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The Impact of Temperature and Rainfall Volatility on Food Prices—Evidence for Uganda

Christopher Adam and Prabhmeet Kaur Matta

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Prepared by Christopher Adam and Prabhmeet Kaur Matta

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ABSTRACT: While Uganda has been exposed to an increase in the frequency of extreme weather events—most commonly localised flooding, leeching and mudslides associated with increased intensity of rainfall – changes in the aggregate level patterns of rainfall and temperature have been relatively modest and have evolved relatively slowly. As a consequence, it is unsurprising that conventionally measured weather variation appears to have a modest impact on food prices at the aggregate level. Instead, this paper uses highly granular earth-observation weather data in combination with spatially disaggregated price data to examine the impact of spatial and temporal variability in rainfall and temperature on the short-run price dynamics of domestically produced staple food crops in Uganda. We find that measures of weather variability computed across the agricultural cycle do impact the evolution of prices for locally-produced agricultural commodities, but the estimated effects are fragile and relatively small. Hence, a failure to reflect these effects in near-term forecasting to inform inflation models is unlikely to lead to significantly larger forecast errors.

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Author’s E-Mail Address:	christopher.adam@economics.ox.ac.uk; prabhmeet.matta@economics.ox.ac.uk

WORKING PAPERS

The Impact of Temperature and Rainfall Volatility on Food Prices—Evidence for Uganda

Prepared by Christopher Adam and Prabhmeet Kaur Matta[1]

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Contents

I. Introduction

Climate change is transforming the physical world and is doing so particularly rapidly in sub-Saharan Africa, where temperatures are rising faster than global averages and extreme events are becoming more frequent and more intense across much of the continent (IPCC 2021, Thomas et al. 2022, WMO 2023). Relative to the rest of the world, these changes translate into greater economic risk in part because large sectors of many African economies, most notably agriculture, are vulnerable to climate-related risks, and in part because limited adaptation capacity undermines economic resilience.

Climate risks present a range of macroeconomic management challenges, including for central banks. One such set concerns policy responses to periodic extreme weather events such as tropical storms, heatwaves floods and droughts where the focus is how the stance of monetary and fiscal policies should adjust (see for example, Cantelmo et al 2023, 2024). However, while such events are becoming more frequent, they still represent relatively rare draws from the tails of the weather distribution. A second and arguably more pressing set of concerns arises from the broader consequences of the gradual change in the moments of the weather distribution—specifically the mean, variance and skewness of weather measures—and how these may challenge central banks' ability to deliver on their core mandate of price stability and ensuring the resilience of the financial sector to stability and resilience (for example NGFS 2024 and 2024a). One particular concern, which provides the background to this paper, is the effect of increased weather volatility on agricultural production and the consequences for food prices and food security. An emerging published literature is beginning to explore these effects, for example Cornejo et al. (2023), Erdogan et al. (2024), Odongo et al. (2022), and Ado et al. (2025). This preliminary work has reinforced the view that increased weather volatility has translated into greater volatility in food prices and by implication, near-term forecasting (NTF) models need to pay explicit attention to the role of climate-related volatility in inflation forecasting models.

However, it has, at least to date, proven difficult to establish robust evidence on the impact of weather volatility on food price inflation. There are at least two explanations for this. First, there are 'facts on the ground' explanations which suggests that changes in underlying weather volatility are either too small to have a measurable impact on food prices or, alternatively (or in addition), the effects of weather volatility are being effectively mitigated by changes in farming practices (e.g. more resilient seeds), improved price-stabilising international and domestic trade, or even by public policy, such as the use of strategic storage and release of supply.

The second set of approaches can be thought of as a 'failure of methods' interpretation which argues that the traditional statistical forecasting methods are not appropriate to detect (true) effects of climate change on food prices. This critique embraces a range of issues including: questions about functional form and how to reflect various non-linearities in the (reduced-form) relationship between weather changes and market prices for food; questions about spatial and commodity-specific heterogeneity in the relationship; and the absence and/or poor quality of key data on production and internal trade in food commodities.

Connecting the facts-on-the-ground and the failure-of-methods explanations is the fact that we are trying to address what is an 'over the horizon' problem'. The reason is that while the processes generating climate change are already taking place, their sizable effects will only possibly manifest themselves over time. As such, methods that currently rely on historical data will struggle. This caveat applies to this paper. As such, it is best thought of as an exercise in method rather than providing a definitive set of results on the link between climate volatility and domestic food prices in Uganda.

The remainder of this paper considers these two explanations. Section 2 lays out a basic framework into which the exercise described later in the paper fits. Section 3 then reviews the 'facts on the ground' and Section 4 describes the data used in the case of Uganda. Sections 5 and 6 then presents some preliminary results from this alternative approach and Section 7 concludes by discussing the next steps in the analysis.

II. Analytical Framework

This paper is concerned with near-term forecasting of food price changes and as such will concentrate on simple reduced-form models. It is appropriate, however, to embed this approach within a more general framework for forecasting inflation, in which inflation is anchored in the long-run by both demand-side or monetary factors on the one hand and supply-side and open economy price arbitrage factors on the other.[1]

A natural starting point is the standard sectoral decomposition of headline inflation between three sub-indices: for food, energy, and core prices such that,

(1) $$P_t = P_{Ft}^{\beta} P_{Et}^{\gamma} P_{Ct}^{1-\beta-\gamma},$$

where F, E and C denote food, energy and core prices, respectively, and β and γ are the weights of food and energy in the consumption basket and t denotes time. Headline inflation can then be written as a weighted average of the sectoral inflation rates:

(2) $$\pi_t = \beta\pi_t^F + \gamma\pi_t^E + (1-\beta-\gamma)\pi_t^C$$

Each of these sectoral rates can be further defined as a geometrically-weighted average of the price of tradable (T) and non-tradable (N) goods and services such that $P_{jt} = P_{Tjt}^{\alpha j} P_{Njt}^{1-\alpha j}$ where α_j is the share of tradables in $j = \{F, E, C\}$.

