Recency Effect of Weather Shocks on Fertilizer Adoption: Evidence from Nigeria

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Abstract

Fertilizer use in sub-Saharan Africa remains below recommended levels, contributing to low yields and persistent poverty. This study investigates whether weather-induced recency bias, a tendency to overweigh recent weather events when forming expectations about future conditions, affects fertilizer use among maize farmers in Nigeria. Using nationally representative household panel data matched with geo-referenced weather and soil data, I find that recent weather shocks significantly influence fertilizer decisions, and the effect goes beyond what can be explained with a liquidity constraint. This effect is negatively asymmetric: negative shocks reduce fertilizer use, while positive shocks do not generate equivalent increases. In addition, I find that this behavioral bias explains much of the effect of previous season's weather shocks on fertilizer use, which has been mainly attributed to liquidity constraints following adverse weather conditions. These results suggest that recency effect could partly explain low fertilizer use in SSA. Improving access to accurate and timely weather forecasts can help farmers make more efficient input decisions and increase productivity.

Keywords: Recency Effect, Fertilizer, Weather Shocks, Nigeria

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1 Introduction

Low crop yields in sub-Saharan Africa (SSA) pose a significant challenge to food security. For example, maize yields in SSA (1.4 T/ha), significantly lag behind average yields for the rest of the world (5.7 T/ha) (FAOSTAT, 2021; Ray et al., 2012). A primary reason for low yields is the low use of chemical fertilizers by farmers in the region (Breman and Debrah, 2003; Vanlauwe et al., 2010; Leitner et al., 2020). For instance, the average application rate of fertilizer in SSA is just 14 kg/ha which is considerably less than the average rate in South Asia (141 kg/ha), the European Union (154 kg/ha), South America (175 kg/ha), or East Asia (302 kg/ha) (see Figure 1 for current fertilizer consumption by region) (FAOSTAT, 2021).

Many economic and agronomic explanations have been offered for low fertilizer[1]. Recently, behavioral explanations have been explored, such as time preferences, risk aversion, beliefs about soil quality, and distrust in the quality of input markets (Duflo et al., 2011; Hoel et al., 2024; Michelson et al., 2021; Bold et al., 2017; Harou and Tamim, 2024). This study explores weather-induced recency effect as an additional behavioral explanation for the low use of fertilizers in developing countries. Weather-induced recency effect is a cognitive bias that occurs when farmers' expectations about future weather are overly influenced by recent weather events (Camerer and Loewenstein, 2004; Hogarth and Einhorn, 1992; Murdock Jr, 1962). This bias can cause individuals to overemphasize recent developments and neglect historical context, resulting in inefficient input allocation (DeNisi and Pritchard, 2006; Tversky and Kahneman, 1973; Marsh, 1987).

This paper asks whether farmers' fertilizer adoption decisions are overly influenced by recent weather events and explores the implications of this behavior for agricultural productivity in SSA. This question is important for three reasons. First, fertilizer use decisions must be made before or early in the growing season, at a time when actual weather conditions are still uncertain. Without timely and reliable forecasts, farmers may form expectations about upcoming weather based primarily on recent experiences. Third, while extensive research documents the impacts of climate shocks on agricultural outputs in developing countries (see Kala et al., 2023, for a review), we have relatively little understanding of how farmers might adapt to these changes. This study helps

[1]see among others Holden and Lunduka (2014); Adjognon et al. (2017); Lambrecht et al. (2014); Quansah et al. (2001); Minten et al. (2013); Burke et al. (2017); Koussoubé and Nauges (2017); Liverpool-Tasie et al. (2017); Marenya and Barrett (2009a); Jayne et al. (2013); Marenya and Barrett (2009b); Alem et al. (2010); Harou et al. (2022).

address this knowledge gap by quantifying the role of recency bias in fertilizer adoption decisions, informing policies aimed at enhancing farmers' adaptive capacity.

Maize farming in Nigeria provides an ideal context for examining the research question for two primary reasons. First, Nigerian agriculture, including maize production, is predominantly rainfed and therefore highly sensitive to weather variability, making farmers' fertilizer adoption decisions particularly susceptible to weather-induced recency effects (Ajetomobi et al., 2015). Given Nigeria's pronounced vulnerability to climate-related impacts, farmers may disproportionately rely on recent weather events when forming expectations about future growing conditions. Second, maize ranks among the three most important cereal crops in Nigeria, along with sorghum and millet (USAID, 2010; Liverpool-Tasie et al., 2017). Therefore, low fertilizer adoption driven by uncertainty over weather conditions can substantially undermine maize yields, posing significant risks to food security and rural livelihoods in Nigeria. Using nationally representative household panel data matched with geo-referenced historical weather and soil data, I empirically test whether recent weather observations disproportionately influence households' current fertilizer-use decisions compared to more distant weather events. Furthermore, I explore how this weather-induced recency effect contributes to persistently low fertilizer adoption and its broader implications for agricultural productivity.

First, I develop a conceptual framework grounded in the farm household model (Sing et al., 1986) to isolate the behavioral impact of recent weather shocks from the profits and liquidity channels. For each household location, weather shocks are defined as deviations of the mean growing-season rainfall and maximum temperature from their respective historical 30-year averages (Maggio et al., 2022; Michler et al., 2022). To explicitly exclude liquidity constraints as a confounding mechanism, I adopt a control-function approach, predicting the previous season's maize yields (a proxy for past profits) using a machine learning model trained on climatic and soil variables. Household-level predictors, such as fertilizer use, are omitted from the maize yield prediction model because these variables are not observed for lagged years (2009, 2011, and 2014) in my panel dataset, which includes observations only for the 2010, 2012, and 2015 agricultural seasons. An advantage of machine learning models over traditional approaches is that, rather than imposing a restrictive functional form, they allow the data to flexibly capture complex and nonlinear relationships between yield and its predictors. In the main empirical analysis, I regress fertilizer use outcomes on recent weather shocks (lags of 1 to 5 years), distant weather shocks (defined as the block averages for the past 6-10, 11-15, 16-20 and 21-25 years), predicted maize yield from the previous season, market prices, and additional control variables. This econometric approach exploits the plausibly exogenous nature of weather shocks conditional on household and location-specific covariates, a method widely employed in the existing literature. Finally, I identify a 'recency effect' if coefficient(s) on recent weather shocks are statistically significant from zero, while those on distant weather shocks are not. Additionally, a joint significance test should reject the null hypothesis of zero coefficients for recent shocks but fail to reject the same hypothesis for distant shocks, reinforcing that recent weather observations disproportionately shape households' fertilizer adoption decisions even after controlling for past profits.

I find that, contrary to the conventional view that past weather shocks influence fertilizer use through liquidity constraints (e.g., Alem et al. (2010); Bora (2022); Dercon and Christiaensen (2011); Heisse and Morimoto (2024)), households' fertilizer use decisions remain significantly influenced by recent weather experiences even after controlling for past profits. Specifically, a positive rainfall shock in the previous season substantially increases fertilizer adoption[2], while rainfall shocks from the intermediate season (t-2, t-3, and t-4) do not show a significant impact. In contrast, higher rainfall deviations five years earlier unexpectedly reduce fertilizer adoption rates. Regarding fertilizer use rates, increased rainfall deviations in the immediate past (t-1) and five years ago (t-5) significantly increase current fertilizer use rates, while intermediate and more distant shocks do not have a significant effect. Temperature shocks present a slightly different pattern. Although none of the single-year lagged temperature shocks individually have strong statistical significance for the incidence of fertilizer adoption, collectively, recent temperature deviations (over the last three years) exhibit a marginally significant joint influence, suggesting farmers integrate temperature information from multiple recent seasons into their decision-making. For fertilizer use rates, temperature shocks from three years ago significantly impact current use rates, and collectively recent temperature shocks exhibit strong joint significance. These findings align with existing research highlighting farmers' behavioral responses to recent weather experiences in agricultural input decisions (Karlan et al., 2014; Huang et al., 2024; Demnitz and Joslyn, 2020; Lee, 2024; Che et al., 2020; Sesmero et al., 2018; Gallagher, 2014).

[2]The outcome variables are the binary measure of fertilizer adoption and unconditional fertilizer use rates in kg/ha

After establishing the presence of weather-induced recency bias, I examine whether its impact on fertilizer use is asymmetric, i.e., whether farmers cut fertilizer use more after bad weather than they expand it after good weather. Following Kaur (2019), I classify last season's rainfall as a negative shock (below the 25th percentile), a positive shock (above the 80th percentile), or no shock (in between), based on each location's historical rainfall distribution. I then re-estimate the fertilizer demand model using indicators for these rainfall shocks. The results show that, conditional on past profit, a negative rainfall shock significantly reduces the likelihood of fertilizer use by 7 percentage points, while a positive shock raises it by only 1 percentage point, though the latter effect is imprecisely estimated. Fertilizer application rates exhibit a similar pattern: a negative shock leads to a significant decline of 33.06 kg/ha, whereas the increase following a positive shock (19.87kg/ha) is statistically insignificant. Further heterogeneity analysis reveals that the asymmetric response is most pronounced among asset-poor households, suggesting that poorer farmers respond more pessimistically to adverse weather conditions. These results are robust to alternative shock definitions and point to a clear asymmetry: negative rainfall shocks reduce fertilizer use more than positive shocks increase it, underscoring how recency bias may contribute to persistently low input use.

Finally, I quantify the implications of weather-induced recency bias by estimating a standard fertilizer demand model widely used in the literature and comparing it to a specification that explicitly controls for liquidity constraints. Consistent with previous studies, I find that negative rainfall shocks in the previous season significantly reduce fertilizer adoption and application rates (Alem et al., 2010; Heisse and Morimoto, 2024; Bora, 2022). However, when I account for past profits and other liquidity-related pathways, the magnitude of this effect remains largely unchanged. This result suggests that behavioral responses to recent weather, rather than liquidity constraints, may explain much of the observed decrease in fertilizer use after adverse shocks, at least in my context. In other words, a sizable share of what previous studies have interpreted as liquidity-driven input underuse instead appears to reflect farmers' overreaction to recent rainfall experiences.

This paper is broadly related to existing studies that examine the effect of farmers' behavioral responses induced by climate related shocks on agricultural productivity (Lee, 2024; Huang et al., 2024; Karlan et al., 2014; Sesmero et al., 2018; Aragón et al., 2021; Maggio et al., 2022; Jagnani et al., 2021). Using field-level crop choice data from the U.S. Corn Belt states, Lee (2024) uncovers evidence that farmers' crop choice decisions exhibit a recency effect associated with local yield shocks largely driven by random weather. Among these studies, my empirical strategy is closest to that of Huang et al. (2024). In a comparable setting, the authors find that lagged positive rainfall shock leads low-productivity farmers in China to considerably reduce the area of land rented out, increase the time allocated to farm work, and decrease the time allocated to off-farm work. Although Huang et al. (2024) did not explicitly account for the associated effect of farmers' liquidity on factor allocation, they argue that this effect is fully explained by farmers' irrational response to exogenous rainfall shocks. I explore the effect of weather-induced behavioral bias on fertilizer use, while explicitly controlling for the confounding effect of liquidity constraints as a potential mechanism through which weather shocks affect fertilizer use.

This paper contributes to the literature on behavioral constraints to fertilizer adoption in developing countries by focusing on the effect of weather-induced recency. Previous studies have emphasized how behavioral factors, such as time preferences, misperceptions, and belief updating, shape fertilizer use. Duflo et al. (2011) find that Kenyan farmers have present-biased preferences: they express the willingness to buy fertilizer after harvest but do not save enough to follow through. In Tanzania, Michelson et al. (2021) show that farmers underuse fertilizer due to mistaken beliefs about its quality, and Harou and Tamim (2024) show that farmers' subjective beliefs about soil quality strongly influence their input decisions, especially when learning that their soil is more fertile than they had assumed. Although these studies reveal how static beliefs affect behavior, little is known about how farmers' dynamic beliefs, particularly about weather, shape input decisions. Building on these studies, I provide the first evidence of how weather-induced recency bias affects fertilizer use in a developing country context. By introducing this new dimension to the discussion of behavioral constraints, my study fills a critical gap and expands our understanding of the factors that hinder fertilizer adoption among farmers.

I also contribute to the literature on fertilizer use and weather shocks by demonstrating that recent weather shocks may influence fertilizer demand through mechanisms beyond liquidity constraints. Existing studies in this area have largely attributed the effects of lagged weather shocks on current input use to income or liquidity channels (Alem et al., 2010; Bora, 2022; Dercon and Christiaensen, 2011; Heisse and Morimoto, 2024). Alem et al. (2010) finds that favorable rainfall in Ethiopia increases fertilizer adoption by improving yields and, in turn, farmers' ability to purchase inputs. Similarly, Heisse and Morimoto (2024) associate extreme temperature events with reduced fertilizer use in subsequent seasons, potentially due to income effects, while acknowledging the need for deeper research into the behavioral factors influencing smallholder decisions. My study adds to this conversation by providing empirical evidence that weather-induced recency bias may also play a role, particularly in contexts where farmers form expectations about future growing conditions based on recent experiences. This perspective complements the existing literature and highlights the value of considering both financial and behavioral responses when analyzing farmers' input decisions.

The findings of this paper offer important insights for agricultural policy in rain-fed systems like Nigeria's. In the absence of accurate and timely weather forecasts, farmers can rely heavily on recent weather experiences to guide input decisions, leading to suboptimal fertilizer use. My results suggest that some of the adverse effects of past weather shocks on fertilizer adoption, commonly attributed to liquidity constraints, may instead reflect behavioral responses shaped by recent events. As such, policy interventions that focus exclusively on easing liquidity constraints may fail. Complementary strategies that improve farmers' access to reliable seasonal forecasts and provide targeted extension services can help correct misinformed expectations and support more resilient fertilizer use. This approach is especially relevant for asset-poor households, who are more sensitive to weather variability and most likely to benefit from improved weather information (Rosenzweig and Udry, 2013, 2019; Zerfu and Larson, 2010).

The remainder of the paper proceeds as follows. After laying out the conceptual model in Section 2, I describe the data sources and methodology in Section 3. In Section 4, I present the empirical framework and identification strategy. In Section 5, the main empirical results are presented, followed by a series of robustness checks and asymmetric impact analysis. Sections 6 and Sections 7 present and discuss additional implications of recency effect. Lastly, Section 8 concludes.

