capture wet events, that is higher rainfall. As such, hot and dry conditions are represented by large and negative SPEI values, heavy rains by large and positive ones. SPEI values close to zero indicate close to no deviation from the usual water balance for that time of the year and location.

We aggregate SPEI data at the district level by averaging all pixels within district boundaries. Then, for each district, we produce our main SPEI weather indicator: $SPEI_{t,av.}$, that is the average in month t of SPEI values since the beginning of the crop-specific sowing and growing season. This variable is first used in its original form, then split into positive and negative deviations, and finally further split into small (<= the 90th percentile) and large (above the 90th percentile) positive and negative deviations. The assumption underlying this choice of constructing *cumulative* weather variables is that traders observe weather conditions from the beginning of the sowing-growing period, incorporate cumulative weather news as the season unfolds, and react accordingly by updating their harvest expectations. This is consistent with the intra-annual competitive storage model depicted in Section 3. However, we later show that even abandoning this assumption and adopting a contemporaneous, rather than cumulative, model does not affect our core findings. Table A.1, in the online supplementary Appendix, provides additional descriptive statistics on the year-to-year variation of district-level prices and SPEI values.

A simple visual inspection (Figure 2), free from the constraints of any parametric model, shows that, in our sample, when looking at monthly prices (in Indian Rupees with code INR) during the cropping period (Panel A), the lower quantiles of SPEI distribution across districts (highly negative SPEI values, i.e., strong water deficits) are associated with sowing and growing season monthly prices that are about 10% higher than the overall average. This price-SPEI pattern disappears and almost reverses in the months following the completion of the harvest, which we will later use in a placebo test (Panel B). It is noted that these descriptive statistics only show correlation. Causation is established through the implementation of our empirical strategy in the following section.

4 | EMPIRICAL APPROACH AND ESTIMATES

4.1 | Empirical Approach

As outlined in Section 3, to isolate the anticipatory effects of weather anomalies on pre-harvest prices, our identification strategy leverages the time lag between weather shocks and the ensuing supply shocks to identify and estimate price reactions that are solely due to a change in expectations regarding future prices ($E_t[p_{t+1}]$). Drawing on Osborne (2004)'s seasonal model with weather news, we estimate a pooled model and reformulate Equation 4 as follows:

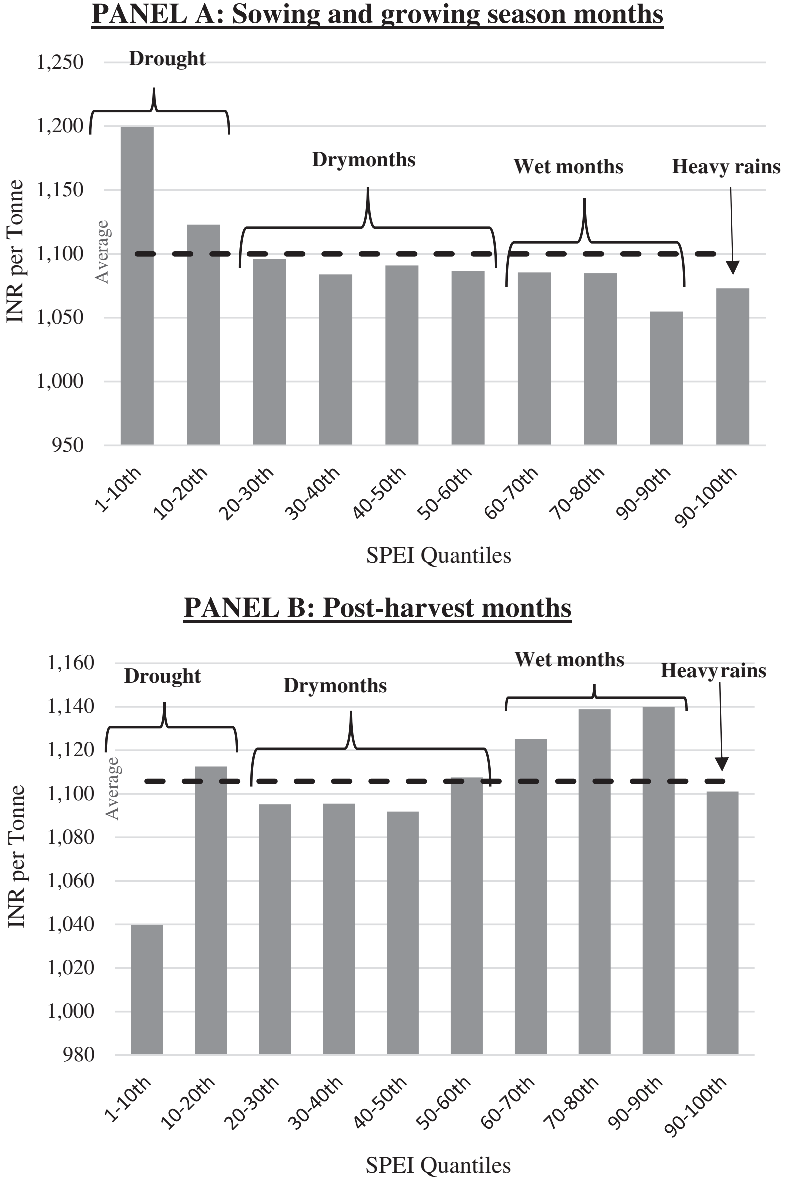

FIGURE 2 Prices under normal conditions and anomalies (SPEI). *Note:* Whole sample used in the descriptive statistics (three crops). INR stands for Indian Rupees

$$p_{cdt} = \beta_0 + \beta_1 V_{dt} + \sum_{r=1}^{4} \varphi_m + \tau_1 t_s + \tau_2 t_s^2 + \gamma t_c + \phi_d + \eta_{dt} \tag{5}$$

where p_{cdt} is the set of monthly district wholesale crop-specific prices in the pre-harvest season (which embed the effects of agents' expectations induced by weather news as proxied by weather anomalies), and V_{dt} represents the set of weather anomalies observed for each district d in month t. Weather variables are measured by the cumulative cropping-period SPEI values (alternatively in its original form, split between negative and positive SPEI values, and then split into small and large positive and negative deviations). Monthly variations of inventories, I_t, are represented by region-specific monthly seasonal cycles ($\sum_{r=1}^{4} \varphi_m$) with φ_m being a set of monthly dummies for each region r. Regions are defined here as four groups of states (eastern, northern, southern and western states).[11] These region-specific monthly seasonal cycles are included to capture the broad climatic differences that shift the production cycles across the country. In addition to the regional seasonal cycles, each specification includes state-specific quadratic time trends ($\tau_1 t_s$ and $\tau_2 t_s^2$) and a linear crop-specific time trend (γt_c) to control for MSP policy interventions as well as other general price drivers, and account for multiple time-varying confounders and gradual changes.[12] District fixed effects (ϕ_d) capture characteristics that do not change every month, such as, for instance, infrastructures and soil quality fixed effects, thus offsetting many potential sources of omitted variable bias. Time trends and district fixed effects absorb the depreciation and storage loss parameters from our structural model described in Section 3. Finally, the error term, η_{dt}, is clustered at the district level to capture heteroskedasticity.

4.2 | Food Price Reactions to Weather Anomalies

Table 3 reports the outcomes of the pooled regressions carried out with the identification strategy set out in Equation 5. The estimates show the monthly food price reactions to cumulative weather anomalies throughout the sowing and growing season, captured by cumulative SPEI during sowing and growing season months. We first look only at the entire SPEI domain (Column 1), then we separate between positive and negative SPEI spells (Column 2) to provide further details on the direction of the investigated relationship, and finally we further split positive and negative spells between small (<= the 90$^{\text{th}}$ percentile) and large (above the 90$^{\text{th}}$ percentile) ones (Column 3). The coefficients provide a quantification of the average percentage price deviation from their state-specific seasonal cycles. The absolute value of the SPEI was used for the negative shocks, to ease the interpretation of coefficient signs. Looking only at the aggregate SPEI variable in Column 1, cumulative average SPEI negatively affect food prices, with coefficient estimates significant at the 1% level. An increase in the SPEI, that is wetter weather conditions, leads to a fall in prices. Vice versa, the reaction to a decrease in SPEI$_{t,av}$, due to lower rainfall, is that of an increase in food prices in wholesale markets. More specifically, each month with a positive (or negative) cumulative SPEI deviation results in a fall (or rise)

[11]States are mapped to regions as follows: eastern India includes Assam, Bihar, Chhattisgarh, Jharkhand, Manipur, Odisha, Tripura, and West Bengal; northern India comprises Haryana, Himachal Pradesh, Jammu and Kashmir, Punjab, and Uttar Pradesh; southern India groups Andhra Pradesh, Karnataka, Kerala, Puducherry, Tamil Nadu, and Telangana; western India comprises Gujarat, Madhya Pradesh, Maharashtra, and Rajasthan.