By the small-country price-taking assumption, tradable prices are defined as $P_{Tjt} = E_t(1+\tau_{jt})P_{Tjt}^{*}$, where P_{Tj}^{*} denotes the world price of the tradable component of j, E_t is the suitably-defined nominal exchange rate and τ denotes tariff or other relevant price wedges, including transport costs. If the latter are constant over time, and letting $\hat{E}_t$ denote the depreciation of the nominal effective exchange rate, the inflation rate

[1] This approach dates from work by Sargan (1980) and Hendry (2001) and applied more recently to Tanzania by Adam et al (2012).

for tradable goods is given by the relevant 'world' inflation rate for tradables and the depreciation of the appropriate trade-weighted exchange rate $\pi_t^{Tj} = \hat{E}_t + \pi_t^{*Tj}$.

Inflation in non-tradable components is determined by the balance of excess supply and demand in the domestic economy. On the demand side it is conventional to focus on the determinants of (excess) aggregate nominal demand; on the supply side, a range of factors are adduced, the most important being the transmission of weather variation to agricultural output and the pass-through of the price of (tradable) inputs such as energy prices. The evolution of domestic food prices will also reflect variations in domestic and international supply conditions.

This simple structure can then be represented in a generalized framework in which inflationary pressures emerge from the deviation from equilibrium in a number of different markets. The excess aggregate demand channel operates through the domestic money market and the pass-through from world prices for food, fuel and manufactured goods, while on the supply side, the focus is primarily on agricultural output, assuming implicitly that the non-food output gap is essentially demand-determined.

A natural way of expressing this structure is the following error correction form

$$\begin{aligned} \pi_t^j = \beta_0 + \sum_j \sum_{l=1}^{k} \beta_l^j \pi_{t-l}^j + \sum_{l=1}^{k} \mathbf{\Gamma} Z_{t-l} + \alpha_1^j (m - \widehat{m})_{t-m} + \alpha_2^j (e^f - \hat{e}^f)_{t-n} + \alpha_3^j (e^e - \hat{e}^e)_{t-p} \\ + \alpha_4^j (e^c - \hat{e}^c)_{t-q} + \alpha_5^j (y^a - \hat{y}^a)_{t-r} + \sum_{s=1}^{11} \phi_s D_t^s + \varepsilon_t \end{aligned} \tag{3}$$

where π_t^j is the month-on-month change in the log of price index i where $j = \{headline, food, energy, core\}$. The deviations from long-run anchors are: $(m - \widehat{m})$, the deviation of real money from its equilibrium value; $(e^f - \hat{e}^f)$, $(e^e - \hat{e}^e)$ and $(e^c - \hat{e}^c)$ the deviations of domestic (tradable) food, energy and core prices from their relative PPP values respectively; and $(y^a - \hat{y}^a)$, a measure of 'excess supply' in agriculture, and the vector D^s denotes seasonal dummy variables. The parameter vector $\boldsymbol{\alpha^j} = (\alpha_1^j \dots \alpha_5^j)'$ denotes the feedback effects from the long-run price anchors onto the relevant inflation rates. These long run effects are defined such that we expect $\alpha_1^j \geq 0$ for all *j*: excess monetary demand relative to the long-run equilibrium demand imparts and inflationary impulse.[2] For the coefficients α_2^j, α_3^j and α_4^j we expect own effects to be negative and cross effects positive. Thus for example we would expect $\alpha_2^j < 0$ and α_3^j *and* $\alpha_4^j \geq 0$ when *j=food.* In other words, when the domestic food price exceeds the exchange rate-adjusted world price, domestic food price inflation will fall to eliminate the disequilibrium but excess energy and core prices will, other things equal, increase food inflation. Likewise for energy and core prices. The vector ***Z*** consists of other exogenous short-run inflation determinants including a small

[2] Instead of expressing this excess monetary demand in terms of real money aggregates, it could alternatively be written in terms of the deviation of the real interest rate from its natural rate (in which case the sign of the error correction coefficient α_1^j would be reversed).

number of dummy variables introduced to pick up measurement changes in the price indices. All elements of **Z** are either stationary or transformed to be so.

The agricultural output gap

The principal focus of this paper is the measurement of the agricultural supply gap, $(y^a - \hat{y}^a)$ and food prices. The gap is simply the deviation of actual from potential agricultural output, where the latter is defined as output under 'normal' growing conditions. The agricultural supply gap could be computed directly from production data, using standard Hodrick-Prescott or other filtering methods to estimate potential output as a latent variable from time series data on actual production. In practice, this approach is severely hampered by the lack of consistent time series on agricultural output on anything higher than annual frequency.[3]

In order to circumvent these measurement problems, this paper proposes to use high-frequency and disaggregated weather data as a direct proxy for the variation in agricultural supply. Food crop agriculture, particularly the production of staple food crops—maize, beans, matoke, for instance—is overwhelmingly rain fed so that conditional on planting decisions (i.e. on choices over land, labor and fertilizer inputs), yield variation is highly dependent on rainfall variation. Hence in the absence of high-frequency data on agricultural output we develop a proxy for short-term variations in agricultural output based on the idea that agricultural output reflects weather deviations from its long-run seasonal mean in the principal food-producing districts of the country at critical points in the planting/growing/harvesting cycle.

This is a strong identifying assumption. Domestic agricultural production reflects a range of factors beyond variations in weather conditions through the agricultural cycle including changing factor inputs, productivity-enhancing technologies, adaptation measures such as crop switching and so forth. Hence the relationship between weather and crop production is much more complicated than our simple proxy admits. However, the key point is that many of these factors produce either low-frequency changes in potential output or are pre-determined at the time weather-related shocks occur, so that over the short-run weather-related variations are expected to play a dominant role in explaining variations in yields.