2 Conceptual Framework

This section develops a conceptual framework to analyze how past weather shocks influence current fertilizer adoption among households, particularly focusing on the role of the recency effect and liquidity constraints. The primary goal is to establish a testable hypothesis that allows us to

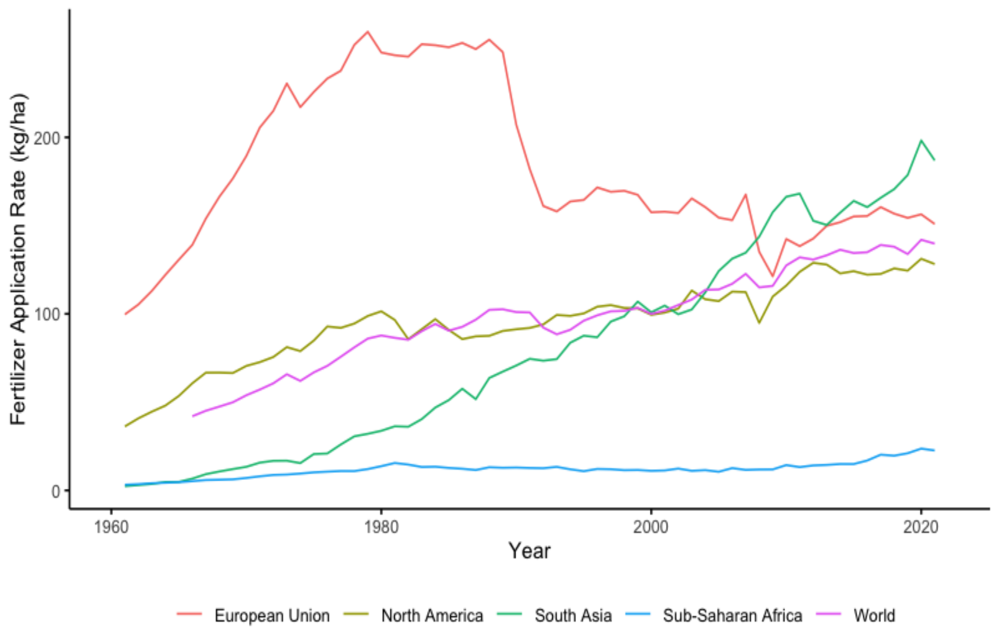


Figure 1: Fertilizer application rate (kg/ha of arable land) by region. Source: World Development Indicators (2023)

use coefficients on weather shocks to infer the presence of recency effect arising from households' observations of past weather events on their current fertilizer demand.

To conceptualize the role of the recency effect in households' fertilizer use, I consider a simple dynamic farm model with financial market failures so that households face a liquidity constraint. I start with the assumption of a risk-neutral maize farming household that seeks to maximize expected profit in the current period. Consequently, each household must decide on the input mix that maximizes household profits. Let π_t denote household's profit function at period t, household's expected profit maximization problem at the beginning of period t can be presented as follows:

$$\begin{aligned} \max_x E_t(\pi_t) &= \max_x E_t(P_t^M q_t - w_t' X_t) \text{ subject to} \\ q_t &= F(X_t; z_t) \\ w_t' X_t &\leq \pi_{t-1}^*(w_{t-1}, P_{t-1}^M; z_{t-1}) \\ X_{i,t} &\geq 0, \end{aligned} \tag{1}$$

where P_t^M is the price of maize at period t, q_t is the household's expected maize output at period

t, X_t is an Mx1 vector of inputs used to produce maize in period t, z_t is a vector of anticipated weather outcomes for growing period t, and w_t' is 1xM of input costs. I further assume that the production technology $F(*)$ is twice continuously differentiable concave production function in inputs and weather variables for maize crop. The third equation sets a borrowing constraint on the acquisition of inputs in the current season. That is, household's current expenditure on inputs should not exceed last season's profit π_{t-1}^*. This borrowing constraint reflects the financial market failures prevalent in developing countries, where imperfect rural credit markets prevent households from borrowing to invest in inputs due to liquidity constraints and high transaction costs (Croppenstedt et al., 2003; Conning and Udry, 2007). Consequently, households must rely on past profits to finance current input expenditures. Lastly, line four sets a non-negativity constraint on the input used. For simplicity and tractability, I assume the household's only variable input in equation (1) is fertilizer (X) which has a price w_t.

Given an interior solution, the first order necessary condition to equation (1) with respect to fertilizer gives:

$$E_t\left[P_t^M \frac{\partial F(.)}{\partial x_t} - w_t\right] - \lambda w_t = 0 \tag{2}$$

where λ denotes the Lagrange multiplier. The solution to equation (2) yields the reduced-form optimal fertilizer demand function at the beginning of period t as:

$$X_t^* = f[E_t(P_t^M), E_t(w_t), \pi_{t-1}^*(w_{t-1}, P_{t-1}^M; z_{t-1}); E_t(z_t)] \tag{3}$$

Thus, by equation (3), the household will choose the fertilizer level X_t^* that maximizes his expected contemporaneous profit. It is worth noting that from equation (3), household's optimal fertilizer level at the beginning of the planting period is a function of expected maize price, expected weather outcome, expected fertilizer price and last season's profit. The expected maize price, expected fertilizer price and expected weather outcome are the only uncertain variables that determine household fertilizer demand. Since the household is a price taker in the maize and fertilizer market (i.e, $E_t(P_t^M) = P_t^M$ and $E_t(w_t) = w_t$), a belief about the current season's expected weather observation is sufficient for a belief about current season's optimal fertilizer demand.

There is empirical support for the idea that farmers form beliefs about weather expectations based on adaptive expectations. Previous research indicates that farmers react to biophysical events and patterns, such as local climate and weather, over both short and long terms, which in turn influences production decisions (Nerlove, 1958; Morton et al., 2017). Although in a different context, Wilke and Morton (2017) show that farmers in the Mid-western US base their future climate and weather expectations on references to past historical events and cycles. Therefore, following Ramsey et al. (2021), I consider a process whereby households form beliefs about current season's weather based on past seasons as follows:

$$E_t[z_t] = S(p_l; z_{t-1}, z_{t-2}, \ldots, z_{t-L}); l = 1, 2, \ldots, L \tag{4}$$

where p_l is the weight that the household assigns to previous weather observations and $S(*)$ is a weighting function.

In forming perceptions about current weather, households are likely to generalize distant past observations, a simplification strategy rooted in cognitive ease (Kahneman, 2011). This approach would be consistent with the psychological principle of recency effect, wherein recent memories are more vivid while earlier ones tend to decay over time (Murdock Jr, 1962; Ebbinghaus, 2013). Consequently, I assume that the weight assigned to past weather observation stabilizes after period $t-b$, such that from $t-(b+1)$ onward, the household assign equal weights on weather observations (i.e., $p_{b+1} = p_{b+2} = \cdots = p_L = p^a$). As an example, Figure 2 shows how a typical household's assigned weight to past weather observations could stabilize from starting period $t-(b+1)$.

Thus I can simplify equation (4) as:

$$E_t[z_t] = p_l S(z_{t-1}, z_{t-2}, \ldots, z_{t-b}) + p^a S(z_{t-(b+1)}, \ldots, z_{t-L}); l = 1, \ldots, b \tag{5}$$

where p_l is household's weight assigned to the recent past time periods $t-1$ to $t-b$ and p^a is the equal weight assigned to the more distant past up to time horizon L. Thus, I expect the weight a household places on past weather observation to be monotonically increasing in time t.

The weight placed on past events will depend on factors such as cognitive processes, level of ambiguity, and other considerations (Hogarth and Einhorn, 1990). For instance, a household might respond sensitively to a higher-than-normal rainfall intensity last season, if the farmer considers it

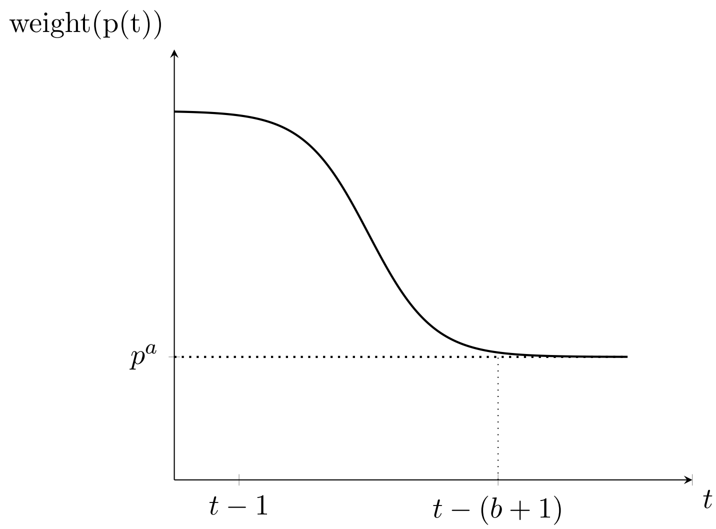


Figure 2: Illustration of How Households May Assign Weights to Past Weather Observations
Note: The figure depicts how households may assign weights to past weather observations when forming expectations about current weather conditions. The horizontal axis indicates time periods relative to the current period t, while the vertical axis shows the weight $p(t)$ assigned to each past period's weather outcome. The curve demonstrates that households place larger weights on recent weather observations ($t-1$ to $t-b$) and that the weights decrease and stabilize at a constant value p^a for more distant past periods ($t-(b+1)$ to $t-L$).

as a signal of larger rainfall occurring this season or consider it as a signal of lower-than-normal rainfall occurring. Household's current weather expectation would be fully informed by the previous season's weather if it places larger weight on previous weather events. Instead, household would be free of recency bias if they put equal weights on past seasons weather observations. In this case, last season's weather shock would have little impact on the household's expectations for this season's weather, which would instead be based on the full historical weather distribution at that site.

Returning to the household's objective, I substitute equation (5) into equation (3) to have the optimal fertilizer demand function as;

$$X_t^* = f\left(P_t^M, w_t, \pi_{t-1}^*(w_{t-1}, P_{t-1}^M, z_{t-1}), E_t[z_t] = S(p_l; z_{t-1}, \dots, z_{t-L})\right); l = 1, 2, \dots, L \qquad (6)$$

Here, the model in equation (6) is to be viewed as illustrative rather than assertive. To understand the total effect of previous weather shock $(t-1)$ on fertilizer demand, I partially differentiate equation (6) w.r.t last season's weather outcome as:

$$
\begin{aligned}
\frac{\partial X_t^*}{\partial z_{t-1}} &= \frac{\partial f(*)}{\partial E_t[z_t]} \cdot \frac{\partial E_t[z_t]}{\partial z_{t-1}} + \frac{\partial f(*)}{\partial \pi_{t-1}^*} \cdot \frac{\partial \pi_{t-1}^*}{\partial z_{t-1}} \\
&= \underbrace{p_1 S'(p_l; z_{t-1}, \ldots, z_{t-L})}_{\text{Recency Effect}} + \underbrace{\frac{\partial f(*)}{\partial \pi_{t-1}^*} \cdot \frac{\partial \pi_{t-1}^*}{\partial z_{t-1}}}_{\text{Liquidity Effect}}
\end{aligned} \tag{7}
$$

Thus, from equation (7) I decompose the effect of recent past weather shocks on fertilizer demand into two components: the first component from recency bias ($p_1 S'(*)$), and the second component stems from how weather shocks influence households' current fertilizer demand through past farm profit ($\frac{\partial f(*)}{\partial \pi_{t-1}^*} \cdot \frac{\partial \pi_{t-1}^*}{\partial z_{t-1}}$).

Weather-induced recency effects on fertilizer adoption could operate through two possible channels. First, recency could amplify the effect of liquidity constraints stemming from the previous season's weather; that is, negative weather shocks in the prior season could signal the likelihood of similar adverse conditions in the current season, leading farmers to reduce fertilizer application even further beyond what liquidity constraints alone would suggest. Second, recency could partially or fully offset the liquidity effect if farmers interpret recent negative shocks as temporary and anticipate a subsequent return to normal conditions, thus choosing to maintain or even increase fertilizer use despite immediate liquidity constraints. The direction and magnitude of the recency effect (p_1) depend on whether farmers perceive recent weather outcomes as predictive of future conditions, either positively or negatively.

Economic theory suggests that fertilizer, being a normal good, should exhibit increased (decreased) demand following good (bad) weather in the previous season due to the corresponding liquidity changes. Although there is empirical support for this (e.g. Alem et al. (2010)), evidence from some studies also suggests that this may not always be the case. In particular, Rosenzweig and Udry (2013) finds evidence from India showing that while rainfall positively impacts crop profits, these higher profits do not significantly affect input decisions in the following season. These findings highlight that the relationship between weather shocks, recency, and liquidity effects on fertilizer use is nuanced, context-specific, and influenced by how farmers interpret recent weather events in shaping their expectations.

It is also important to note that recency bias can affect fertilizer demand asymmetrically depending on whether past weather shocks were favorable or unfavorable. Specifically, a negative weather shock in the previous season can lead households to substantially lower their expectations of returns from fertilizer use, leading to a significant reduction in fertilizer adoption during the current season. In contrast, a positive weather shock might not induce a proportionally equivalent increase in fertilizer use. This asymmetry could be due to behavioral factors such as procrastination, particularly between harvest and the next planting period, which can delay input purchases despite positive liquidity shocks from higher yields (Duflo et al., 2011).

2.1 Implications for Empirical Analysis

The conceptual model described in equation (6) provides a foundation to formulate testable hypotheses to determine the presence of weather-induced recency effects. Although the specific weights (p_i) farmers assign to past weather outcomes when forming expectations about the current season's weather are not directly observable, I test the presence of recency effect based on the observed regression coefficients derived from estimating equation (6). If recency effect is present, conditional on past profit, the regression coefficient(s) associated with recent weather shocks should be statistically significant, whereas those related to more distant weather shocks are not statistically different from zero. In contrast, the absence of a recency effect would imply a uniform impact on all past weather shocks, recent and distant, with no clear difference in their statistical significance.

This approach will enable me to isolate and quantify the behavioral component, recency effect, different from the liquidity constraints embedded in the fertilizer adoption decisions of households. I discuss the empirical strategy in detail in Section 4.

3 Data and Variable Definitions

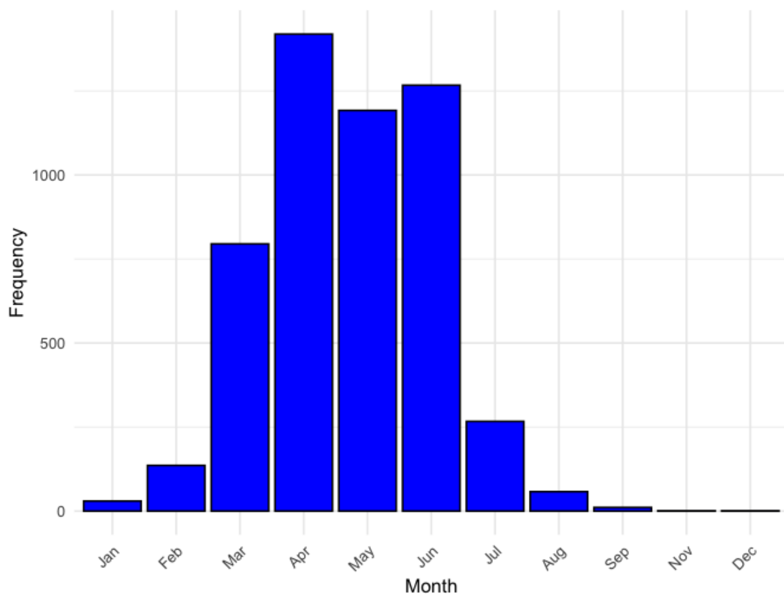
I use household-level data from the first three waves (2010, 2012, 2015) of the Nigeria Living Standards Measurement Study-Integrated Survey on Agriculture (LSMS-ISA), managed by the World Bank, the National Bureau of Statistics (NBS), and the Federal Government of Nigeria (FGN). This dataset includes urban and rural areas across all thirty-six states and the Federal Capital Territory, covering 5000 households in the first wave. The data is nationally representative, reflecting the diverse demographics and geopolitical zones of Nigeria. The LSMS-ISA provides geo-referenced plot details and comprehensive information on input use, cultivation practices, and agricultural output, collected over two visits per household per survey cycle. The first visit, which covers post-planting activities, occurs between August and October, while the second visit, covering post-harvest activities, takes place between February and April. For this research, I construct variables of interest based on information collected during the main planting season.