[12]Adjemian (2012) found that the largest "announcement effect" of USDA reports, which include details such as growing season conditions, on prices are observed mainly in years when stocks are low. We acknowledge that, although we capture intra-annual cyclicality of stock levels that could drive some seasonality in prices, given the monthly frequency of our data, we are not able to capture inter-annual variations, that is, deviations of inventories from their annual cycle that might also increase price sensitivity to weather news. In addition, between September 2007 and October 2011 (resp. February 2007 and April 2012), the government of India implemented a set of export restriction measures for various crops, including the three we focus on. These measures isolated the domestic market from international commodity turmoil and increased domestic grain reserves. To capture these deviations from the typical year-to-year stock variations, we introduce a quadratic term to the state-specific trends associated with seasonal cycles.

TABLE 3 Sowing and growing season impact of cumulative weather deviations on crop prices

	Dependent variable: log of monthly price		
	(1)	(2)	(3)
$SPEI_{t,av.}$	−0.00971*** (0.00153)		
$+SPEI_{t,av.}$		0.00452 (0.00375)	
$\lvert -SPEI_{t,av.}\rvert$		0.0213*** (0.00261)	
$+SPEI_{t,av.}^{Small}$			−0.0167*** (0.00478)
$+SPEI_{t,av.}^{Large}$			0.0192*** (0.00405)
$\lvert -SPEI_{t,av.}^{Small}\rvert$			0.0158*** (0.0036)
$\lvert -SPEI_{t,av.}^{Large}\rvert$			0.0183*** (0.00272)
N	28,524	28,524	28,524
adj. R^2	0.520	0.521	0.522

Note: district-level pooled regressions including district fixed effects, State-specific quadratic time trends, crop-specific linear time trends, and region-level seasonal cycles. Standard errors clustered at the district level in parentheses.
$^*p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.

in monthly prices of about 1%. To explore possible asymmetries in price sensitivity to hot and dry spells, we break down the SPEI indicators in their positive and negative domains.[13] Results are given in Column 2. Whereas wet anomalies have a positive, but small and nonsignificant, impact on monthly food prices, drought spells (i.e., *negative* SPEI deviations) have a large, positive, and very significant impact on prices. A one-unit increase in negative SPEI results in a 2.1% price hike. By way of a further breakdown, we examine the differences in small versus large deviations of both positive and negative spells. As shown in Column 3, small and large positive deviations seem to have a varied impact: Small positive deviations (slight increases in water balance) improve cropping conditions and lead to a significant fall in prices, but large positive deviations (heavy rains/water surplus) are damaging for crops, and as one would expect, prices significantly increase in this case. Hot and dry conditions, on the other hand, are always associated with price increases, growing higher in the case of more severe drought spells.

These pooled estimates suggest that crop prices increase in reaction to droughts and extreme temperatures during the cropping period, thus mirroring the biophysical relationship between crops and rainfall. But as we focus on cumulative weather conditions during the sowing and growing season alone, when crops are still being planted and grown, and we adopt wholesale prices as our dependent variable, we argue that, because no yield effect has yet materialized, the price reactions we detect must be caused by traders anticipating upcoming supply shocks and their consequent upward pressure on prices.[14] If this is the case, then we should observe a stronger price increase effect in the last month of the growing season, when traders realize that prolonged droughts or extreme temperatures (or heavy rains) throughout the cropping period are about to determine a significant supply shortfall. This is exactly what we find: In Table 4, we give the results of the same model run only on the prices of the last month of the growing season. Point estimates suggest indeed much larger

[13]To ease interpretability, negative SPEI deviations are expressed in absolute values, so that to an increase in this variable corresponds an increase in price.
[14]Traders also likely take into consideration the levels of stock available. Specifically, if grain stocks levels are low relative to historical levels, then traders would adjust prices to a greater degree than if they were near historical averages.

impacts than in the corresponding columns of Table 3, in line with our hypothesis and theoretical model.[15]

Having discovered that expectations matter, the next question is this: To what extent? Estimates are statistically significant, but magnitudes may seem not that large. We thus need a test to gauge the magnitude of this expectation channel.