Moving beyond domestic production, the evolution of domestic food prices will also reflect variations in international supply conditions. International trade in food accounts for a relatively small share of total: there is some cross-border trade in maize and staples from DRC, Rwanda and Kenya, but most food consumed is produced domestically. Though modest in aggregate, the potential for cross-border trade will nonetheless place limits on how far domestic food prices can deviate from world prices. If transport was costless and there were no other frictions, trade in food would arbitrage away *any* deviations of domestic prices from world prices. In reality, however, the degree of arbitrage will be limited by: imperfect substitutability in consumption (which may be substantial in the case of highly specialized commodities such as matoke); constraints on trade, most notably high transport costs; policy barriers to trade in food, such as regional trade embargos; and monopoly power in food distribution, such that the mark-up of transport and distribution rates may increase at times of increased demand. As a result, the domestic food

[3] Despite facing similar data limitations, Durevall et al (2013) adopt this approach, first interpolating agricultural GDP in Ethiopia from annual to monthly frequency and applying a Hodrick-Prescott filter.

prices will move around within a band without triggering price-stabilizing international trade. This 'parity band' is defined by the export- and import-parity prices respectively as

$$(1-c)(1-t_X)EP_F^* \leq P_F \leq (1+c)(1+t_I)EP_F^*$$

where world food prices P_F^* are exogenously given in dollar terms, c denotes the (constant) marginal transport cost of moving good from the world to the domestic market (expressed as a proportion of the landed world prices) and where t_X and t_I are the relevant trade taxes. Clearly, the higher are tariffs, per-unit transport costs (as a result of higher fuel prices, for example) and other components of transport and distribution activities, the wider the bands and the more 'non-tradable' domestic food prices will be. These effects may well be exacerbated in the presence of imperfect competition in trade and distribution as monopolists' will mark-up their prices over cost pro-cyclically with (world) food prices.[4]

To reflect this 'partial tradability' of food we model domestic food inflation as a function of both domestic supply factors, measured as shocks to yields, and international price arbitrage constraints operating directly through food prices and indirectly though fuel prices, in each case intermediated by movements in the exchange rate.[5] Which of these dominates depends not just on the evolution of domestic and external conditions but also on the degree of openness to trade in food, in which case transport costs are therefore likely to play a central role in leveraging up the role of food prices in explaining overall inflation.

The remainder of this paper focuses on the construction of a proxy for the agricultural supply gap but before getting to this and to set the scene we briefly review some aggregate evidence.

III. The facts on the Ground: Aggregate Picture

To provide context for what follows, this initial section briefly examines recent overall price developments and patterns of weather change and Uganda. This initial analysis is consistent with a 'facts on the ground' interpretation that suggests the change in weather volatility has been relatively modest to date and, at least at an aggregate level, there appears to be no robust link between aggregate weather volatility and food prices, at least using conventional reduced-form time-series approaches to modelling the relationship between the two.

Food prices and the cost of moving food from producer to consumer play a central role in overall inflation in Uganda. Based on data from National Household Surveys, the food share in total household consumption (including the consumption of own-produced food) was 42 percent of total consumption in

[4] Faced with constant marginal costs, the monopolist's mark-up will be increasing in the price *in*elasticity of demand. By Engel's Law, household demand of necessities such as food is likely to be highly inelastic and increasingly so as food consumption falls towards the subsistence threshold. It follows that for a net food importing country with imperfectly competitive importers, food is likely to become less tradable – due to a rising mark-up over the world price – at precisely the time it is most scarce on the domestic market.

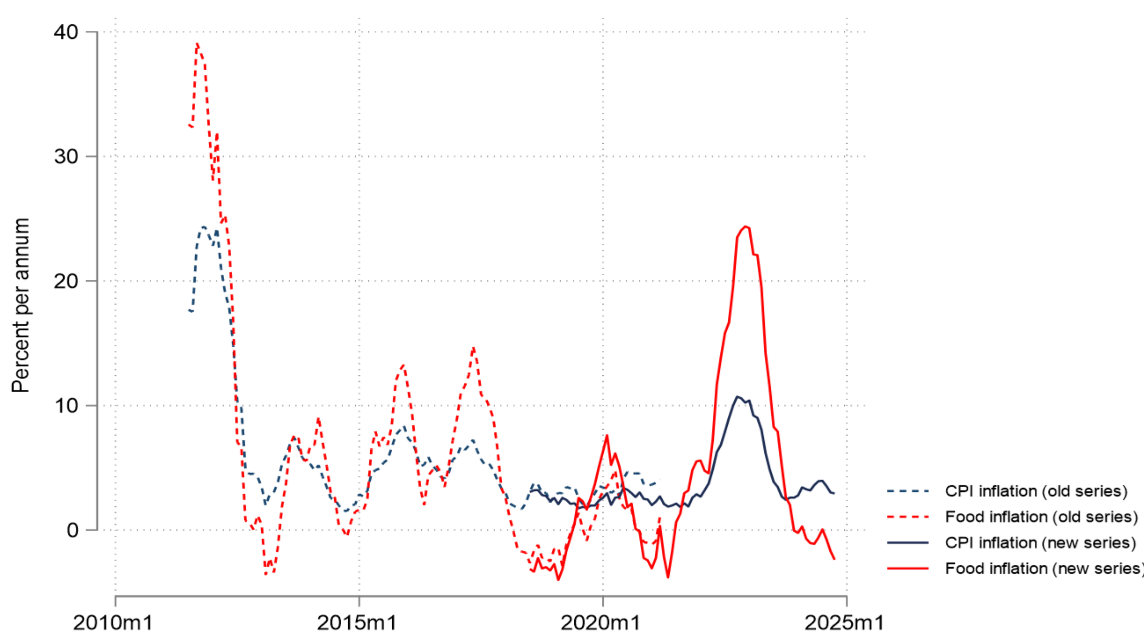
[5] Note that if food were fully tradable, prices at the margin would be tied down by the import/export parity price; the characteristics of domestic demand would be irrelevant.

2019/20, down from around 50 percent in the early 2000s.[6] Since it only measures consumption of marketed food, the food share in the CPI is lower. In the current CPI (re-based in 2016/17) the share of food (excluding non-alcoholic beverages) in total CPI is 25.4 percent. This is still the largest single component, with transport (10.5 percent) and housing, water, electricity and gas (10.4 percent) the next largest categories. The food share in the total consumption basket varies across the country ranging from a low of 18 percent for high-income Kampala to 36 percent in Arua in the North West of the country.[7]

Price data

Annual headline inflation in Uganda has been in single-digits for the last decade and has consistently been at or below the Bank of Uganda's 5 percent per annum target since around 2017 except during the second half of 2022 (Figure 1). Food price inflation has, by contrast, been much more volatile, with major spikes in 2011 and again in mid-2022, the latter following the global spike in world food, fuel and fertilizer prices following Russia's invasion of Ukraine in March of that year.