Second, I merge household-level data with historical rainfall and temperature data at the local government area (LGA) level. The rainfall analysis uses daily precipitation datasets from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) for the period 1981 to 2016 (Funk et al., 2015). CHIRPS combines 0.05 degree resolution satellite imagery with *in situ* station data to generate gridded rainfall time series that support trend analysis and seasonal drought monitoring. Similarly, I also use monthly maximum temperature data from the WorldClim version 2.0 database (Fick and Hijmans, 2017), which spans 1980 to 2016. WorldClim 2.0 offers global climate datasets with a fine spatial resolution of 2.5 arc minutes—approximately 21 km^2—at the equator derived from weather station data and satellite observations.

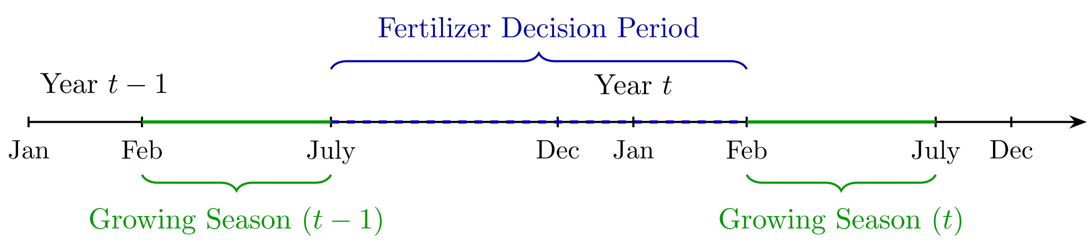
Although climatological studies suggest that Nigeria's maize growing season spans from March or May to September or October, depending on the agro-ecological region (Odekunle, 2004), I adopt the definition by Aragón et al. (2021) and Mayorga et al. (2025), identifying the growing season as the six-month period in which most of the planting occurs. Even though maize planting is a season-round activity (Figure 3), it is particularly concentrated between February and July, so I define the growing season by these months.

The final sample includes only household-wave units that meet two criteria. First, the household reports a non-zero amount of maize harvested during the main growing season. Second, the area of the maize plot is non-zero. Hence, I exclude all household-wave observations with zero maize harvest and plot area. I use GPS-measured areas for all maize plots to mitigate the effects of measurement error. However, when GPS data are not available, the farmer's self-reported plot area is used. Finally, I have an unbalanced panel of 1,640 unique households and 2,843 household-wave observations. This subset represents about 35% of all farm household-wave observations and more than 60% of the plots within the study sample. Although the results may not be nationally representative, they can be considered representative of the main agricultural system for maize production in Nigeria.

I present the summary statistics of the variables that enter my estimation model in Table



(a) Monthly Distribution of Maize Planting in Nigeria



(b) Growing Seasons and Fertilizer Decision Period

Figure 3: Maize Planting, Weather Shocks and Fertilizer Decision Timeline

Notes: The bar plot in panel (a) illustrates the frequency of maize planting activities across different months in Nigeria in my sample. In Panel (b), the green indicators represent the maize growing seasons, while the blue indicator marks the decision period between the end of the previous season and the start of the current season, during which households decide whether to use fertilizer based on the prior season's weather outcomes.

1. The average area dedicated to maize cultivation is 0.43ha, suggesting that maize farming is mostly dominated by smallholders. Approximately 54% of the households engaged hired labor for their maize cultivation, indicating a significant reliance on external labor resources beyond family labor. Regarding cropping practices, the study data indicates that 22% of the household maize farm were used exclusively for maize cultivation, which implies no inter-cropping. This means that approximately 78% of the maize farms were involved in inter-cropping with other crops. This prevalence of inter-cropping underscores the diversification strategies employed by farmers in my sample.

3.1 Fertilizer Use Outcomes

In this study, I examine two primary outcome variables related to fertilizer use among maize farming households. The first variable, household fertilizer use rate (intensive margin), is constructed by aggregating the amount of fertilizer (specifically NPK and Urea) applied per hectare across all maize plots (including zero values) by the household during the main growing season. Data on fertilizer usage are derived from survey questionnaires in all waves, which record the quantity of various fertilizers used on each maize plot. For each maize plot, the amount of fertilizer used is divided by the GPS-measured plot area to estimate the fertilizer application rate per hectare. To mitigate the influence of extreme values, I winsorize fertilizer use rate at the 99th percentile by replacing observations larger than the 99th percentile with value at the 99th percentile. In instances where the estimated fertilizer use rate exceeds 1 ton per hectare, I cap the value at 700 kg/ha, consistent with the methods employed by Liverpool-Tasie et al. (2017) and Sheahan et al. (2014). Subsequently, I define the second outcome variable, fertilizer adoption (extensive margin), as a dummy variable coded as 1 if the aggregate use of fertilizers at the household level is positive, indicating adoption, and 0 otherwise.

Table 1 shows that 52% of the households use fertilizer on their maize farm during the main growing season. However, the mean unconditional fertilizer application rate in the households surveyed is 188.30 kg / ha, with a standard deviation of 269.14 kg/ha, indicating significant variability in the intensity of fertilizer use in my sample.

Table 1: Summary Statistics of Key Variables

Dependent Variables	Mean	St. Dev	Min	Max
Unconditional Fertilizer Use (kg/ha)	188.30	269.14	0.00	987.24
Fertilizer Adoption (1/0)	0.52	0.50	0.00	1.00
Independent Variables				
Growing Season Mean Rainfall Deviation (mm)	-0.02	0.17	-0.99	1.00
Growing Season Max Temp. Deviation (°C)	0.36	0.37	-0.85	1.51
Male Household Head (1=Male, 0=Female)	0.88	0.32	0.00	1.00
Household Size (Adult Equivalence Unit)	4.36	2.07	1.00	25.90
HH Head Education (years)	4.54	5.04	0.00	18.00
Area of Maize Plot (hectares)	0.43	0.37	0.01	1.74
Maize Yield (kg/ha)	1857.43	1674.14	10.99	10037.41
Maize Price (Naira/kg)	86.29	32.93	10.00	250.00
Fertilizer Price (Naira/kg)	76.71	16.45	23.33	150.00
Hired Labor (1=Yes, 0=No)	0.54	0.49	0.00	1.00
Value of Household Assets Owned (000' Naira)	33.60	30.32	0.05	180.25
No other crop planted (1=Yes, 0=No)	0.22	0.41	0.00	1.00
Chicken ownership (1=Yes, 0=No)	0.87	0.33	0.00	1.00
Cattle ownership (1=Yes, 0=No)	0.79	0.40	0.00	1.00
Small livestock ownership (1=Yes, 0=No)	0.87	0.33	0.00	1.00
Free fertilizer (1=Yes, 0=No)	0.02	0.13	0.00	1.00
Access to credit (1=Yes, 0=No)	0.23	0.43	0.00	1.00
HH distance to population center w/ 20000+ people (km)	27.59	19.93	0.10	101.50
Plot Slope (%)	3.10	2.72	0.00	40.40
Plot Elevation (mm)	377.38	268.17	10.00	1427.00
N	2,843			

Source:Authors' calculation using LSMS-ISA data (2010, 2012 and 2015). All prices and monetary values are adjusted to 2010 constant prices using the CPI from World Bank.

3.2 Weather Shock Variables

Building on my conceptual model, I construct weather shocks based on the deviations of the average rainfall of the growing season and the maximum temperature from the site-specific mean over time. Specifically, this is calculated as the difference between the average rainfall (maximum temperature) during the growing season in the year y of the survey, with $y = 2010, 2012, 2015$, and the historical mean of the same season in the local government area of the household, where the historical mean refers to the period [1981,y-1]. In Uganda, Maggio et al. (2022) used similar rainfall and temperature deviations to examine the relationship between high temperatures, total value of crop production, and the adoption of sustainable practices among farmers. In Figure 4, I show the spatial and temporal distribution of growing-season weather shock deviations across maize-growing LGAs in Nigeria. The figure suggests that there exist some variations in the deviations of the weather shocks over time and space. As expected, locations in northern parts experience negative rainfall deviations coupled with positive maximum temperature deviations during the growing season.

A commonly used stylized fact in the literature is that the year-to-year (season-to-season) variation in weather is exogenous (Kaur, 2019; Paxson, 1992; Miguel et al., 2004; Kazianga and Udry, 2006) and does not provide useful information about weather for the subsequent growing season. To formally assess the plausibility of this assumption in my setting, for each LGA, I estimate the following regression: $Y_{d,t} = \lambda_s + \lambda_r Y_{d,t-1} + e_t$, where Y_d is the average deviation of rainfall or the maximum deviation of temperature during the growing season in LGA d. I then test the null hypothesis $H_0 \lambda_r = 0$ against the alternative hypothesis $H_1 : \lambda_r \neq 0$. Table 2 shows the proportion of LGA for which the null hypothesis H_0 is rejected in favor of H_1 at 1% significance level. As the table indicates, for most LGAs, the null hypothesis is not rejected, providing suggestive evidence that weather shocks during the growing season are random from year to year.

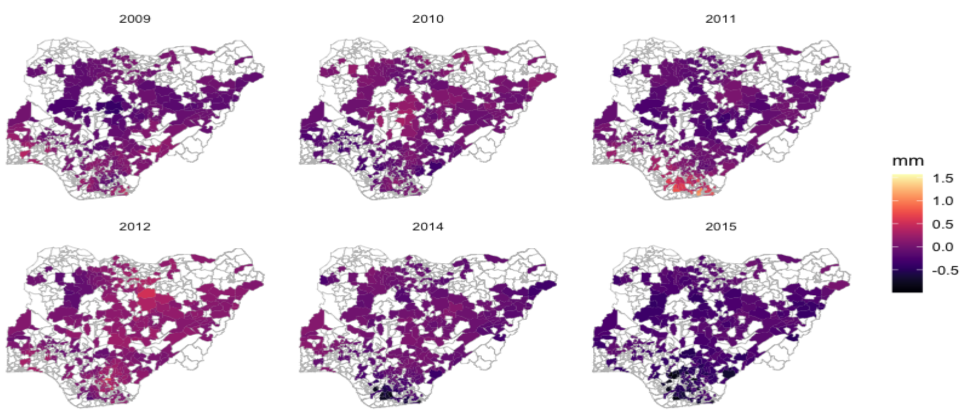
3.3 Maize Yield Prediction

To accurately isolate the recency effect of weather shocks on fertilizer demand, as outlined in equation (6), it is important to control for previous season's profits. However, LSMS-ISA data do not provide household-level profit information for previous non-surveyed seasons (2009, 2011, and

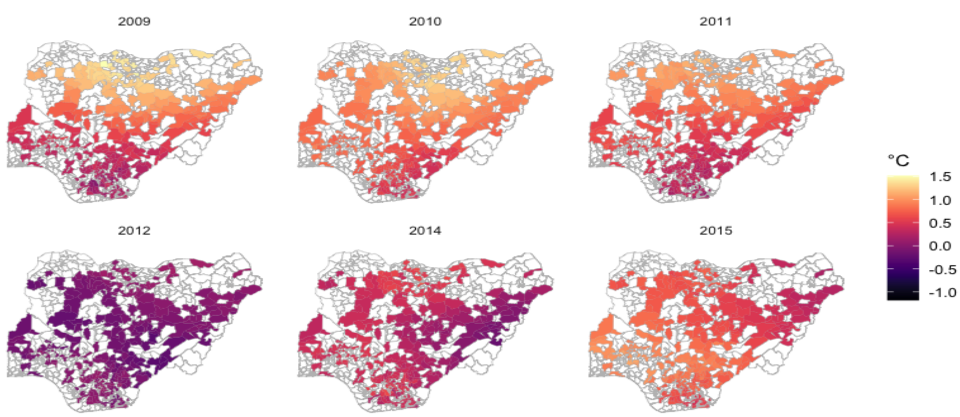
Table 2: Test for Serial Correlations of Weather Shocks

Weather Shock	**Proportion**
Average Rainfall Deviation	0.023
Maximum Temperature Deviation	0.003

Note: This table displays the proportion of LGAs where the null hypothesis $H_0 : \lambda_r = 0$ is rejected at the 1% significance level in the regression $Y_{d,t} = \lambda_s + \lambda_r Y_{d,t-1} + e_t$, where Y_d represents either the average rainfall deviation or the maximum temperature deviation during the growing season in LGA d.



(a) Average growing season rainfall deviation across LGA and season



(b) Growing season maximum temperature deviation across LGA and season

Figure 4: Spatial distribution of growing season weather shock deviations across maize-growing LGAs in Nigeria, spanning both lagged and observed seasons. (a) Average growing season rainfall deviation across LGA and season (b) Growing-season maximum temperature deviation across LGA and season

2014).[3] To overcome this data gap, I employ machine learning (ML) techniques to predict maize yield in these unsurveyed years, using climate and soil variables that are consistently available from geospatial sources. This predicted maize yield then serves as a proxy for the previous season's profit, thus addressing this data gap. In the following, I detail the procedure for training and implementing the ML models.

Recent advances in data science have substantially expanded the use of machine learning (ML) for predicting crop yields (Van Klompenburg et al., 2020). An advantage of ML methods in yield prediction is their high predictive accuracy, primarily because they are data-driven and do not rely on restrictive assumptions about the functional form imposed by researchers. Unlike traditional regression-based approaches, ML models can flexibly capture complex and nonlinear relationships between yields and their predictors (Athey and Imbens, 2019; Mullainathan and Spiess, 2017). Additionally, ML methods leverage hyper-parameter tuning through techniques such as grid search, further enhancing their predictive power and robustness, particularly when the precise functional form linking predictors to yields is unknown or ambiguous (Athey and Imbens, 2019; Van Klompenburg et al., 2020; Mullainathan and Spiess, 2017). While standard yield prediction models typically incorporate detailed plot-level climate, soil, and field management variables, the unavailability of household and field management data in my setting requires one to rely solely on climate and soil data for yield prediction. Although omitting management practices may slightly reduce predictive performance, given their importance in yield determination (Van Klompenburg et al., 2020), geospatially available soil and climate data offer a practical alternative for yield prediction in my setting.