4.3 | Gauging the Magnitude of the Expectation Channel

To understand how much of the total price impact of weather shocks traders' anticipate by updating expectations, we exploit the discontinuity between the last month of the growing season and the first harvest month. Specifically, first, we pool together the prices of the last growing season month (i.e., the sample used for Table 4) and the prices of the first harvest month. Second, we amend our model by introducing a "harvest" dummy that signals if a given price refers to the harvest month or not. Finally, we interact this dummy with the growing-season weather shocks. Note that, regardless of whether the price is that of the last growing season month or that of the first harvest month, we always test the effects of *growing-season* SPEI shocks. In this way, we are able to assess the share of price impacts anticipated by the expectation channel by comparing the main SPEI coefficients with the coefficients of the interactions between the "harvest" dummy and the SPEI variables, which capture the "residual" effects of growing-season shocks on the prices of the first harvest month. Should expectations totally anticipate the price effect of the supply shortfalls, then we should observe

TABLE 4 Impact of cumulative weather anomalies on crop prices of the last growing-season month

	Dependent variable: log of monthly price		
	(1)	(2)	(3)
$SPEI_{t,av.}$	−0.0354*** (0.00350)		
$+SPEI_{t,av.}$		−0.0331*** (0.00872)	
$\|-SPEI_{t,av.}\|$		0.0375*** (0.00592)	
$+SPEI^{Small}_{t,av.}$			−0.0483*** (0.00897)
$+SPEI^{Large}_{t,av.}$			0.0240 (0.0215)
$\|-SPEI^{Small}_{t,av.}\|$			0.0341*** (0.00643)
$\|-SPEI^{Large}_{t,av.}\|$			0.0298*** (0.00769)
N	6717	6717	6717
adj. R^2	0.533	0.533	0.534

Note: district-level pooled regressions including district fixed effects, State-specific quadratic time trends, crop-specific linear time trends, and region-level seasonal cycles. The dependent variable is log(price) of the last growing-season month. Standard errors clustered at the district level in parentheses.
*$p < 0.10$. **$p < 0.05$. ***$p < 0.01$.

[15] A note of caution here regarding the interpretation of the results of Column 3, where more severe droughts appear to have a slightly smaller price-increasing effect compared to smaller negative deviations: As we are focusing on only one month and observations with negative deviations larger than 90%, we have very few observations for severe droughts in these regressions. The same applies to large positive deviations, which are insignificant here.

interacted coefficients close to zero. If, on the other hand, expectations do not matter, we would expect a much larger impact on the first harvest month. As shown in Table 5, the estimates are definitely more in line with the first hypothesis. For the sake of comparability, let us focus on negative deviations in Column 2: A back-of-the-envelope calculation, based on the values of the main and interacted coefficients, suggests that expectations account for about 85% of the total price impact of growing-season droughts. Therefore, the expectation channel anticipates a major share of the biophysical effects on production and, hence, prices that materialize at the time of the harvest.

TABLE 5 Gauging the magnitude of the expectation channel: Impacts of growing-season anomalies on the prices of the last growing season month and of the first harvest month

	Dependent variable: log of monthly price		
	(1)	(2)	(3)
$SPEI_{t,av.}$	−0.0377*** (0.00345)		
$SPEI_{t,av.}$ * Harvest	−0.00987** (0.00483)		
$+SPEI_{t,av.}$		−0.0301*** (0.00860)	
$+SPEI_{t,av.}$ * Harvest		−0.0123 (0.0107)	
$\lvert -SPEI_{t,av.} \rvert$		0.0443*** (0.00598)	
$\lvert -SPEI_{t,av.} \rvert$ * Harvest		0.00758 (0.00849)	
$+SPEI^{Small}_{t,av.}$			−0.0458*** (0.00881)
$+SPEI^{Small}_{t,av.}$ * Harvest			−0.00388 (0.0112)
$+SPEI^{Large}_{t,av.}$			0.0296 (0.0217)
$+SPEI^{Large}_{t,av.}$ * Harvest			−0.0348 (0.0262)
$\lvert -SPEI^{Small}_{t,av.} \rvert$			0.0411*** (0.00667)
$\lvert -SPEI^{Small}_{t,av.} \rvert$ * Harvest			0.0151 (0.00927)
$\lvert -SPEI^{Large}_{t,av.} \rvert$			0.0352*** (0.00719)
$\lvert -SPEI^{Large}_{t,av.} \rvert$ * Harvest			−0.00516 (0.0107)
Harvest	−0.0824*** (0.0214)	−0.0830*** (0.0214)	−0.0801*** (0.0217)
N	12,700	12,700	12,700
adj. R^2	0.487	0.487	0.488

Note: District-level pooled regressions including district fixed effects, state-specific quadratic time trends, crop-specific linear time trends, and region-level seasonal cycles. The dependent variable is log(price) either of the last growing season month or of the first harvest month. "Harvest" is a dummy taking value 1 if the price is that of the first harvest month and 0 if the price is that of the last growing season month. SPEI variables refer to the last growing-season month. Standard errors clustered at the district level in parentheses.
*$p < 0.10$. **$p < 0.05$. ***$p < 0.01$.