Figure 1. Headline and food price inflation Uganda 2011 - 2025



Source: Uganda Bureau of Statistics (UBOS)

[6] Uganda National Household Survey 2002/03 and 2019/20 *Uganda Bureau of Statistics* (2003 and 2021).

[7] UBOS CPI data, provided by Bank of Uganda (December 2024).

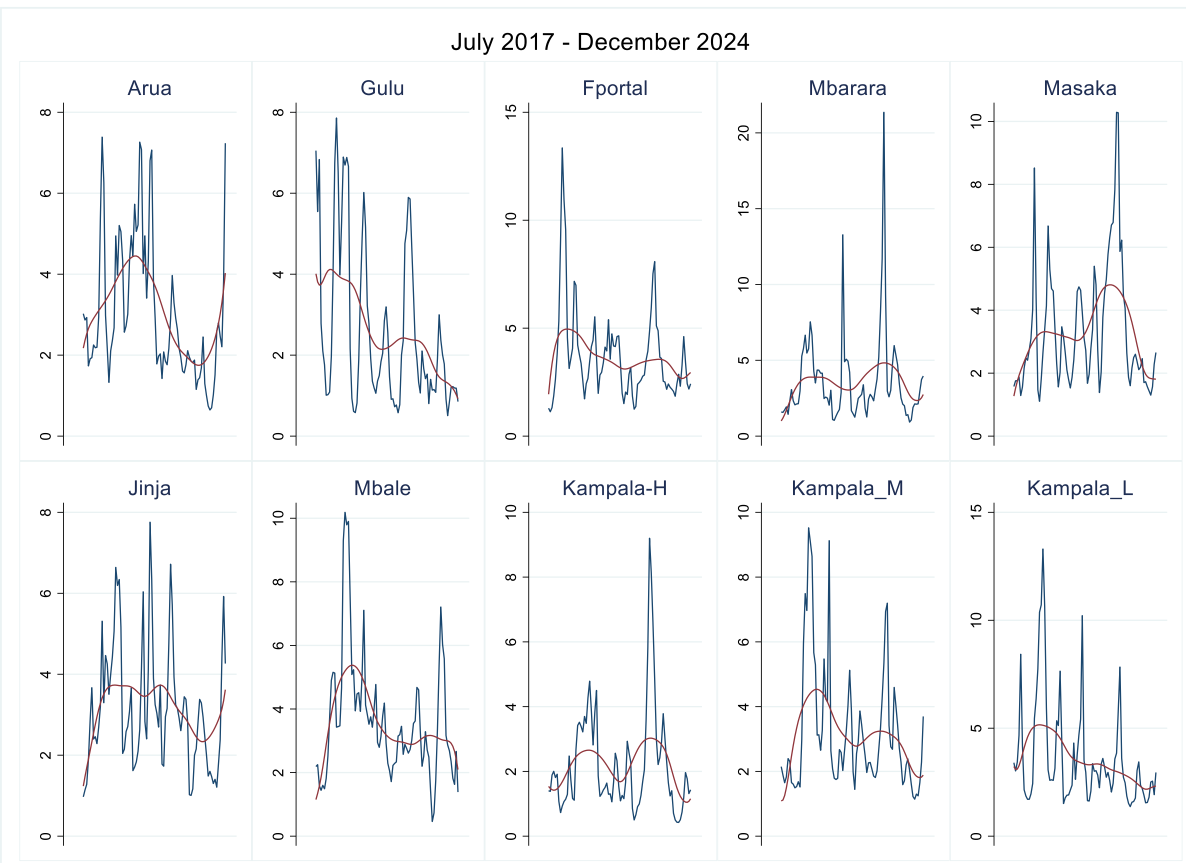
Table 1. Summary aggregate inflation data 2017-2024

	2017m7 - 2020m4			2020m5-2024m12			2017m7 - 2024m12		
	CPI	Food	Non-Food	CPI	Food	Non-Food	CPI	Food	Non-Food
Mean	2.42	0.62	3.07	4.34	5.87	3.90	3.79	4.35	3.66
Std dev	0.45	3.82	1.62	2.72	8.54	0.40	2.46	7.83	1.51
CoV	0.19	6.14	0.53	0.63	1.45	0.10	0.65	1.80	0.41

Source: UBOS Consolidated CPI data

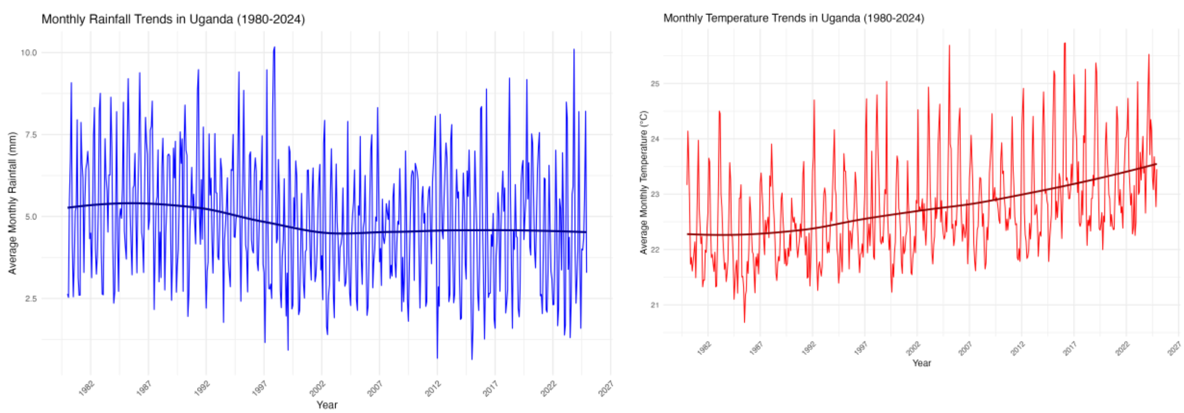
Figure 2, which is based on the aggregate food price indices for each of the ten UBOS price collection locations (see Figure 12 and Section 4 below for details), shows that food prices are not only substantially more volatile than overall prices on average (between two and eight times more volatile) but that there are also significant spatial and compositional differences in local price indices.

Figure 2. Relative Volatility of Food Prices to Overall CPI at UBOS Price Collection Locations



Note. Volatilities measured as six-month moving standard deviations (with Lowess smoother).