The climate variables used in the model include total seasonal rainfall, rainfall in the previous season, and average maximum daily temperature during the current and previous seasons. Soil variables includes soil cation exchange capacity, soil pH, soil organic carbon, soil nitrogen content, soil texture (proportion of silt and clay), bulk density and soil potential wetness index. These soil characteristics are extracted from the high resolution SoilGrids250m 2.0 dataset provided by ISRIC-World Soil Information (ISRIC, 2023). In addition, site characteristics such as GPS coordinates (latitude and longitude), elevation, slope percentage, and normalized difference vegetation index

[3]Household-level survey data are only available for the years 2010, 2012, and 2015.

(NDVI) are included during the first five months of the growing season[4] Appendix Table B.1 presents summary statistics for all predictor and response variables.

Following Villacis et al. (2023), I optimize the hyper-parameters of the ML models through a rigorous validation procedure, which evaluates model error rates across repeated subsamples. Specifically, data from the three available LSMS-ISA survey waves (2010, 2012, and 2015) are randomly partitioned into a training set (80%) and a test set (20%). Within the training set, I implement ten-fold cross-validation, where the data are divided into ten subsets, with each subset serving as a validation set once, while the remaining subsets are used for model training. The results of these iterations are averaged, providing robust metrics for selecting optimal hyperparameter configurations (James et al., 2013). Subsequently, the finalized models are evaluated on the independent 20% testing sample. To enhance robustness, I predict maize yields in both levels and logarithmic forms, given the potential of log-transformation to improve prediction accuracy by compressing distributional spread. Hyper-parameter tuning ranges are detailed in Appendix Table B.2.

I train and compare three widely used machine learning algorithms known for their robust predictive performance in regression tasks: Random Forest (RF), eXtreme Gradient Boosting (XGB), and Artificial Neural Networks (ANN) (Athey and Imbens, 2019). The predictive accuracy of each model is evaluated using root mean square error (RMSE), normalized root mean square error (NRMSE), and mean absolute error (MAE), with lower values indicating superior predictive accuracy. Results presented in Table 3 show that while all three algorithms perform well, the XGB model consistently delivers the highest predictive accuracy, particularly when predicting log-transformed maize yields. Consequently, I adopt the XGB model (log-form) as my preferred method for predicting maize yields in the non-surveyed lagged seasons. In addition, in the empirical section, I perform additional diagnostics to verify that the model fully captures the relationship between maize yields and the underlying soil and climatic factors. Appendix Figure A.1 provides further insight by illustrating the relative importance of each predictor variable within the selected XGB model.

In summary, the methodology adopted involves: (1) training the ML models on climate, soil

[4] GPS coordinates, elevation, and slope data are extracted from LSMS-ISA, while NDVI data come from NASA's MOD13A2 Version 6 dataset (Didan, 2015).

and observed maize yield data from available survey years (2010, 2012, and 2015), (2) using the preferred ML model (log-form XGB) to predict maize yield for unsurveyed years (2009, 2011, and 2014), and (3) employing this predicted maize yield as a proxy for previous season's profit in the empirical analysis specified in equation 9.

Table 3: Comparison of Model Performance in Predicting Maize Yield

Response Variable	Model	Model Validation			Model Testing		
		(80% training sample)			(20% held-out sample)		
		RMSE	MAE	NRMSE (%)	RMSE	MAE	NRMSE (%)
1. Maize Yield (kg/ha)	RF	941.80	718.44	18.79	1098.34	840.14	22.18
	XGB	1020.92	782.76	20.37	1080.10	831.49	21.81
	ANN	1107.34	851.69	22.10	1113.43	864.61	22.48
2. Log of Maize Yield	RF	0.75	0.57	14.75	0.87	0.66	17.26
	XGB	0.80	0.60	15.64	0.86	0.66	17.21
	ANN	0.91	0.70	17.83	0.92	0.72	18.37

Note: RF = Random Forest, XGB = XGBoost, ANN = Artificial Neural Network. RMSE (Root Mean Squared Error) measures the average squared difference between the predicted and observed values, MAE (Mean Absolute Error) measures the average absolute difference, and NRMSE (%) (Normalized RMSE) expresses RMSE as a percentage of the observed mean. Model validation is performed on an 80% training subset, while model testing uses the remaining 20% held-out sample. A lower RMSE, MAE, or NRMSE indicates better predictive performance.

3.4 Additional Controls for Household Liquidity and Asset Pathways

Households facing limited cash on hand at planting can often turn to alternative liquidity sources or convert assets—especially poultry, goats, sheep, or cattle—into cash needed to purchase inputs such as fertilizer (Alem et al., 2010; Dercon and Christiaensen, 2011). Other evidence underscores how credit access and in-kind assistance (e.g., subsidized fertilizer) alleviate households' financial constraints (Croppenstedt et al., 2003; Melkani et al., 2024), potentially stabilizing or even increasing fertilizer application after a poor season. For example, in Ethiopia, Alem et al. (2010) show that oxen ownership strengthens the link between high rainfall in the previous season and the current season's fertilizer use. These studies suggest that multiple liquidity channels—ranging from asset liquidation to formal or subsidized programs—can buffer the negative effects of adverse past weather events on fertilizer investments.

Therefore, I build on the approaches of Kusunose et al. (2020) and Melkani et al. (2024), leveraging LSMS-ISA data to capture multiple liquidity pathways. Specifically, I include dummies for poultry ownership, cattle ownership, and small livestock ownership (pigs, sheep, or goats), an indicator for credit access at the start of the year (i.e., use of any formal financial service) and a dummy for receiving free fertilizer—a proxy for access to the national fertilizer subsidy program. By explicitly modeling these liquidity channels, I can isolate the behavioral effect of prior-season rainfall shocks (via recency bias) from the mitigating influence of assets and credit. Although the predicted maize yield for previous season serves as a proxy for past profit, these additional controls address broader liquidity mechanisms that might otherwise confound estimates of the recency effect.

3.5 Fertilizer and Maize Prices

Using farmer-reported quantities of purchased fertilizer, I derive unit values for each household and agricultural season. To mitigate unit value bias in fertilizer purchase prices—which may arise from 'fertilizer-loving' households purchasing larger quantities—I calculate the median value of fertilizer across households within the same geographic area and agricultural season. With this approach, households within the same enumeration area face similar market prices at any given time. In instances where fewer than three observations are available at the enumeration area level, the missing price is imputed using the median price from a progressively larger administrative area, first the local government area, then the state, and finally the zone.

I used the methods described above to derive the market price of maize for each household at the enumeration area level, utilizing data from the community questionnaire. The questionnaire records the unit price of maize for each enumeration area during the survey period. When multiple unit prices are reported within the same enumeration area, I compute the mean of these prices to establish a representative unit price for maize in the enumeration area.

4 Empirical Framework

Building on the conceptual framework, I empirically examine how recent growing-season weather realizations influence households' current fertilizer use decisions, beyond the effects of liquidity constraints. To do so, I estimate a reduced-form fertilizer demand model (equation 6), derived from a Cobb-Douglas production function, following the empirical approaches of Aragón et al. (2021) and Dillon and Barrett (2017).

Since households' beliefs regarding current season weather conditions are unobserved, I approximate their expectation formation using a flexible linear weighting approach of past weather realizations (Nerlove, 1958). Specifically, households are assumed to formulate expectations as:

$$E_t[z_t] = p_1 z_{t-1} + p_2 z_{t-2} + \cdots + p_L z_{t-L} \tag{8}$$

where each p_l denotes the (unobserved) weight assigned to previous weather outcomes from l seasons ago. Given data constraints, I operationalize this approach by including separate lagged seasonal rainfall and temperature shocks, capturing both recent (1–5 years) and distant (block moving averages of 6–10, 11–15, 16–20, and 21–25 years) weather events. Thus, the empirical fertilizer demand function is specified as:

$$\begin{aligned} X^*_{idt} = &\sum_{k=1}^{5} \beta_k \, R_{dt-k} + \beta_m \, \overline{R}_{dt_{6:10}} + \beta_n \, \overline{R}_{dt_{11:15}} + \beta_s \, \overline{R}_{dt_{16:20}} + \beta_v \, \overline{R}_{dt_{21:25}} \\ &+ \sum_{k=1}^{5} \theta_k \, T_{dt-k} + \theta_m \, \overline{T}_{dt_{6:10}} + \theta_n \, \overline{T}_{dt_{11:15}} + \theta_s \, \overline{T}_{dt_{16:20}} + \theta_v \, \overline{T}_{dt_{21:25}} \\ &+ \delta \, \hat{\pi}_{idt-1} + \mathbf{D'}_{idt} \, \Gamma + \gamma_t + \varepsilon_{idt}. \end{aligned} \tag{9}$$

The dependent variable X^*_{idt} is either a binary indicator of fertilizer adoption (extensive margin) or a continuous measure of fertilizer application rates (intensive margin) for household i in LGA d and period t. The key explanatory variables are lagged growing-season weather deviations: R_{dt-k} and T_{dt-k} represent deviations of rainfall and maximum temperature, respectively, from their long-term (30-year) seasonal averages, lagged by $k = 1, \ldots, 5$ years. To capture more distant weather history, $\overline{R}_{dt_{6:10}}$ and $\overline{T}_{dt_{6:10}}$ denote the average growing-season rainfall and temperature deviations over the past 6–10 year lag window, respectively. Similarly, $\overline{R}_{dt_{11:15}}$ and $\overline{T}_{dt_{11:15}}$, $\overline{R}_{dt_{16:20}}$ and $\overline{T}_{dt_{16:20}}$, and $\overline{R}_{dt_{21:25}}$ and $\overline{T}_{dt_{21:25}}$ correspond to moving averages of rainfall and temperature deviations for the past 11–15, 16–20, and 21–25 year lag periods, respectively.

I include $\hat{\pi}_{idt-1}$, the log of predicted maize yield for the previous season (discussed in Section 3.3), to proxy for last season's profits. The vector $\mathbf{D'}_{idt}$ includes the market prices for maize and fertilizer, as well as variables that control for other liquidity channels, such as indicators for poultry ownership, cattle ownership, small livestock ownership (pigs, sheep, or goats), credit access at the beginning of the season (i.e., use of any formal financial service), receipt of free fertilizer vouchers (Melkani et al., 2024; Kusunose et al., 2020) —proxy for access to the national fertilizer subsidy program —and additional household-level controls[5]. The model includes season fixed effects γ_t to control for common shocks in a given season, and ε_{idt} is the idiosyncratic error term. Standard errors are clustered at the enumeration area level to account for the potential correlation of errors within the enumeration areas.

The coefficients β_k for $k = 1, \ldots, 5$ and θ_k for $k = 1, \ldots, 5$ capture the effects of recent growing-season rainfall and temperature deviations, respectively, on fertilizer use decisions. The coefficients $\beta_m, \beta_n, \beta_s, \beta_v$ and $\theta_m, \theta_n, \theta_s, \theta_v$ measure the influence of more distant weather shocks, averaged over the past 6–10, 11–15, 16–20, and 21–25 years. δ controls for the effect of previous season's farm profit (liquidity) on fertilizer demand. To assess the presence of recency effects, I test whether recent weather shocks exert a stronger influence than distant shocks after controlling for liquidity. Specifically, if recency bias is present, I expect that at least one of the coefficients on recent shocks (β_k or θ_k) is statistically significant, while all coefficients on distant weather shocks ($\beta_m, \beta_n, \beta_s, \beta_v$ or $\theta_m, \theta_n, \theta_s, \theta_v$) should be statistically indistinguishable from zero, indicating that households overemphasize recent weather when making fertilizer decisions. Additionally, a joint significance test for recent weather shocks should reject the null hypothesis that all recent shock coefficients are zero, whereas the same test for distant shocks should fail to reject this null hypothesis, providing strong evidence consistent with the presence of recency effect.

I estimate the binary outcome of fertilizer adoption (extensive margin) using a Linear Probability Model (LPM) with household fixed effects, and analyze fertilizer use rates (intensive margin) using a Tobit model (Tobin, 1958) with LGA fixed effects to account for censoring at zero. The key identifying assumption is that the variation in past weather shocks is exogenous to time-varying unobserved household (or LGA) level characteristics, an assumption justified by the random nature of seasonal weather patterns (Table 2). Furthermore, by explicitly controlling for last season's maize yield ($\hat{\pi}_{idt-1}$), which proxies for liquidity constraints arising from previous weather shocks, I isolate the behavioral effect of recency. Thus, any remaining association between lagged weather shocks and current fertilizer use, after conditioning on liquidity, can be interpreted as evidence of recency effect.

[5]Additional control variables include: the size of the household (in adult male equivalents), the level of education of the head of the household, the area of the cultivated maize plot, the distance to the nearest population center with more than 20,000 inhabitants, the mean slope and elevation of the household plot, the value of the assets owned and dummies for marital status and gender of the household head and whether the household hired labor on their maize plots

A potential concern is that if prediction errors from the machine learning (ML) model of last season's maize yield are correlated with lagged weather shocks, then the residual effects of weather shocks estimated in equation 9 may not solely reflect recency effects. Specifically, if the ML model systematically fails to capture certain aspects of the relationship between weather shocks and maize yield, then the remaining impact of weather shocks might be incorrectly attributed to behavioral responses rather than model misspecification. For instance, if a simple linear relationship was imposed between maize yield and weather shocks in the first-stage (Section 3.3) prediction, conditioning on this predicted maize yield in equation 9 would leave any unmodeled nonlinear or interactive effects incorrectly interpreted as recency bias. The strength of ML approaches lies precisely in their flexibility and ability to approximate complex functional forms, including nonlinearities and interactions among predictors, without overfitting, a significant improvement over traditional econometric models that often rely on restrictive functional form assumptions ((Mullainathan and Spiess, 2017; Athey and Imbens, 2019)). However, this flexibility comes with the drawback of reduced interpretability, as ML models often function as a "black box." Consequently, an accompanying diagnostics to validate the adequacy of the ML predictions would be reassuring.

To address this, I perform a diagnostic check by regressing the prediction error term (actual minus predicted maize yield) from the ML model on current and previous weather shocks. If this diagnostic regression reveals statistically significant correlations between the prediction errors and lagged weather shocks, it suggests that the ML model inadequately captured the relationship between maize yield and weather shocks. Such a result would undermine the validity of attributing residual weather effects in equation 9, conditional on past maize yield, solely to behavioral responses. Conversely, finding no significant correlation would strengthen the confidence in the ML model's predictive accuracy, supporting the interpretation that any residual effects of weather shocks reflect behavioral (recency) effects rather than misspecification. I discuss the results of this test in the results section.