4.4 | Robustness Checks

We reinforce the validity of the above findings by performing three robustness checks. The first is a "common trend" test of the differential impacts of the expectation channel across drought-prone ("dry") and non-drought-prone districts. "Dry" districts are defined as those in which the average cumulative monthly SPEI across our entire timespan has a negative value. Such districts, therefore, are more often exposed to drought spells than those in which the average monthly SPEI is positive. We generate a dummy variable based on this distinction, which can be interacted with our weather indicators. The results of this test are given in Table 6. The impact of negative spells in dry districts is always stronger, particularly in the case of more severe droughts. This is consistent with the idea that a marginal and negative change in the SPEI is arguably, on average, more damaging in drought-prone (dry) districts than elsewhere, because it

TABLE 6 Drought-prone versus non-drought-prone districts

	Dependent variable: log of monthly price		
	(1)	(2)	(3)
$SPEI_{t,av.}$	−0.00501* (0.00270)		
$SPEI_{t,av.}$ * Dry	−0.00791*** (0.00290)		
$+SPEI_{t,av.}$		0.00137 (0.00521)	
$+SPEI_{t,av.}$* Dry		0.00648 (0.00617)	
$\lvert -SPEI_{t,av.}\rvert$		0.0142*** (0.00509)	
$\lvert -SPEI_{t,av.}\rvert$ * Dry		0.00938* (0.00542)	
$+SPEI^{Small}_{t,av.}$			−0.0240*** (0.00685)
$+SPEI^{Small}_{t,av.}$* Dry			0.0171** (0.00861)
$+SPEI^{Large}_{t,av.}$			0.0172*** (0.00521)
$+SPEI^{Large}_{t,av.}$* Dry			0.00346 (0.00653)
$\lvert -SPEI^{Small}_{t,av.}\rvert$			0.00877 (0.00635)
$\lvert -SPEI^{Small}_{t,av.}\rvert$* Dry			0.0109 (0.00714)
$\lvert -SPEI^{Large}_{t,av.}\rvert$			0.00618 (0.00599)
$\lvert -SPEI^{Large}_{t,av.}\rvert$* Dry			0.0151** (0.00618)
N	28,524	28,524	28,524
adj. R^2	0.521	0.521	0.522

Note: District-level pooled regressions including district fixed effects, state-specific quadratic time trends, crop-specific linear time trends, and region-level seasonal cycles. "Dry" is a dummy taking value 1 if the average within-district value of monthly SPEI is negative and 0 otherwise. Standard errors clustered at the district level in parentheses.

*$p < 0.10$. **$p < 0.05$. ***$p < 0.01$.

represents a negative change to a base level that is already very dry. Therefore, a drought in a dry district may imply going from difficult to impossible growing conditions, whereas in non-dry districts, it would only mean going from normal to difficult conditions.

The second test is a replacement of our cumulative model with a contemporaneous one. Readers may be concerned that the results we attribute to the expectation mechanism are driven by the particular cumulative construction of our weather indicators. Although the cumulative structure is a key part of our theoretical model and of the related empirical application, it is thus important to check whether there are also price effects of *contemporaneous* shocks. We therefore replace our cumulative weather indicators with their corresponding *monthly* SPEI values, and add one-month lagged values of the weather indicators to account for slightly delayed adjustment effects. The outcome of this test is given in the online supplementary Appendix, Table A.2. Contemporaneous monthly shocks do affect prices in a manner that is qualitatively analogous to our cumulative model. Impacts, however, are notably smaller, and lagged values seem to be as large as, if not larger than, contemporaneous spells, pointing to the relevance of cumulative effects.