Figure 3. Mean monthly rainfall and temperature for Uganda 1980-2024



Source: European Centre for Medium-Term Weather Forecasts (ECMWF) ERA 5 data.

Weather data

We now turn to ‘overall’ weather volatility in Uganda. We delve into the collection and definition of these data in more detail in the next section, but Figure 3 plots monthly country-wide average rainfall levels and average daytime temperatures for Uganda from 1980 to 2024 based on data from the European Centre for Medium-Term Weather Forecasts (ECMWF). Table 2 provides a simple summary of these data.

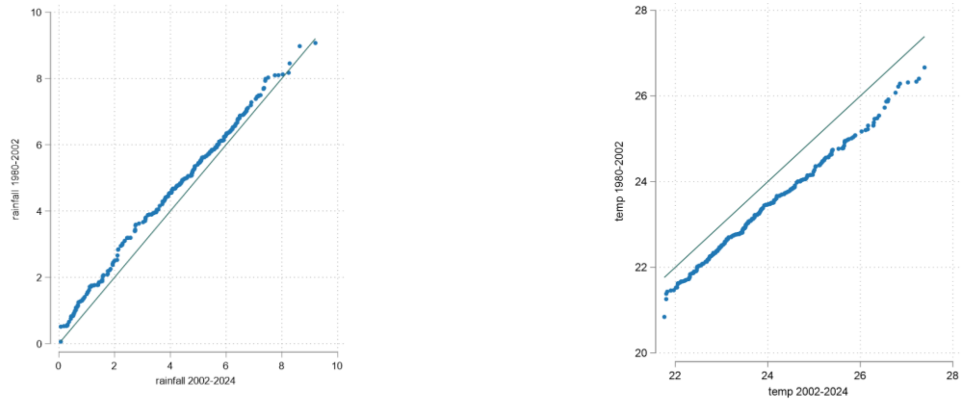
Table 2. Uganda: Weather Summary Statistics
(five-year averages)

	1980-85	1985-90	1990-95	1995-00	2000-05	2005-10	2010-15	2015-20	2020-25	1980-2025
					Rainfall (mm)					
Mean	4.65	4.83	4.61	4.38	3.98	4.14	4.36	4.03	3.96	4.33
SD	2.27	2.01	2.03	2.14	1.91	1.94	2.16	2.36	2.32	2.14
CoV	0.49	0.42	0.44	0.49	0.48	0.47	0.50	0.59	0.59	0.49
Skewness	-0.39	-0.53	-0.4	-0.17	-0.38	-0.36	-0.65	-0.02	-0.06	-0.31
										[0.095]
Pr: Komolgorov-Smirnov (split at 2001m12)										
					Temperature (degrees celsius)					
Mean	23.12	23.07	23.28	23.54	23.54	23.67	23.6	24.14	24.19	23.57
SD	1.23	1.11	1.13	1.25	1.17	1.19	1.2	1.44	1.19	1.26
CoV	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.05	0.05
Skewness	0.83	0.29	0.55	0.68	0.69	0.58	0.55	0.69	0.46	0.62
Pr: Komolgorov-Smirnov (split at 2001m12)										[0.000]

Notes: Date source: ECMWF ERA5 (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-complete?tab=overview). Authors' calculations

Figure 4. Quantile-Quantile (QQ) plots of rainfall and temperature in Uganda

a. Rainfall (monthly average mm) b. Temperature (monthly average Celsius)



Source: Authors' calculations using ECMWF ERA5 data.

The Kolmogorov-Smirnov statistics in Table and the QQ plots in Figure 4 confirm this impression that while the temperature distribution has shifted to the right between 1980-2001 and 2002-2025, the decline in rainfall has been less marked.

IV. Proxying agricultural supply from climate data

This section describes the construction of a weather data-based proxy for the agricultural supply gap. The analysis proceeds in a set of steps.

Production and trade

Our proxy is constructed from data on the principal domestically-grown food crops in Uganda. According to the *Annual Agricultural Survey* published by the Uganda Bureau of Statistics (UBOS),[8] these are maize, sorghum, millet, matoke, groundnuts, beans, cassava, sweet potatoes and yams which together account for approximately 22 percent of the national CPI food basket (See Appendix Table I), and a substantially larger share of overall consumption when non-market own-consumption is considered.[9] Chapter 6 of the *Annual Agricultural Survey* provides a detailed narrative description of production locations for each of these crops; this analysis was cross-referenced with data provided by the Famine Early Warning System (FEWSNET).[10]

[8] Uganda Bureau of Statistics (2022), Section 6.

[9] Evans School Policy Analysis and Research Group (2024) estimate that in 2019, approximately 40% of total household consumption in Uganda is from own consumption.

[10] See FEWSNET Uganda Supply and Market Outlook (https://fews.net/east-africa/supply-and-market-outlook/march-2024)

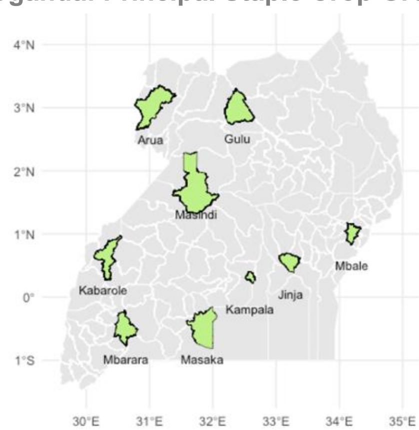
Data on internal and cross-border trade patterns by commodity are extremely sparse. The best data were those compiled by the Famine Early Warning System (FEWSNET) on the basis of qualitative and quantitative data provided by government, international organizations including the World Food Program, and private traders. For the current analysis we used FEWSNET data to determine production and trade pattern by commodity. Figure 6 provides an example for just one of the staple commodities, maize.

Weather anomalies

The next step is to compute relevant measure of weather variability across the growing areas for each crop. A number of organizations collect data on local weather patterns in Uganda, either from instrument readings from physical weather-stations, or from earth observation data collected by satellite.[11] In this paper we use earth observation data, specifically the ERA5 data produced by the European Centre for Medium Range Weather Forecasts (www.ecmwf.int). The ERA5 data combines model data with observations from across the world into a globally complete and consistent dataset providing daily data on a range of weather measures (air temperature, dewpoint temperature, precipitation, pressure and wind direction) at a grid resolution of approximately 31km^2.[12]

We compute local area weather variations across the principal growing regions for each staple crop and each market location in Uganda (Figure 7).