Finally, an implication of the specification of equation 9 is that financial market failures are channeled through last year's profit. However, liquidity constraints may be persistent over time; for instance, adverse weather events three years ago could have led to low profits two years ago, affecting the ability of farmers to afford inputs even if subsequent weather conditions improved. To address this concern, as additional robustness checks, I include multiple years of predicted lagged maize yields to control for any persistent liquidity constraints that households may face.

5 Results

This section first presents diagnostic results and then reports the baseline empirical findings on the impact of lagged weather shocks on fertilizer use decisions, conditional on previous season's profit (proxied by maize yields). Diagnostic checks (Appendix Table B.9) confirm that neither current nor lagged weather shocks significantly explain the maize yield prediction errors, implying that the machine learning model accurately captures the yield-climate relationship. Consequently, residual effects of lagged weather shocks in my empirical analyses can be interpreted as behavioral responses rather than model misspecification.

Next, I present Linear Probability Model (LPM) estimates for fertilizer adoption and Tobit estimates for fertilizer application rates based on equation (9). Results suggest recent weather shocks influence fertilizer use decisions more strongly than distant ones, an interpretation explored further in the subsections that follow.

5.1 Recency Effect and the Binary Measure of Fertilizer Adoption

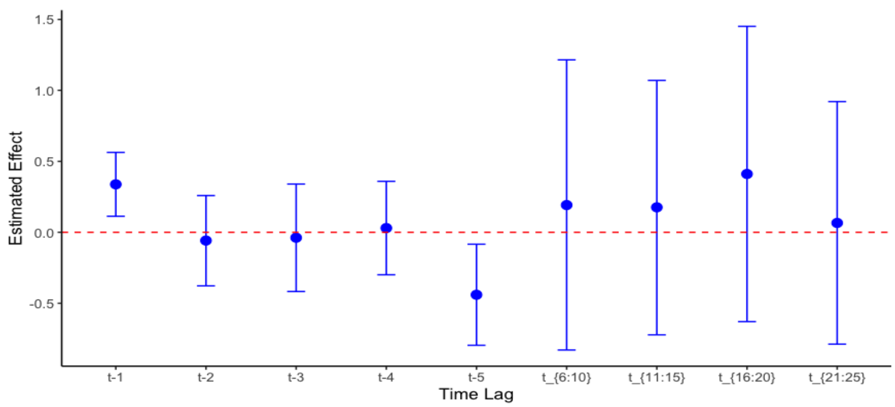
Figure 5a plots the estimated coefficients and their 95% confidence intervals for the lagged rainfall shock variables from Table B.3. The results indicate that, conditional on past profit, the average rainfall deviation from the previous year (t–1) has a statistically significant positive effect, suggesting a 34% increase in the likelihood of fertilizer adoption, equivalent to an 18 percentage point increase in the probability of fertilizer use in my sample. Although difficult to explain, an increase in average rainfall deviation five years prior significantly reduces fertilizer adoption by 44%. Meanwhile, rainfall deviations from the previous two, three, and four years do not show a significant impact, and the coefficients for more distant time periods (averages for the past 6-10, 11-15, 16-20, and 21-25 years) are also statistically insignificant. These findings indicate that, conditional on past profit, recent rainfall shocks have a more pronounced impact on current fertilizer adoption than distant shocks, thus providing evidence of recency effect in fertilizer use decisions. These results align with the existing literature on the impact of farmers' recent weather experiences (prior beliefs) on agricultural production investments (Karlan et al., 2014; Huang et al., 2024; Demnitz and Joslyn, 2020; Lee, 2024; Che et al., 2020; Sesmero et al., 2018).

To further validate these findings, I conduct two separate joint significance tests. First, I test the null hypothesis that all coefficients on recent rainfall shocks (t–1 to t–5) are zero. I reject the null hypothesis that all coefficients on recent rainfall shocks are zero (p-value = 0.00), indicating that recent shocks significantly affect fertilizer adoption. In contrast, the null hypothesis that all coefficients on distant rainfall shocks are zero yield a p-value of 0.80. Hence, I fail to reject the null hypothesis, suggesting that distant shocks have no significant impact. These results further support the presence of recency effect in which recent rainfall shocks play an important role in fertilizer adoption decisions.

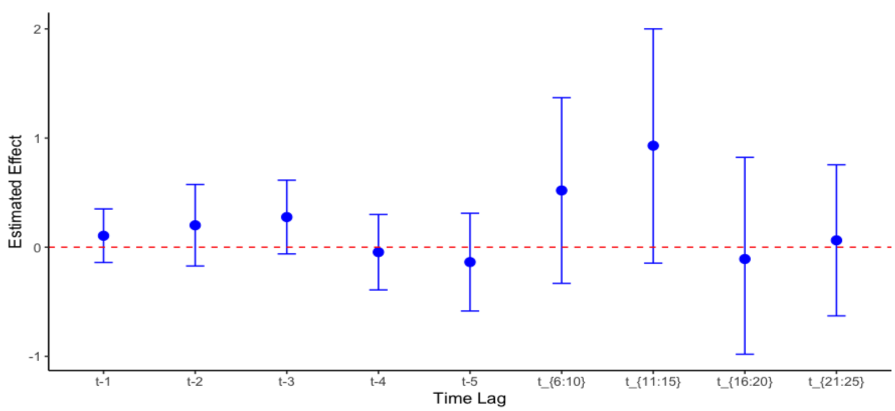
Turning our attention to the effect of lagged temperature shocks on fertilizer adoption, Figure 5b shows that none of the recent single year lags (t - 1 through t - 5) exhibit strongly significant effects on current fertilizer adoption, and the more distant time periods (averages for the past 6-10, 11-15, 16-20, and 21-25 years) also remain statistically indistinguishable from zero. Furthermore, testing the null hypothesis that all coefficients on recent temperature shocks (t-1 through t-5) are zero yield a p-value of 0.06. At a conventional 5% significance level, I fail to reject the null; however, I reject the null hypothesis by adopting a more lenient 10% threshold, suggesting that these recent shocks may have a marginally significant influence on fertilizer use. In contrast, I reject the null hypothesis that all coefficients on distant temperature shocks are zero (p-value=0.47). These findings may provide some support for the presence of recency effect, as recent temperature shocks seem to have more influence on fertilizer adoption than distant shocks. However, because the individual coefficients for both recent and distant temperature shocks are not strongly significant on their own, this conclusion should be interpreted with caution, signaling that while there may be some marginal evidence for a recency effect, the overall statistical evidence is less definitive than in the case of rainfall shocks.

5.2 Recency Effect and Fertilizer Application Rates

Figure 6a plots the average marginal effects of lagged rainfall shocks on fertilizer application rates (kg/ha) from Table B.4. Notably, average rainfall deviations from the previous season (t–1) and the last five seasons (t-5) appear to exert significant effects, while the intermediate recent years (t–2, t–3, t–4) show statistically insignificant impacts on fertilizer use rates. In addition, rainfall



(a) Effect of Lagged Rainfall Shocks on Fertilizer Adoption (1/0)



(b) Effect of Lagged Temperature Shocks on Fertilizer Adoption (1/0)

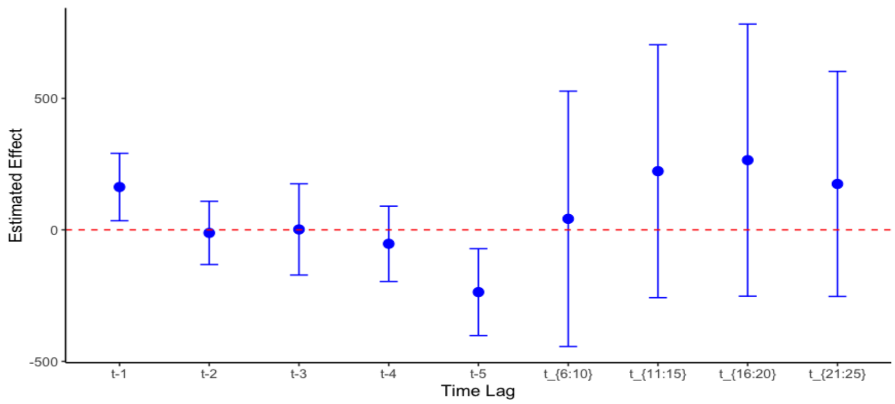
Figure 5: Effect of Lagged Weather Shocks on Fertilizer Adoption (1/0)

Note: This figure plots the estimated coefficients (marginal effects) and 95% confidence intervals for rainfall (a) and temperature (b) shocks, as presented in Table B.3.

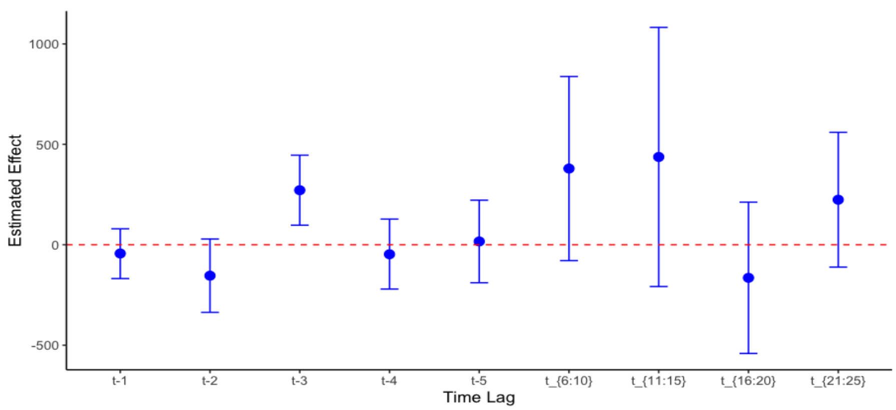
deviations from the more distant time periods (averages for the past 6-10, 11-15, 16-20, and 21-25 years) remain largely indistinguishable from zero. These findings suggest that in fact recent rainfall deviations (t-1 and t-5) are more important than distant rainfall shocks in current fertilizer use rates. To further corroborate this conclusion, I test the null hypothesis that all coefficients on the five recent rainfall shocks are zero and obtain a p-value of 0.014, indicating rejection of the null and suggesting that recent rainfall shocks jointly influence fertilizer use rates. In contrast, the same joint significance test for all distant rainfall shocks yields a p-value of 0.85, implying that these shocks do not collectively affect current fertilizer use rates. Together, these results reinforce the idea that more recent rainfall events are particularly relevant for farmers' fertilizer decisions in terms of application intensity.

Regarding the effect of lagged temperature shocks on fertilizer use rates, Figure 6b presents the average marginal effects of lagged temperature shocks on fertilizer application rates (kg/ha) from Table B.4. Examining the individual coefficients, I find that while the temperature shock from three seasons ago (t-3) appears to have a statistically significant impact on current fertilizer use rates, shocks from the most recent years (t-1, t-2, t-4, t-5) and distant years do not exhibit strong statistical significance. A joint significance test for recent temperature shocks yields a p-value of 0.01, which leads me to reject the null hypothesis that all coefficients on recent temperature shocks are zero. This indicates that, collectively, recent temperature shocks may be more strongly associated with fertilizer use rates, even if individual coefficients do not always reach statistical significance. In contrast, I fail to reject the null hypothesis that all coefficients on distant temperature shocks are zero (p-value = 0.43), implying that these more distant shocks do not have a meaningful combined effect on fertilizer use.

My findings align closely with previous studies that highlight how recent weather experiences shape farmers' agricultural investment decisions (Karlan et al., 2014; Huang et al., 2024; Demnitz and Joslyn, 2020; Lee, 2024; Che et al., 2020; Sesmero et al., 2018; Gallagher, 2014). In Malawi, Sesmero et al. (2018) shows that the scarce and volatile rainfall in the past growing season leads households to lower their expenditures on fertilizer and improved maize varieties, possibly due to pessimistic expectations of the weather, which reduces the perceived returns of these inputs. Similarly, Huang et al. (2024) find that in rural China, farmers become overly optimistic after favorable rainfall shocks, resulting in inefficient input allocation. From a developed-country perspective, Gallagher (2014) demonstrate that insurance uptake spikes immediately following floods, but gradually declines thereafter. Collectively, these studies suggest that without reliable weather forecasts, farmers form expectations about current-season weather based predominantly on recent weather patterns, assuming future conditions will mirror the immediate past.



(a) Effect of Lagged Rainfall Shocks on Fertilizer Application Rate (kg/ha)



(b) Effect of Lagged Temperature Shocks on Fertilizer Application Rate (kg/ha)

Figure 6: Effect of Lagged Weather Shocks on Fertilizer Application Rate Rate (kg/ha)

Note: This figure plots the estimated coefficients (average marginal effect) and 95% confidence intervals for rainfall(a) and temperature shocks (b), as presented in Table B.4.

5.3 Robustness Checks

This section demonstrates that the baseline results reported in Tables B.4 and B.3 remain robust after accounting for the potential persistence of liquidity constraints arising from long-term weather shocks and applying corrections for multiple hypothesis testing.

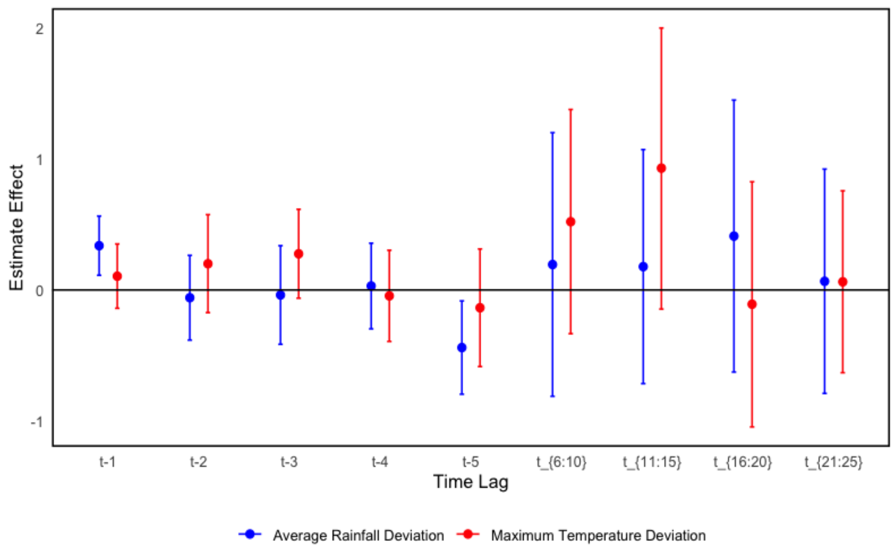
5.3.1 Robustness to Potential Persistence of Liquidity Constraints

Equation (9) treats financial market failures as flowing through last year's profit. However, liquidity constraints may persist for multiple years; for example, adverse weather three years ago could reduce profits two years ago, still limiting farmers' ability to purchase fertilizer even if subsequent weather conditions improve. To address this possibility, as an additional control variable, the yield of maize for the previous two years (t-2) is included in equation (9) to account for the potential long-term liquidity constraints.