Finally, the third test is an amended version of the baseline pooled model in which we also include crop dummies and interact them with the weather shocks. This check is important for two reasons: (i) it allows us to disentangle crop-specific effects; (ii) it can attenuate concerns about the possibility that our results are spuriously driven by on–off switches in the availability of crop-specific prices over time within districts. The estimates, reported in the online supplementary Appendix (Table A.3), confirm that drought conditions do positively affect the prices of all the three crops in our sample (Column 2). Column 3 reveals that maize and wheat are more affected by large negative deviations, rice is more sensitive to small negative deviations. This last result, though, should be interpreted with caution given the drastic loss in the sample size of crop-specific prices above the 90th percentile of the SPEI distribution.

4.5 | Placebo Test

There may also be a concern that the statistically significant associations we detect between SPEI deviations and prices are not triggered by traders' rational expectations about a forthcoming supply shortfall but rather by the disruptive damage that abnormal weather conditions might have on infrastructure and storage facilities, and by weather-related effects on crop quality and costs for drying. The simplest way to address this concern is a standard placebo test: We can check whether prices also respond to SPEI in the months outside the sowing–growing season. However, things are not so straightforward: The group of months outside the growing–sowing season also includes the *harvesting* months, during which the yield effect materializes, and that is indeed the reason why we block that channel by design and focus only on the sowing–growing season, when plants are still being grown, and weather spells cannot affect prices via yields. This implies that, because weather conditions are typically strongly autocorrelated across months, a placebo test using prices for all the months except those in the sowing–growing season would likely capture the effects due to the *yield* channel. Hence, we decided to opt for a slightly different strategy: We focus only on the "post-harvest" period—that is a four-month period between the harvest and new planting.[16] During this period of the agricultural year, for the primary crop-specific growing season on which we focus, there can be no yield channel (as plants are not being grown), no expectation channel (for the same reason), and the only potential impact of weather

[16]Because the MIRCA 2000 calendar only provides information on the cropping months, this period has been identified using the FAO Indian crop calendar (see Figure A.1 in the online supplementary Appendix), in which it is shown that, for maize, rice and wheat, there is an approximate gap of two to four months between the harvest and the new planting. We use four as a conservative upper bound. Note that the FAO crop calendar is one of the main sources used to generate the MIRCA 2000 calendar.

TABLE 7 Placebo test on post-harvest months

	Dependent variable: log of monthly price		
	(1)	(2)	(3)
$SPEI_{t,av.}$	0.00163 (0.00177)		
$+SPEI_{t,av.}$		0.000365 (0.00401)	
$\lvert -SPEI_{t,av.} \rvert$		−0.00297 (0.00359)	
$+SPEI_{t,av.}^{Small}$			−0.000750 (0.00521)
$+SPEI_{t,av.}^{Large}$			0.00155 (0.00416)
$\lvert -SPEI_{t,av.}^{Small} \rvert$			−0.00181 (0.00445)
$\lvert -SPEI_{t,av.}^{Large} \rvert$			−0.00483 (0.00404)
N	27,446	27,446	27,446
adj. R^2	0.565	0.565	0.565

Note: District-level pooled regressions including district fixed effects, state-specific quadratic time trends, crop-specific linear time trends, and region-level seasonal cycles. Standard errors clustered at the district level in parentheses.
$^{*}p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.

shocks on contemporaneous prices could be that of storage and infrastructure damage or other disruptive mechanisms.

To perform our placebo test, we thus regressed the average price during the four months before the new cropping period (our post-harvest period) over the cumulative monthly SPEI variables during the same period, using exactly the same baseline identification strategy with district fixed effects, state-specific quadratic time trends, linear crop-specific time trends, and region-level seasonal cycles. This is to check whether prolonged drought or abnormally heavy rains in the post-harvest period also affect food prices. Results are given in Table 7. Estimates are all insignificant and substantially smaller in magnitude compared to the coefficients obtained in the main specification. Importantly, for the negative SPEI coefficients, even the sign is reversed, pointing to a *price-decreasing* effect, albeit of negligible proportions, of hot and dry conditions on prices during the post-harvest months. Such evidence of no impact of post-harvest SPEI variability on post-harvest food prices allows us to be confident that the role played by storage or infrastructure is not the cause of our baseline results, and that the causal pathway of the relationships we detect points to a "true" expectation effect, that is traders' reactions to prolonged drought spells and future supply shortfalls, that affects price dynamics in wholesale markets during the cropping period and before any harvest-related effect materializes.