Figure 5. Uganda: Principal Staple Crop Growing Areas



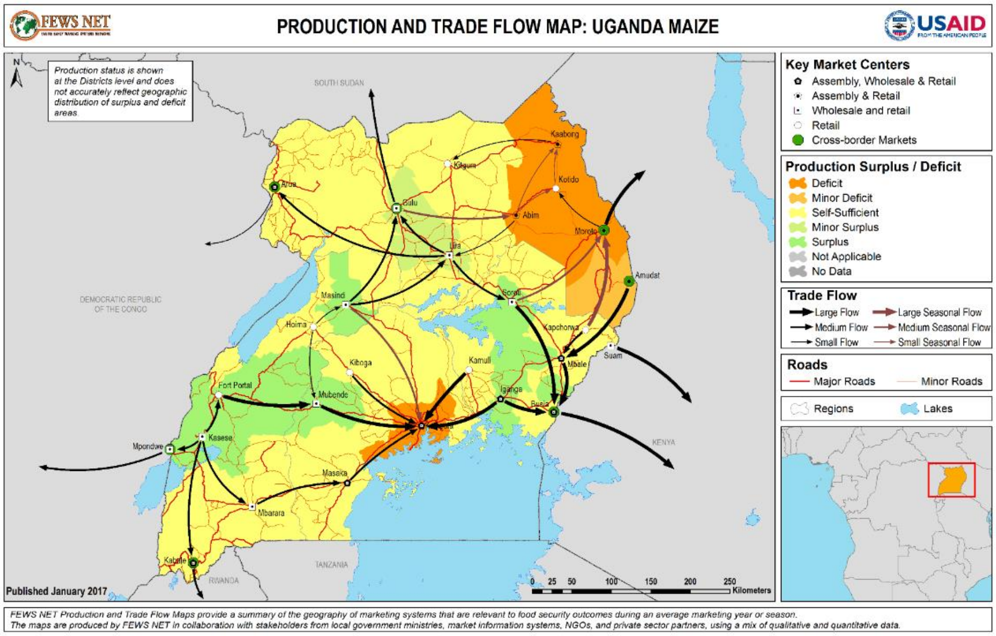
Source: UBOS Annual Agricultural Survey and authors' computation.

Notes: The shaded areas identify Uganda district-level boundaries corresponding to agricultural growing areas contiguous with local price-collection markets (See Figure 12 below). Average precipitation and temperature anomalies across these districts are used to define weather anomalies in production locations. Shapefiles generated using Google Earth Engine.

[11] Instrumental readings are provided by the Uganda National Meteorological Authority (https://meteo.mwe.go.ug/) although these data are proprietary and released with a time lag. Instrument-based data are collated for a large number of countries, including Uganda, by the University of East Anglia Climate Research Unit (https://www.uea.ac.uk/groups-and-centres/climatic-research-unit/data)

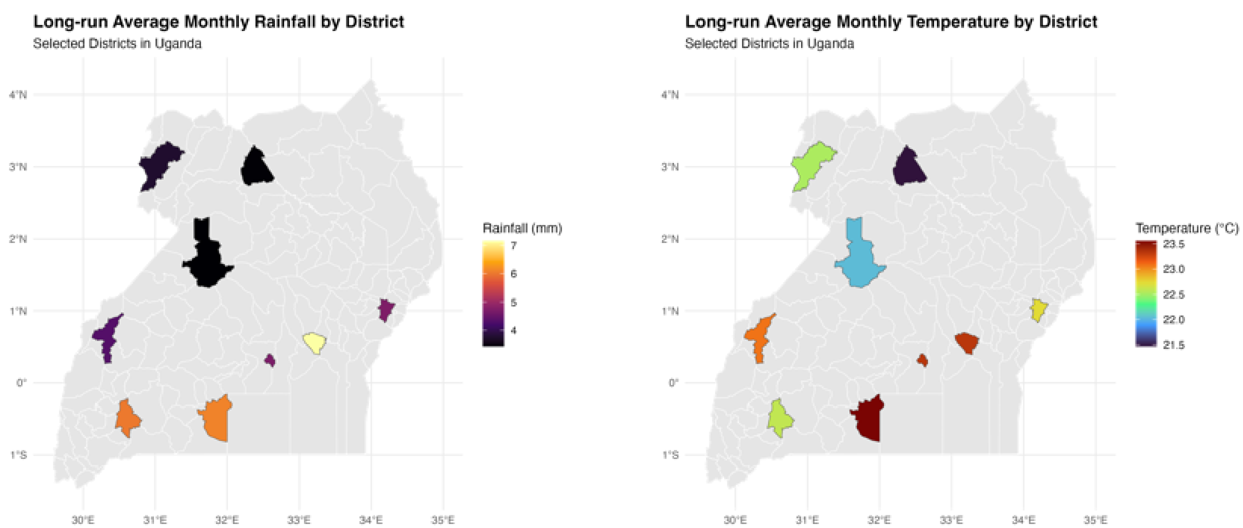
[12] Details on this data set are found here: https://cds.climate.copernicus.eu/datasets/reanalysis-era5-complete?tab=overview

Figure 6. Cross-border and internal trade patterns for Maize 2023



Source: Famine Early Warning System (FEWSNET)

Figure 7. Long-run Average Weather Indicators for Principal Production Districts



Source: Authors' calculations, combining ERA5 weather data from European Centre for Medium Range Weather Forecasts with district boundaries for principal growing areas (Figure 5).

For each location, we define weather anomalies as the monthly deviation of temperature and rainfall from their long-run seasonal mean temperature and rainfall, net of any long-run trend. The literature is replete with a range of alternative measures of anomalous weather events: in the analysis presented below we develop measures based on four basic variations: [13]

i. The *absolute deviation* of rainfall (in mm) and temperature (degrees Celsius) from their long-run monthly average by location;

ii. the *percentage deviation* of rainfall (in mm) and temperature (degrees Celsius) from their long-run monthly average by location;

iii. the *asymmetric deviation* from long-run monthly averages by location where anomalies are split between positive (≥ 0) and negative deviations (< 0), to reflect the possibility that 'too much' rainfall or temperature is differentially impactful on prices from 'too little';

iv. *squared deviations* (for both absolute and asymmetric cases) to reflect possible local non-linearities in climate variation.