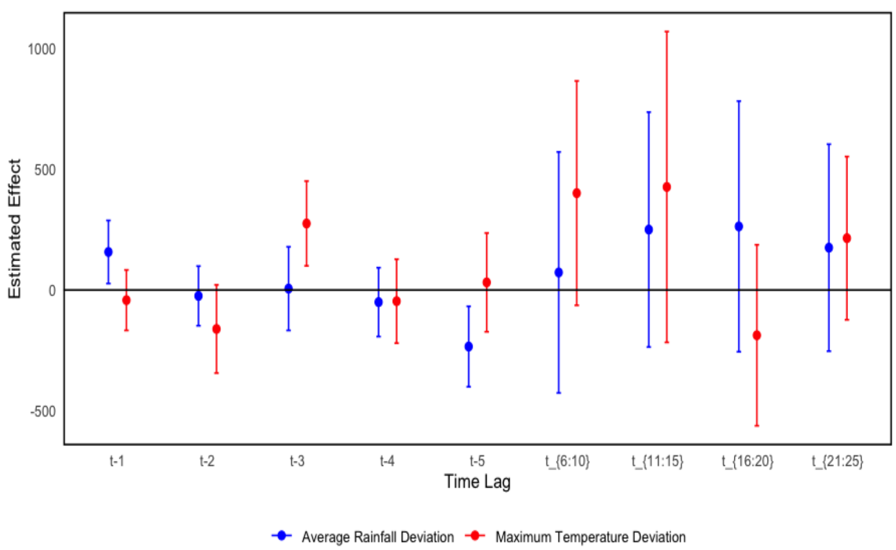
Figure 7 plots the estimated coefficients with their 95% confidence interval from Table B.5. The overall pattern of results remains consistent with the main findings, indicating that controlling for potential liquidity persistence does not materially alter the estimated influence of recent weather events on fertilizer decisions. In particular, the statistically significant coefficients for recent lags and the absence of significance for more distant lags persist, reinforcing the conclusion that recent weather shocks are the primary drivers of fertilizer adoption decisions rather than long-term liquidity constraints.

5.3.2 Robustness to Multiple Hypotheses Tests

In each regression, I estimate the effect of lagged weather shocks on fertilizer use decisions. This means that for each regression, I estimate eighteen separate coefficients relating to the effects of rainfall and maximum temperature shocks. This makes it likely that one or more of these estimates will be statistically significant by chance alone. However, as noted by Romano et al. (2014), this is not a problem if one is focusing on a particular hypothesis a priori. In this case, the decision can be based on the corresponding marginal p-values. The problem arises only if one searches the list of p-values for significant results after the fact. My situation is somewhat intermediate: studies have shown the importance of recent weather experiences in decision-making in agricultural production, so I am not looking for significant results a posteriori. However, I am also open to the possibility that distant weather outcomes could have an effect on current fertilizer adoption. To be conservative, in addition to the standard hypothesis testing explained in the results section, I report whether the statistical significance of my coefficients survives a correction for multiple



(a) Effect of Lagged Weather Shocks on Fertilizer Adoption (0/1)



(b) Effect of Lagged Weather Shocks on Fertilizer Application Rate (kg/ha)

Figure 7: Effect of Lagged Weather Shocks on Fertilizer Adoption (1/0) and Application Rates (kg/ha)

Note: This figure plots the estimated coefficients and 95% confidence intervals for rainfall shocks on fertilizer adoption (a) and application rate (b), as presented in Table B.5.

hypothesis testing. I employ the Romano–Wolf step-down procedure (Romano and Wolf, 2005)[6], which maintains the family-wise error rate at the 5% significance level.

Table B.6, column 2, presents the Romano–Wolf corrected p-values for LPM estimates of the effects of lagged weather shocks on the binary measure of fertilizer adoption[7]. The coefficients that remain statistically significant at the 5% level after this correction are shown in italics. For rainfall shocks, the coefficients for the previous season (t–1) and the previous five seasons (t–5) remain significant, while the other lag estimates are statistically insignificant, consistent with the baseline results in Table B.3. Similarly, none of the coefficients on lagged temperature shocks is statistically significant at 5% after correction, which again aligns with the baseline findings. These results suggest that my baseline results are robust to the problem of multiple hypotheses tests and that coefficients that are statistically significant in my baseline results are unlikely to be spurious as a result of multiplicity of coefficients being estimated.

6 Asymmetric Effects of Weather-Induced Recency

The baseline results provide evidence for the effect of recency in farmers' fertilizer use decisions induced by lagged weather shocks. Specifically, I find that recent weather shocks have a greater influence on fertilizer use than distant shocks. Therefore, farmers may tend to increase fertilizer use after recent favorable weather and reduce it after unfavorable shocks, as they expect current weather conditions to mirror recent outcomes. However, one might argue that if the effect of recency reduces fertilizer use below optimal levels after unfavorable weather but increases it above optimal levels after favorable weather, then the net effect could still increase or leave overall fertilizer use unchanged. Therefore, in principle, recency bias might not have a negative net effect on fertilizer use decisions.

To address this concern, I demonstrate that the weather-induced recency effect has a negative asymmetric impact on households' fertilizer use decisions. Specifically, I show that unfavorable weather shocks in the previous season reduce current fertilizer use, while favorable shocks do not necessarily lead to an equivalent increase. Since the baseline results strongly indicate that last

[6]See Romano et al. (2014) for technical discussion and implementation in Stata.

[7]Because I report average marginal effects from the Tobit results for the effects of lagged weather shocks on fertilizer use rates, I am unable to report the Romano–Wolf corrected p-values for those coefficients.

season rainfall shocks significantly influence both the intensive and extensive margins of fertilizer use, I construct positive, negative and no rainfall shock dummies from the previous season to accomplish this task.[8]. I then compare the effects of positive and negative rainfall shocks against the omitted category of no shock from previous season to assess the asymmetric influence of recency bias.

I follow Kaur (2019) in defining an LGA as subject to a discrete positive (negative) rainfall shock in a given season if the total rainfall is above the 80th percentile (below the 25th percentile) of the historical rainfall distribution for that LGA. Rainfall realizations that fall between these percentiles are classified as no shock.[9] I ran the following empirical model;

$$X_{idlt} = \alpha_0 + \beta_p Pos_{dt-1} + \beta_w Neg_{dt-1} + \mathbf{D'}_{idt}\mu + v_t + \varepsilon_{idt} \tag{10}$$

where X_{idt} is either binary measure of fertilizer use (1/0) or unconditional fertilizer use rate (kg/ha). Pos_{dt-1} and Neg_{dt-1} are indicators for a positive and negative rainfall shock last season, respectively. The omitted category is an indicator for no rainfall shock last season, so the effect of each category is evaluated relative to this omitted category. The model also includes a set of control variables[10], season fixed effect, v_t, and error term ε_{idt}.

Table B.7, Panel A, presents the results for equation 10, examining the impact of last season's rainfall shocks on the binary measure of fertilizer adoption. The findings suggest that, although not statistically significant, a positive rainfall shock in the previous season increases the likelihood of fertilizer use in the current season by 0.1% compared to the absence of a shock. In contrast, experiencing a negative rainfall shock last season significantly decreases the probability of fertilizer use by 7%, an effect that is statistically significant at the 1% level. A similar pattern emerges when

[8] While it would be interesting to show the asymmetric impact of the recency effect using discrete temperature shocks, the lack of definite cutoff points for positive, negative, and no temperature shocks in the literature makes such analysis highly subjective. Thus, I focus on rainfall shocks to illustrate the negative asymmetry of recency bias

[9] As robustness, Tables B.7 and B.8 include columns for alternative percentile cutoffs for defining positive and negative rainfall shocks.

[10] The control variables include: last season's maximum temperature as well as its squared, last season's log of maize yield, fertilizer and maize price, the size of the household (in adult male equivalents), the level of education of the head of the household, the area of the cultivated maize plot, the distance to the nearest population center with more than 20,000 inhabitants, the mean slope and elevation of the household plot, the value of the assets owned and dummies for marital status and gender of the household head and whether the household hired labor on their maize plots, indicators for poultry ownership, cattle ownership, small livestock ownership (pigs, sheep, or goats), credit access at the beginning of the year and the receipt of free fertilizer vouchers as proxy for access to the national fertilizer subsidy program

examining fertilizer application rates (Table B.8, Panel A). Compared to the absence of shock last season, a positive rainfall shock leads to an increase of 19.87 kg/ha in fertilizer use, but this effect is not statistically significant. However, a negative rainfall shock results in a reduction of 33.06 kg/ha, and this effect is statistically significant at 5% level. Consistent with my hypothesis, the results suggest that farmers significantly reduce fertilizer use following unfavorable shocks, yet do not increase it to the same extent after favorable conditions.

6.1 Heterogeneity and Mechanism

Section 6 establishes that recency effect induced by weather shocks exhibits an asymmetric effect on fertilizer use: negative rainfall shocks significantly reduce fertilizer demand, while positive shocks do not proportionally increase it. However, the impact of recency bias is unlikely to be uniform across all households. Asset-poor households, which typically face more severe liquidity constraints, may be particularly sensitive to recent negative weather shocks due to their limited capacity to absorb financial constraints after negative weather shocks (Dercon and Christiaensen, 2011; Alem et al., 2010; Amare et al., 2018). Indeed, existing studies (e.g., Huang et al. (2024); Sesmero et al. (2018)) highlight that poorer or low-productivity households disproportionately drive observed behavioral responses to recent weather events. To this end, I examine heterogeneity in the previously reported results in Section 6 by estimating equation (10) separately across household asset levels, classifying households into asset tertiles ranging from asset-poor to asset-rich.

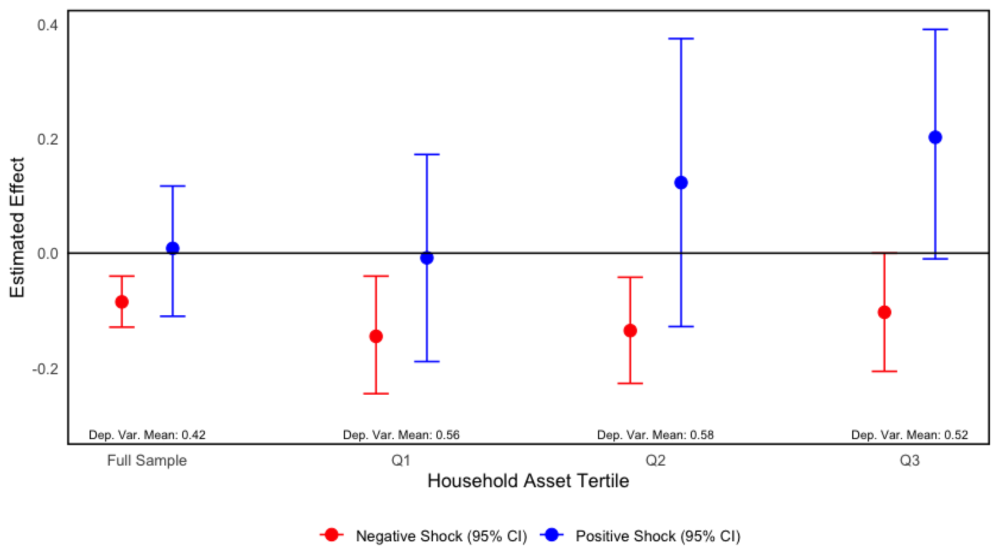
Figure 8 shows the asymmetric effect of recency on fertilizer adoption (Panel A) and fertilizer application rates (Panel B), disaggregated by household asset tertiles. Consistent with my expectations, the behavioral bias induced by recent negative rainfall shocks disproportionately affects asset-poor households (Q1). Specifically, negative rainfall shocks significantly reduce both the likelihood of fertilizer adoption and the quantity of fertilizer applied among asset-poor households, while positive rainfall shocks do not significantly increase fertilizer use. In contrast, asset-rich households (Q2 and Q3) exhibit relatively balanced and statistically insignificant responses to both positive and negative shocks. Moreover, households in the third (richest) asset tertile seem to react more optimistically to recent shocks, a contrast to the overly pessimistic reactions observed among the poorer groups. Taken together, these results confirm that the asymmetric recency bias identified in the full sample is primarily driven by asset-poor households, whose fertilizer decisions are particularly sensitive to recent negative weather experiences.

Regarding the mechanisms underlying increased irrationality to weather shocks, results show that relative asset-rich households are less prone to biases arising from past weather shocks than the asset-poor. Although I am limited in my ability to identify the causes of these patterns, I posit that asset-rich households might be more accessible to timely and accurate weather forecasts. It is also worth noting that due to the limitations of the LSMS-ISA data used in this study, I do not attempt to evaluate the causes or rationality behind weather-induced recency bias. I use the term 'recency bias' to refer to the tendency to weigh recent weather information more heavily than older information when forming beliefs about current season's weather expectations. Weather-induced recency bias can arise for various reasons, such as limited memory, time-varying states, high levels of ambiguity regarding growing-season weather distribution, a strong aversion to ambiguity, and reliance on heuristics due to the complexity of processing information (Hogarth and Einhorn, 1990; Kala, 2017).

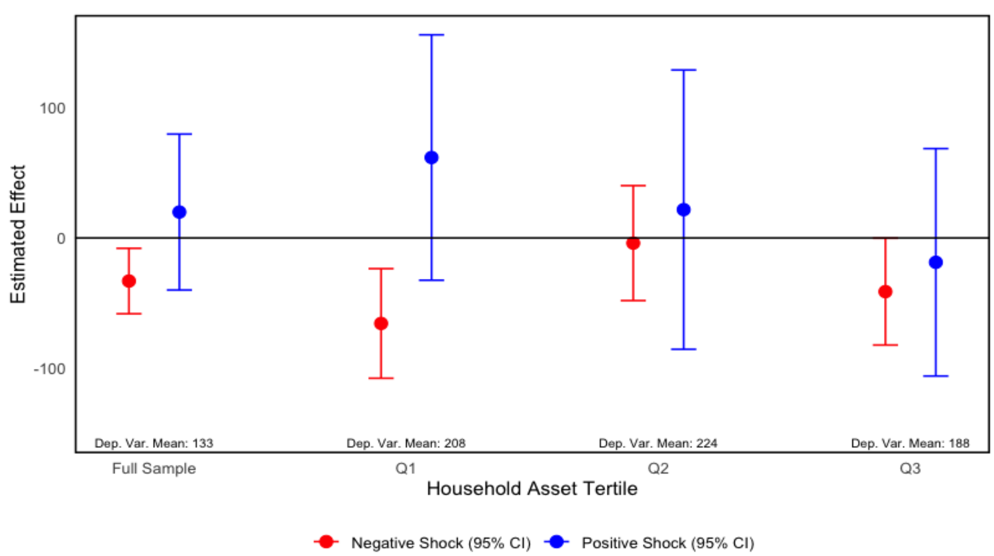
7 Implications of Recency Effect on Fertilizer Use and Agricultural Productivity

The evidence of weather-induced recency bias among maize farmers in Nigeria has important implications for agricultural productivity in sub-Saharan Africa. The asymmetric nature of farmers' responses to recent weather shocks, where negative shocks substantially reduce fertilizer use, while positive shocks do not produce equivalent increases, may generate a persistent downward pressure on fertilizer use over time. In this section, I quantify the impact of this recency bias on fertilizer adoption decisions and situate these findings within the broader literature on the influence of previous weather shocks on fertilizer use in developing countries.