5 | IMPLICATIONS AND CONCLUSION

This paper presents an empirical approach to assess the impact of weather anomalies on traders' expectations and, in turn, on the price dynamics of Indian agricultural markets. By setting up a reduced empirical form drawing from the seasonal competitive storage model with cumulative news depicted by Osborne (2004), we analyze short-run price reactions to weather disruptions in Indian wholesale markets closer to producers, in a context where storage is the main hedging tool. Results from the empirical application confirm that market prices of crops in India contemporaneously react to the non-linear and asymmetric impact of unusual weather on yields. Specifically, we find that hot and dry spells lead food prices to significantly rise during the sowing and growing months, a period in which the biophysical link between crops and rain cannot exert any impact on prices in wholesale markets. We argue that this strong pre-harvest period association between drought spells and food prices is rooted in the expectation channel: Abnormally low rainfall trends are quickly picked up by traders and reflected in contemporaneous prices. In other words, traders anticipate the future supply shortfall and update their pricing and supply decisions accordingly. A placebo test shows the absence of such an effect in the post-harvest period. These findings suggest that appropriate short-run price modeling of weather events should take weather anomalies into account in the expectation function of traders.

Several caveats are necessary. First, identification concerns. Although our conceptual framework relies on a deliberately partial time structure, allowing us to block the biophysical channel by design and isolate the expectation mechanism, the latter is not the only channel that may be at work before the harvest. Although our placebo test suggests that there are no disruption effects, we may be picking up impacts from other weather-related supply shifters, such as local demand mechanisms and potential substitution effects. As for local demand shocks, we argue that such demand-driven shifts in prices are likely to take place over a period longer than the brief period on which we focus. Similarly, substitution effects are ultimately driven by demand shifts and thus take more time to unfold.

Second, our division of sowing–growing *versus* harvesting months is based on state-level crop-specific calendars. Although our identification strategy controls for seasonal cycles and differences in production across months, India is a country with vast states characterized by considerable climatic diversity. In this respect, the availability of district-specific calendars would allow us to more accurately capture district-level heterogeneity in climatic conditions and growing periods. Third, future research could consider refining the estimated price reaction through a granular identification of the role played by aspects such as local connectivity and irrigation facilities, which we do not investigate here, due to both the lack of high-resolution data and the very different transport systems and biophysical characteristics of the crops we pool in our analysis.

Fourth, the standard assumption of the competitive storage model—that farmers do not carry over inventory—is strong. However, the most relevant empirical literature highlights that farmers' decisions to sell or store grain are subject to liquidity constraints and heterogeneous price expectations. Investigating this issue in depth would require a separate and specific analysis based on a totally different theoretical framework. It is worth recalling that such a parallel investigation would not fundamentally alter the findings that pre-harvest prices are responsive to seasonal weather shocks. Possible further empirical refinements would only help to better attribute such expectation effects between farmers and traders, but would not alter the main message.

Despite these limitations, we believe that these preliminary results are a step in the right direction. Understanding how traders use weather information is essential for planning efficient policy interventions for food security and climatic risk assessments and management. In the literature on food prices and weather shocks, the emphasis is usually put only, or mostly, on the direct yield effect that materializes at the time of the harvest as a supply shock. We show here that a substantial share of this effect is already accounted for by traders when the actual yield information becomes available. Traders incorporate expectations on future supply shortfalls and react accordingly, anticipating the upward pressure on prices before the actual effect materializes. Neglecting the importance of this pre-harvest channel can thus have non-trivial repercussions on the efficacy and design of food and agricultural policies, especially in the implementation of early warning mechanisms. Specifically, policymakers should calibrate early warning systems using updated estimates of these short-run price elasticities to *nowcast* likely perturbations on market prices induced by weather anomalies in the pre-harvest season.

Our findings are supported by sound theoretical underpinnings and are in line with the well-established evidence on the key role played by market expectations in different domains of economic policy. They also complement recent literature on market anticipation of possibility future disruptive events induced by climate change losses. As such, they call for a more comprehensive investigation of the relationship between prices and weather shocks in agricultural commodity markets to shed more light on the often neglected role played by economic agents' expectations and relative implications for current policy design. In turn, this could also improve efforts to identify institutional and other marketing-related interventions aimed at reducing traders' forecast errors. These guidelines appear to be particularly valid for India, where traders play a key role in the current mandi system, and will likely become even more relevant in the near future, as the changes brought about by the new set of reforms will further enhance the importance of anticipatory channels.

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SUPPORTING INFORMATION

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