We also compute cumulative anomalies over the growing season for each crop-location pair (see below).

Figure 8 illustrates the distribution of monthly rainfall and temperature relative to their long-run monthly averages computed over the 45-year period from January 1980.

Seasonal variation

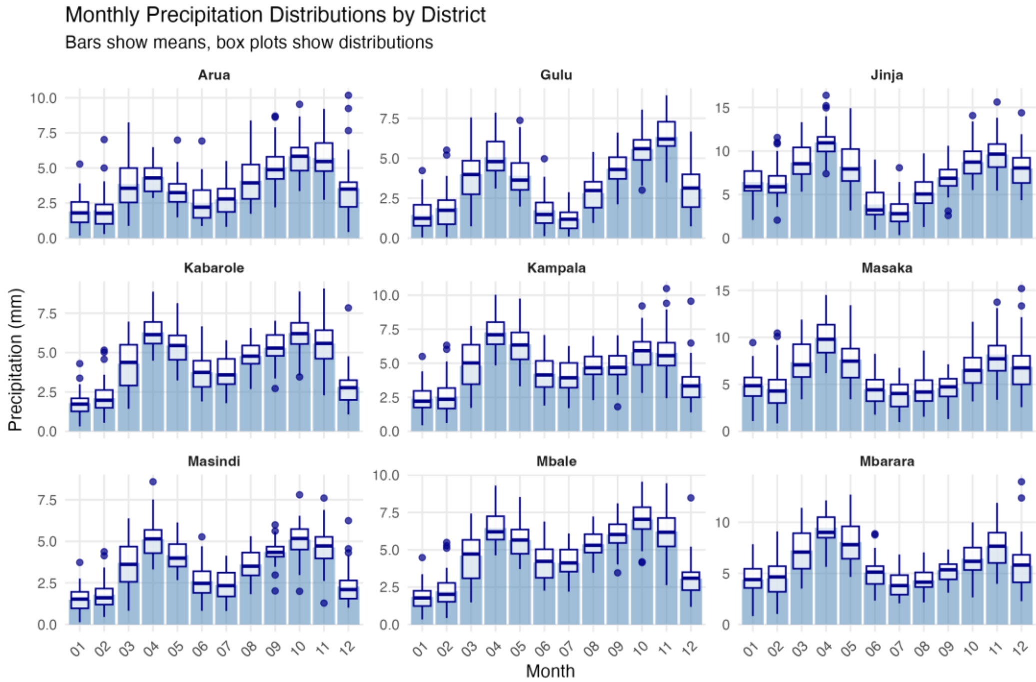
Not all monthly weather deviations are relevant for crop production. Instead, what matters are the weather anomalies during the planting, growing and harvesting phases of the agricultural cycle. There are two seasons for maize, sorghum, millet and beans. Matoke is grown year-round while cassava has a single growing season. Figure 9 indicates the general agricultural season for Uganda in the bi-modal rainfall areas (where the staple crops are predominantly grown). Based on this general pattern we then use the agronomic literature[14] describing the specific characteristics of each commodity to develop a calendar that determines the planting, growing and harvesting patterns for each crop and then for each location and each commodity.

[13] We also experiment with other commonly-used measures of weather anomalies including measure of 'runs' of extreme values (e.g. the prevalence of runs of 5 or 7 days of temperatures above, say, 80 percent of the seasonal maximum recorded, or the number of spells of days of no rain. Results are not presented here.

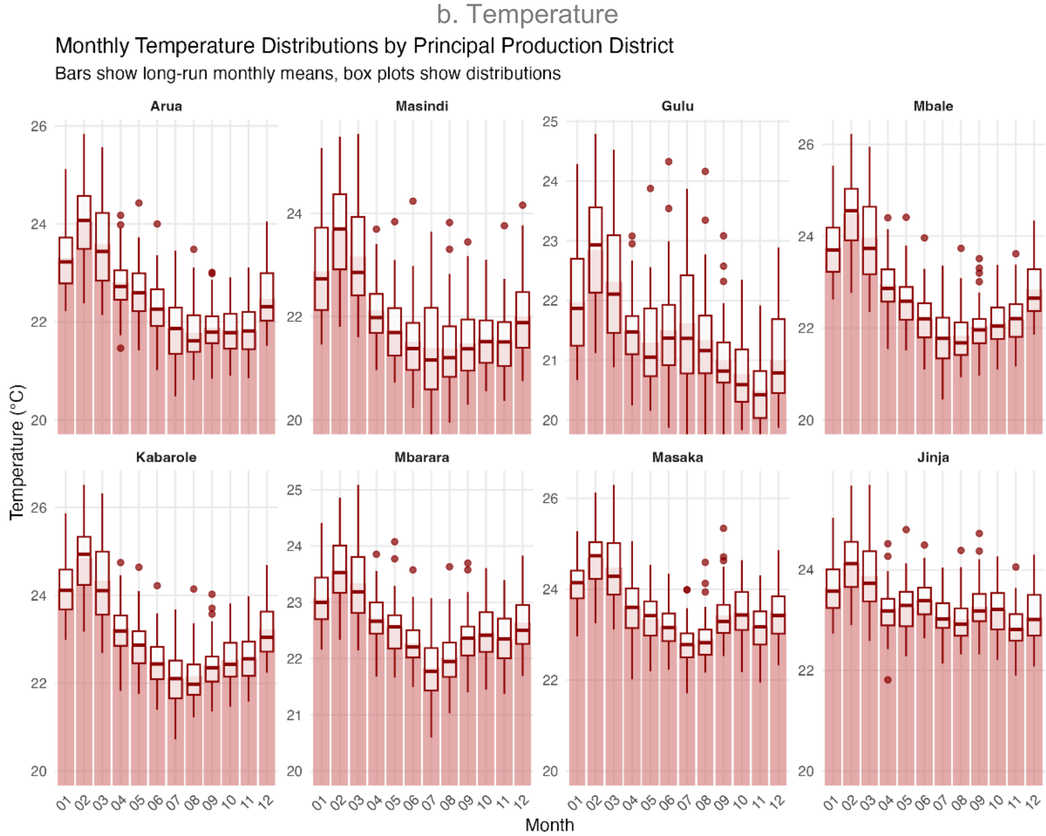
[14] FAO crop information database. https://www.fao.org/land-water/databases-and-software/crop-information/en/