To quantify this impact, I first estimate the standard regression model commonly employed in existing literature to examine how rainfall shocks from the previous season affect current-season fertilizer decisions (e.g., Alem et al. (2010); Heisse and Morimoto (2024); Bora (2022)). Considering Nigeria's evolving climate—characterized by decreasing rainfall, rising temperatures, and increased frequency of drought (Amanchukwu et al. (2015); Elisha et al. (2017); Ebele and Emodi (2016); Pörtner et al. (2022))—I specify the regression model as follows:



(a) Asymmetric effect of recency bias on fertilizer adoption (1/0)



(b) Asymmetric effect of recency bias on fertilizer use rate (kg/ha)

Figure 8: Asymmetric Effect of Recency by Household Asset Tertile

$$X_{idlt} = \alpha_0 + \beta_q Neg_{dt-1} + \mathbf{F'}_{idt}\mu + v_t + \varepsilon_{idt}, \tag{11}$$

where $X_{idlt}, Neg_{dt-1}, v_t$, and ε_{idt} maintain the definitions given in equation (10), and $\mathbf{F'}_{idt}$ represents a vector of household-level control variables excluding previous season's maize yield and other liquidity-related indicators described in the data section. The coefficient β_q captures the total effect of the previous season's negative rainfall shock on fertilizer use decisions. Traditional interpretations of this coefficient primarily attribute it to liquidity constraints, reasoning that unfavorable rainfall reduces yields, thereby limiting farmers' ability to finance fertilizer purchases the following season. However, this interpretation tends to overlook an important behavioral dimension, the recency effect, where farmers place disproportionate weight on recent weather outcomes in forming expectations about current-season weather conditions.

To explicitly isolate the recency mechanism, I re-estimate equation (11) while explicitly controlling for liquidity pathways by including previous season's maize yields and other liquidity-related variables discussed in the data section. The residual impact of past rainfall shocks that persists after controlling for these liquidity constraints can be interpreted as capturing a behavioral response consistent with the recency effect. Unlike previous studies, this refined approach enables me to clearly distinguish and quantify the influence of weather-induced recency bias on farmers' fertilizer adoption decisions.

Table 4 presents the estimated effects of negative rainfall shocks in the previous season on fertilizer adoption and application intensity. Columns (1) and (3) report estimates from a standard specification commonly employed in the literature, in which fertilizer use is regressed solely on lagged rainfall shocks and standard control variables, without explicitly accounting for potential liquidity channels. Columns (2) and (4) extend this specification by explicitly controlling for liquidity constraints using lagged maize yields and additional liquidity indicators. Consistent with findings from previous studies (Alem et al. (2010), Heisse and Morimoto (2024), and Bora (2022))—which document increased (decreased) fertilizer use following favorable (adverse) weather—I find that negative rainfall shocks significantly reduce the probability of fertilizer adoption by approximately 40 percentage points (column 1) and reduce fertilizer application rates by 25 kg/ha (column 3). Accounting explicitly for past liquidity via lagged maize yields has a negligible impact on these estimates, with coefficient magnitudes slightly increasing to 42 percentage points for adoption likelihood (column 2) and 25.6 kg/ha for application intensity (column 4).

These findings suggest that liquidity constraints alone cannot fully account for the observed reduction in fertilizer use following negative rainfall shocks. Even after explicitly controlling for liquidity effects through lagged maize yields, the adverse impact of rainfall shocks on fertilizer adoption remains substantial and increases slightly in magnitude. This indicates that the recency effect plays an important role, possibly explaining a larger portion of previously documented results than has been recognized.

Therefore, policies aimed at reducing the adverse effects of weather shocks through liquidity-enhancing measures, such as credit access, may be ineffective unless combined with interventions addressing the effect of recency, such as providing timely and accurate weather forecasts. Using farm-level data in India, Burlig et al. (2024) show that farmers adjust critical agricultural decisions, including land use, crop selection, and input expenditures, in response to credible weather forecasts. Farmers who receive accurate forecasts regarding the timing of the Indian Summer Monsoon update their expectations accordingly: those interpreting forecasts positively expand cultivated areas, increase farm expenditures, plant more cash crops, and reduce engagement in off-farm activities. In contrast, farmers who perceive forecasts as negative relative to their initial expectations reduce cultivated areas and farm expenditures while intensifying their participation in off-farm business activities.

8 Conclusion

SSA's crop yields are significantly lower than global averages, with maize yields at 1.4 T/ha compared to the global average of 5.7 T/ha. To close this gap, an increase in fertilizer use is essential. However, the current average fertilizer application rates in the region is considerably lower than in regions such as South Asia, the European Union, South America, and East Asia (FAOSTAT, 2021; Ray et al., 2012; Leitner et al., 2020). In this study, I integrate data from multiple sources, including household and plot-level information from the first three waves of the Nigeria LSMS-ISA to investigate whether fertilizer adoption decisions of maize households in Nigeria are overly sensitive to recent weather outcomes and its implications on agricultural productivity. This focus on

Table 4: Effect of Previous Negative Rainfall Shock on Fertilizer Use

	Fertilizer Adoption (1/0)		Fertilizer Use Rate (kg/ha)	
	(1)	(2)	(3)	(4)
Negative Shock (t-1)	-0.040*	-0.042*	-25.000**	-25.559**
	(0.022)	(0.021)	(11.811)	(11.679)
Log Maize Yield (t-1)		-0.153		-84.626
		(0.152)		(67.260)
Controls	Yes	Yes	Yes	Yes
HH FE	Yes	Yes	No	No
District FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-Squared	0.045	0.046	0.080	0.080
N	2,843	2,843	2,843	2,843

Note: This table presents the results for equation (11). Columns 1 and 2 uses the LPM regression while columns 3 and 4 uses the Tobit model for estimation. Control variables for columns 1 and 3 include: prices for maize and fertilizer; age, education, gender (1/0) of household head; household size (adult equivalence unit), household hired labor (1/0), household planted maize crop only (1/0), average slope (%) of plot, average elevation in meters of plot, distance to nearest population center with over 20,000 inhabitants, value of household owned assets ('000 Naira) and area of maize plot (ha). In columns 2 and 4 we add indicators for poultry ownership, cattle ownership, small livestock ownership, credit access and the receipt of free fertilizer vouchers as additional controls for liquidity pathways. Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

behavioral mechanisms, often overlooked in previous studies that examined the effects of recent weather shocks on fertilizer adoption in SSA, provides new insights into factors that could in part explain the low level of fertilizer use in SSA.

I find that, conditional on past profits, recent weather shocks exert a stronger effect on fertilizer use decisions than more distant shocks. This finding suggests that households disproportionately weigh recent weather experiences when making expectations about future growing conditions, which subsequently shapes their investment decisions in fertilizer for the current season. Such behavioral patterns are striking, given that in the study region, growing season weather shocks are exogenous and provide little reliable information about weather in subsequent seasons. These results add to a growing body of evidence documenting how behavioral biases among farmers can hinder agricultural productivity (Duflo et al., 2011; Huang et al., 2024; Michelson et al., 2021; Wouterse and Odjo, 2021; Karlan et al., 2014; Fufa and Hassan, 2006; Hoel et al., 2024).

My results also reveal that the recency effect exerts an asymmetric influence on fertilizer use, with negative rainfall shocks leading to sharp reductions in adoption, especially among poorer households, while positive shocks have limited upward effects. This pattern suggests that adverse weather experiences weigh more heavily on farmers' decisions, reinforcing both underinvestment in fertilizer and existing inequalities in input use. I also show that much of the decline in fertilizer use after adverse weather - previously attributed to liquidity constraints (e.g. Alem et al. (2010); Heisse and Morimoto (2024); Bora (2022)) - can be explained by farmers' behavioral responses to recent rainfall shocks. Even after controlling for past profits, the effect remains large, underscoring the central role of recency bias in shaping input decisions.

My findings have important implications for improving fertilizer use and agricultural productivity among maize farming households in Nigeria. Although liquidity enhancing measures, such as credit access, are necessary, they may be insufficient on their own to sustain fertilizer adoption following adverse weather shocks. Since weather-induced recency bias plays a critical role in shaping farmers' fertilizer decisions, policies must also aim to improve farmers' expectations about future weather conditions. Providing accurate and timely weather forecasts before the growing season would allow farmers to make better informed input decisions, mitigating the adverse effects of recent unfavorable weather experiences. Given that low fertilizer use is often associated with information and knowledge gaps (Rosenzweig and Udry, 2013, 2019; Zerfu and Larson, 2010), targeted educational programs, especially for asset-poor households that are most vulnerable to weather shocks, could further improve fertilizer adoption and strengthen agricultural resilience in sub-Saharan Africa.

Despite the valuable insights from this study, some limitations must be acknowledged. First, due to data constraints, I do not directly observe the weight households place on past weather shocks. Instead, I infer this from the direct effect of lagged weather shocks after controlling for past profit. Lastly, a limitation of my study is the assumption of risk neutrality in the profit maximization approach. While this assumption is commonly made in agricultural economics literature, it may be contested, as farmers are generally found to be risk- and loss-averse in SSA (Duflo et al., 2011; Shin et al., 2022; Alemayehu et al., 2019).

The limitations of this study highlight the need for further research to use primary data to directly observe how households form weather expectations based on past weather events and to assess the rationality of their behavioral responses. In addition, comparative studies across different crops and regions are necessary to validate the generalizability of my findings and to better understand weather-induced behavioral factors affecting fertilizer use in SSA.

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A Appendix A. Additional Figures

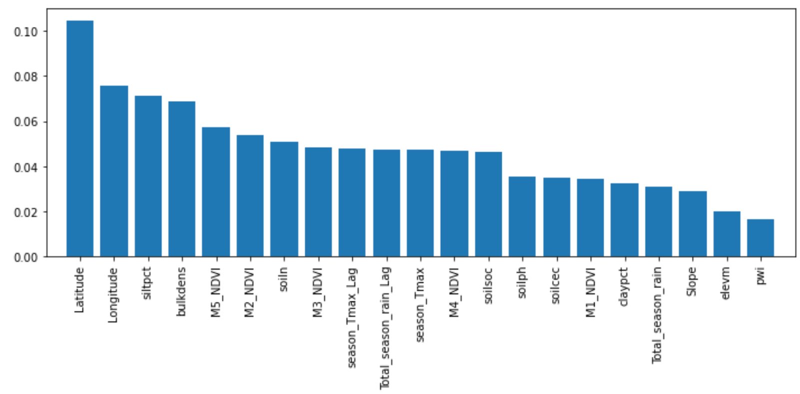

Figure A.1: Variable Importance in the XGBoost Model

Notes: Importance is reported as the mean increase in mean square error for the regression model if that variable was removed from the analysis. The climate variables include: total precipitation in the 1st and 2nd months of the growing season (precip _p1), during the 3rd month (precip_p2), and during the 4th and 5th months (precip_p3), average daily temperature during the 1st and 2nd months of the growing season (tmax_p1), during the 3rd month (tmax_p2), and during the 4th and 5th months (tmax_p3). The soil variables include: soil pH as determined in a soil/water mixture (soilph), soil clay content share by volume (claypct), soil silt content share by volume (siltpct), soil nitrogen content in g per kg soil (soiln), the site's elevation (elevm).

B Appendix B. Additional Tables

Table B.1: Summary Statistics of Response and Predictor Variables

Variables	Mean	St. Dev	Min	Max
Response Variables				
Maize Yield (kg/ha)	1857.43	1674.14	10.99	10,037.41
Log Maize Yield	6.99	1.04	2.39	8.58
Predictor Variables				
Total Season Rainfall (mm)	269.56	117.39	41.53	850.20
Lag Total Season Rainfall (mm)	273.00	120.57	41.86	918.56
Season Max Temperature (°C)	33.40	1.75	28.38	39.04
Lag Season Max Temperature (°C)	33.43	1.84	28.62	38.92
NDVI_M1	0.31	0.11	0.16	0.68
NDVI_M2	0.32	0.12	0.15	0.66
NDVI_M3	0.35	0.14	0.15	0.76
NDVI_M4	0.41	0.15	0.15	0.76
NDVI_M5	0.43	0.13	0.09	0.81
Soil Clay Content (%)	19.15	4.00	10.18	36.20
Soil Silt Content (%)	21.57	7.66	6.39	64.23
Soil Nitrogen Content (g/kg)	15.52	5.07	8.10	38.28
Site Elevation (m)	377.38	268.17	10.00	1427.00
Soil Bulk Density (g/cm^3)	0.13	0.01	0.11	0.15
Soil Potential Wetness Index	13.77	2.09	11.00	36.00
Soil Slope (%)	3.10	2.72	0.00	40.40
Cation Exchange Capacity (cmolc/kg)	9.38	1.93	5.17	17.35
Soil Organic Carbon (g/kg)	18.40	7.72	4.99	42.92
N	2843			

Note: NDVI_M1 to NDVI_M5 denote the mean Normalized Difference Vegetation Index values for the first to fifth months of the growing season, respectively. The total season rainfall is the aggregated precipitation across the growing season, while lagged total season rainfall and lagged maximum temperature refer to the previous season's values. Soil variables are extracted from 0–5 cm depth.

Table B.2: Model Parameters

Model	Parameter Tuning Details
RF	`n_estimators`: {100, 200, 300, 500} `max_features`: {`auto`, `sqrt`, `log2`} `max_depth`: {10, 20, 30, None} `min_samples_split`: {2, 5, 10} `min_samples_leaf`: {1, 2, 4} RandomizedSearchCV with 100 iterations, 10-fold CV
XGB	`n_estimators`: {100, 200, 300, 500} `max_depth`: {3, 5, 7, 10} `learning_rate`: {0.01, 0.05, 0.1} `subsample`: {0.7, 0.8, 1.0} `colsample_bytree`: {0.7, 0.8, 1.0} RandomizedSearchCV with 100 iterations, 10-fold CV
ANN	`hidden_layer_sizes`: {(50,), (100,), (50,50), (100,50)} `alpha`: {0.0001, 0.001, 0.01} `learning_rate_init`: {0.0001, 0.001} `activation`: {`tanh`, `relu`} RandomizedSearchCV with 100 iterations, 10-fold CV

Table B.3: LPM Results for the Effect of Lagged Weather Shocks on Fertilizer Adoption (1/0)

		Fertilizer Adoption (1/0)	
		(1)	(2)
Variable		Coeff.	Std. error
Avg Rainfall Dev:			
	t-1	0.34***	0.11
	t-2	-0.06	0.16
	t-3	-0.04	0.19
	t-4	0.03	0.17
	t-5	-0.44**	0.18
	t:{6:10}	0.19	0.52
	t:{11:15}	0.18	0.46
	t:{16:20}	0.41	0.53
	t:{21:25}	0.07	0.43
Max Temperature Dev:			
	t-1	0.11	0.12
	t-2	0.2	0.19
	t-3	0.28	0.17
	t-4	-0.05	0.18
	t-5	-0.14	0.23
	t:{6:10}	0.52	0.43
	t:{11:15}	0.93*	0.55
	t:{16:20}	-0.11	0.47
	t:{21:25}	0.06	0.35
Log Maize Yield (t-1)		-0.16	0.16
Log Fertilizer Price		-0.07	0.06
Log Maize Price		0.08	0.06
Controls			YES
Household FE			YES
Year FE			YES
Within R-squared			0.09
Observation			2,843

Note: This table presents the LPM results for equation (9). The time lags are defined as follows: t-1, t-2, t-3, t-4, t-5 refers to the past year, past two years, past three years, past four years and past five years respectively. t:{6:10}, t:{11:15}, t:{16:20}, t:{21:25} represents the averages for the past 6 to 10 years, past 11 to 15 years, past 16 to 20 years and the past 21 to 25 years respectively. Control variables include: indicators for poultry ownership, cattle ownership, small livestock ownership, credit access and the receipt of free fertilizer vouchers; age, education, gender (1/0) of household head; household size (adult equivalence unit), household hired labor (1/0), household planted maize crop only (1/0), average slope (%) of plot, average elevation in meters of plot, distance to nearest population center with over 20,000 inhabitants, value of household owned assets ('000 Naira) and area of maize plot (ha). Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.4: Tobit Results for the Effect of Lagged Weather Shocks on Fertilizer Use Rate

		Fertilizer Appl. Rate (kg/ha)	
		(1)	(2)
Variable		Coeff.	Std. error
Avg Rainfall Dev:			
	t-1	162.84**	65.42
	t-2	-11.6	61.33
	t-3	1.67	88.45
	t-4	-52.92	73.04
	t-5	-236.63***	84.17
	t:{6:10}	42.02	247.63
	t:{11:15}	223.02	245.24
	t:{16:20}	264.98	263.89
	t:{21:25}	174.63	218.27
Max Temperature Dev:			
	t-1	-44.45	63.17
	t-2	-154.00*	93.16
	t-3	271.63***	88.92
	t-4	-46.37	88.82
	t-5	16.49	104.88
	t:{6:10}	437.09	329.10
	t:{11:15}	436.70	328.76
	t:{16:20}	-164.55	192.15
	t:{21:25}	224.26	171.17
Log Maize Yield (t-1)		-119.61*	67.69
Log Fertilizer Price		-92.80***	26.19
Log Maize Price		19.59	24.05
Controls			YES
District FE			YES
Year FE			YES
Pseudo R-squared			0.08
Observation			2,843

Note: This table shows the Tobit estimation results for equation (9), with coefficients representing the average marginal effects calculated using the *margins* command in STATA. The time lags are defined as follows: t-1, t-2, t-3, t-4, t-5 refers to the past year, past two years, past three years, past four years and past five years respectively. t:{6:10}, t:{11:15}, t:{16:20}, t:{21:25} represents the averages for the past 6 to 10 years, past 11 to 15 years, past 16 to 20 years and the past 21 to 25 years respectively. . Control variables include: indicators for poultry ownership, cattle ownership, small livestock ownership, credit access and the receipt of free fertilizer vouchers; age, education, gender (1/0) of household head; household size (adult equivalence unit), household hired labor (1/0), household planted maize crop only (1/0), average slope (%) of plot, average elevation in meters of plot, distance to nearest population center with over 20,000 inhabitants, value of household owned assets ('000 Naira) and area of maize plot (ha). Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.5: Robustness to Persistence to Profit Effect

		Fertilizer Adoption (1/0)		Fertilizer Appl. Rate (kg/ha)	
		(1)	(2)	(3)	(4)
Variable		Coeff.	Std. error	Coeff.	Std. error
Avg Rainfall Dev:					
	t-1	0.34***	0.12	157.58**	66.62
	t-2	-0.06	0.17	-24.46	62.96
	t-3	-0.04	0.19	5.80	88.34
	t-4	0.03	0.17	-50.14	72.73
	t-5	-0.44**	0.18	-234.26***	85.06
	t:{6:10}	0.19	0.51	72.73	254.72
	t:{11:15}	0.18	0.45	250.31	248.24
	t:{16:20}	0.41	0.53	263.39	264.95
	t:{21:25}	0.07	0.44	175.32	218.72
Max Temperature Dev:					
	t-1	0.11	0.13	-42.10	63.86
	t-2	0.20	0.19	-161.44*	93.20
	t-3	0.28	0.17	275.55***	89.57
	t-4	-0.05	0.18	-46.27	88.70
	t-5	-0.14	0.23	31.50	104.34
	t:{6:10}	0.52	0.44	401.33*	237.20
	t:{11:15}	0.93*	0.55	426.91	328.47
	t:{16:20}	-0.11	0.48	-187.57	191.29
	t:{21:25}	0.06	0.35	214.76	172.51
Log Maize Yield (t-1)		-0.16	0.16	-150.92**	72.98
Log Maize Yield (t-2)		0.01	0.12	61.18	67.00
Log Fertilizer Price		-0.07	0.06	-92.65***	26.58
Log Maize Price		0.08	0.06	19.69	23.90
Controls			YES		YES
Household FE			YES		NO
LGA FE			NO		YES
Year FE			YES		YES
R-squared			0.09		0.09
Observation			2,843		2,843

Note: This table shows the estimation results for equation (9) with Log Maize yield for past two seasons as an additional independent variable to control for persistent of profit effect as discussed in Section 4. Column (1) is estimated using the LPM with household fixed-effects while column (3) is estimated with a Tobit model with LGA fixed effect. The coefficients of column (3) represents the average marginal effects calculated using the *margins* command in STATA. The time lags are defined as follows: t-1, t-2, t-3, t-4, t-5 refers to the past year, past two years, past three years, past four years and past five years respectively. t:{6:10}, t:{11:15}, t:{16:20}, t:{21:25} represents the averages for the past 6 to 10 years, past 11 to 15 years, past 16 to 20 years and the past 21 to 25 years respectively. Control variables include: indicators for poultry ownership, cattle ownership, small livestock ownership, credit access and the receipt of free fertilizer vouchers; age, education, gender (1/0) of household head; household size (adult equivalence unit), household hired labor (1/0), household planted maize crop only (1/0), average slope (%) of plot, average elevation in meters of plot, distance to nearest population center with over 20,000 inhabitants, value of household owned assets ('000 Naira) and area of maize plot (ha). Standard errors are clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.6: Robustness to Multiple Hypothesis Testing

Variable		Fertilizer Adoption (1/0) (1) Coeff.	(2) Romano-Wolf p-values
Avg Rainfall Dev:			
	t-1	*0.34******	0.04
	t-2	-0.06	0.70
	t-3	-0.04	0.90
	t-4	0.03	0.91
	t-5	*-0.44****	0.04
	t:{6:10}	0.19	0.76
	t:{11:15}	0.18	0.73
	t:{16:20}	0.41	0.55
	t:{21:25}	0.07	0.89
Max Temperature Dev:			
	t-1	0.11	0.59
	t-2	0.20	0.45
	t-3	0.28	0.19
	t-4	-0.05	0.87
	t-5	-0.14	0.64
	t:{6:10}	0.52	0.39
	t:{11:15}	0.93*	0.18
	t:{16:20}	-0.11	0.83
	t:{21:25}	0.06	0.92

Note: The time lags are defined as follows: t-1, t-2, t-3, t-4, and t-5 refer to the past one, two, three, four, and five years, respectively; t:{6:10}, t:{11:15}, t:{16:20}, and t:{21:25} represent the averages for the past 6–10, 11–15, 16–20, and 21–25 years, respectively. Additional variables include: log of maize yield for previous season, prices of maize and fertilizer, indicators for poultry ownership, cattle ownership, small livestock ownership, credit access, and receipt of free fertilizer vouchers; age, education, and gender (1/0) of the household head; household size (in adult equivalence units), household hired labor (1/0), whether the household planted only maize (1/0), average plot slope (%), average plot elevation (meters), distance to the nearest population center with over 20,000 inhabitants, value of household assets (in '000 Naira), and area of the maize plot (ha). *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Coefficients in italics survives a correction for multiple hypothesis testing on a 5% significance level

Table B.7: LPM Results for the Asymmetric Effect of Lagged Rainfall Shock on Fertilizer Adoption (1/0)

	Percentile Cut-off for Positive/Negative Shocks		
	80/25	80/20	85/25
Panel A: Full Sample	(1)	(2)	(3)
Positive Shock (t-1)	0.01	0.03	-0.02
	(0.06)	(0.06)	(0.09)
Negative Shock (t-1)	-0.07***	-0.05*	-0.09***
	(0.02)	(0.03)	(0.02)
Observation	2,843	2,843	2,843
Panel B: First Tertile (Q1)			
Positive Shock (t-1)	-0.01	-0.01	0.27**
	(0.09)	(0.09)	(0.11)
Negative Shock (t-1)	-0.15***	-0.16***	-0.14***
	(0.050)	(0.05)	(0.05)
Observation	949	949	949
Panel C: Second Tertile (Q2)			
Positive Shock (t-1)	0.12	0.20	0.11
	(0.13)	(0.13)	(0.15)
Negative Shock (t-1)	-0.14***	0.014	-0.14***
	(0.05)	(0.05)	(0.04)
Observation	947	947	947
Panel D: Third Tertile (Q3)			
Positive Shock (t-1)	0.20**	0.22**	0.12
	(0.10)	(0.10)	(0.09)
Negative Shock (t-1)	-0.10	-0.11	-0.11**
	(0.05)	(0.06)	(0.05)
Observation	947	947	947

Note: This tables examines robustness of the results to alternate cut-offs for positive and negative shocks. The dependent variable is dummy for fertilizer adoption (1/0). In each column, positive and negative shocks are defined under different cut-offs, as labeled at the top of each column. E.g., in Column (1), a positive (negative) shock is defined as rainfall above (below) the 80th (25th) percentile of the historical distribution. This correspond to the definition of shocks in the main specification in the paper. Similarly, in Column (2), a positive (negative) shock is defined as rainfall above (below) the 80th (20th) percentile of the historical distribution, and so on. All regressions include lagged maximum temperature and its square, lagged maize yield in log, log of maize and fertilizer prices. Additional control variables are: indicators for poultry ownership, cattle ownership, small livestock ownership, credit access and the receipt of free fertilizer vouchers; age, education, gender (1/0) of household head; household size (adult equivalence unit), household hired labor (1/0), household planted maize crop only (1/0), average slope (%) of plot, average elevation in meters of plot, distance to nearest population center with over 20,000 inhabitants, value of household owned assets ('000 Naira) and area of maize plot (ha). Standard errors are in parenthesis and clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.8: Tobit Results for the Asymmetric Effect of Lagged Rainfall Shock on Fertilizer Application Rate (kg/ha)

	Percentile Cut-off for Positive/Negative Shocks		
	80/25	80/20	85/25
Panel A: Full Sample	(1)	(2)	(3)
Positive Shock (t-1)	19.87	30.30	12.90
	(30.52)	(30.57)	(41.03)
Negative Shock (t-1)	-33.06**	-11.65	-33.56***
	(12.78)	(14.61)	(12.75)
Observation	2,843	2,843	2,843
Panel B: First Tertile (Q1)			
Positive Shock (t-1)	61.71	79.47	74.92
	(45.67)	(49.57)	(74.10)
Negative Shock (t-1)	-65.61***	-52.02**	-65.01***
	(14.47)	(22.73)	(19.47)
Observation	949	949	949
Panel C: Second Tertile (Q2)			
Positive Shock (t-1)	21.72	32.39	54.41
	(54.66)	(53.70)	(69.47)
Negative Shock (t-1)	-3.96	31.48	-2.03
	(22.50)	(26.81)	(22.64)
Observation	947	947	947
Panel D: Third Tertile (Q3)			
Positive Shock (t-1)	-18.69	-9.13	-58.09
	(44.53)	(44.71)	(53.20)
Negative Shock (t-1)	-41.20**	-22.18	-43.35**
	(20.90)	(22.42)	(21.39)
Observation	947	947	947

Note: This tables examines robustness of the results to alternate cut-offs for positive and negative shocks. The dependent variable is fertilizer application rate (kg/ha). The coefficients represents the average marginal effects calculated using the *margins* command in STATA. In each column, positive and negative shocks are defined under different cut-offs, as labeled at the top of each column. E.g., in Column (1), a positive (negative) shock is defined as rainfall above (below) the 80th (25th) percentile of the historical distribution. This correspond to the definition of shocks in the main specification in the paper. Similarly, in Column (2), a positive (negative) shock is defined as rainfall above (below) the 80th (20th) percentile of the historical distribution, and so on. All regressions include lagged maximum temperature and its square, lagged maize yield in log, log of maize and fertilizer prices. Additional control variables are: indicators for poultry ownership, cattle ownership, small livestock ownership, credit access and the receipt of free fertilizer vouchers; age, education, gender (1/0) of household head; household size (adult equivalence unit), household hired labor (1/0), household planted maize crop only (1/0), average slope (%) of plot, average elevation in meters of plot, distance to nearest population center with over 20,000 inhabitants, value of household owned assets ('000 Naira) and area of maize plot (ha). Standard errors are in parenthesis and clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.9: Error in Maize Yield Prediction and weather shocks

	Predicted Error		Sq. Predicted Error	
	(1)	(2)	(3)	(4)
Avg. rain dev (t)	0.0645	0.0082	0.1276	0.0583
	(0.0965)	(0.2743)	(0.1918)	(0.4753)
Avg. rain dev (t-1)	-0.1954	-0.3696	0.0300	0.3783
	(0.1215)	(0.2660)	(0.2125)	(0.3168)
Tmax dev (t)	0.0396	0.1338	0.0095	-0.4067
	(0.0479)	(0.2420)	(0.0834)	(0.3287)
Tmax dev (t-1)	0.0182	-0.1130	-0.0279	0.3115
	(0.0510)	(0.2115)	(0.1059)	(0.2995)
HH FE	No	Yes	No	Yes
Wave FE	No	Yes	No	Yes
R squared	0.0013	0.0037	0.0005	0.0043
N	1990	1990	1990	1990

Note: Standard errors are in parenthesis and clustered at the enumeration area level. *, **, *** indicate the statistical significance at the 10%, 5%, and 1% level, respectively.