Figure 8. Uganda: Monthly Weather Distribution by Production Location

a. Precipitation

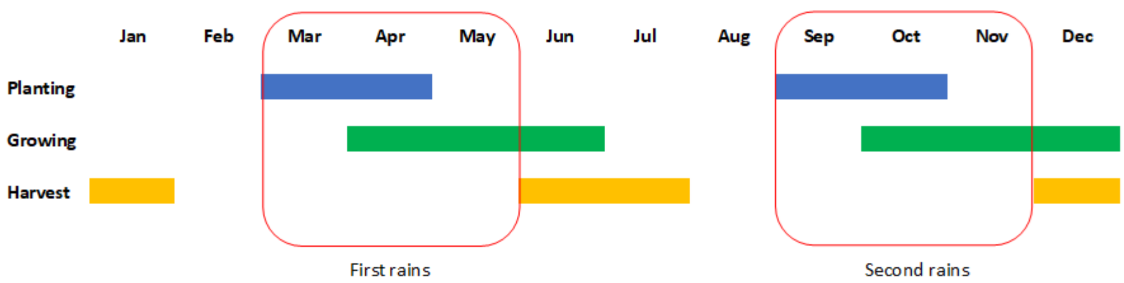


b. Temperature



Source: Authors' calculations (See Figures 5 and 7).

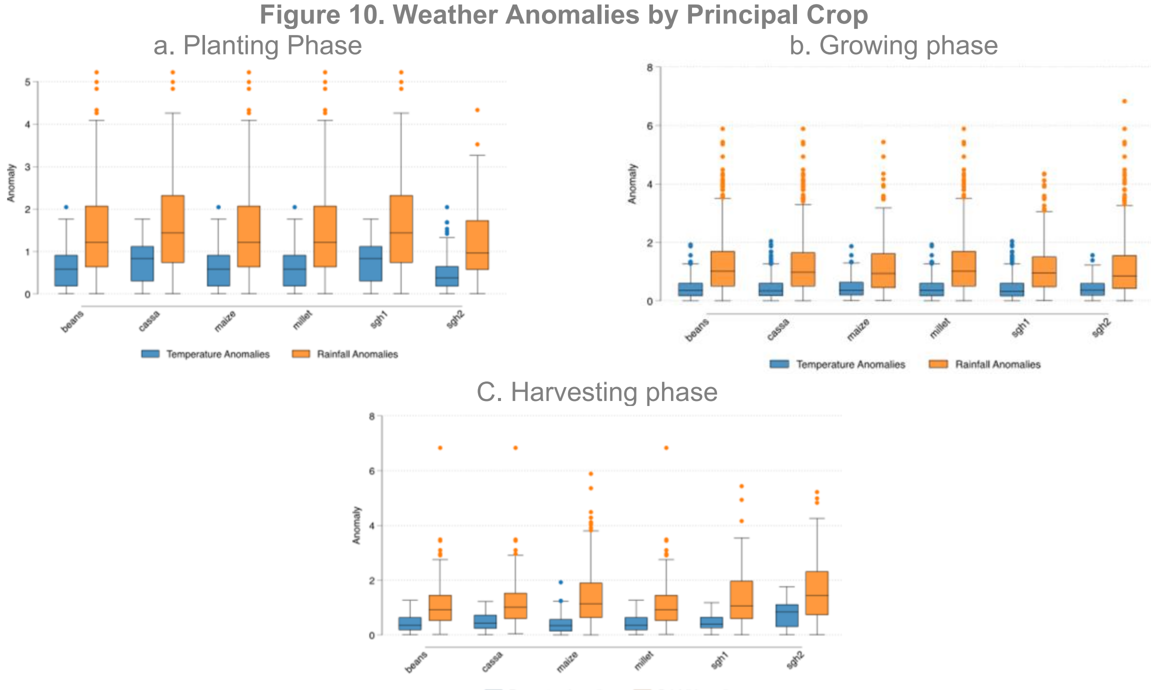
Figure 9. Uganda: General Agricultural cycle
(bimodal rainfall areas)



Source: Authors' calculations based on Famine Early Warning System (FEWSNET)

This calendar is then used to classify weather anomalies occurring during the three phases (planting, growing, and harvesting) of the agricultural cycle for each crop. Figure 10, which computes the distribution of absolute rainfall and temperature anomalies across the three phases of the cycle, provides a summary of these measures by showing the extent to which weather anomalies vary across the agricultural cycle for key crops in Uganda. As described in the next section, the actual data used in our empirical analysis exploits alternative measures of weather anomalies *by crop* and *by location* separately.

Figure 10. Weather Anomalies by Principal Crop



Source: Authors' calculations.

Notes: Each figure plots the distribution of temperature and rainfall (in percentage terms) *relative* to its de-trended long-run seasonal average across the relevant months of the phases and locations for each crop. Variations in the distributions across crops therefore reflect differences in growing locations and in the timing of phases. For sorghum there are two crops per year (represented by Sgh1 and Sgh2 respectively). By contrast, matoke (a tree crop) is grown year-round and therefore the decomposition by phase does not apply.

V. An empirical framework

We now turn to the empirical evidence. Section 5.1 starts by discussing the ‘null results’ with which the Bank of Uganda and central banks elsewhere in the region are finding, namely the apparently weak relationship between measures of weather volatility and food (and headline) price inflation. As noted in the introduction, this (non-) result is consistent with either or both a ‘facts on the ground’ or a ‘failure of methods’ approach. In Section 5.2. we therefore seek to address the latter interpretation by exploring the extent to which exploiting more granular weather, crop and price data can lead to a better representation of the agricultural supply gap and hence food price inflation.

Weather variation and aggregate headline and food prices

Near-term forecast models for aggregate headline and food price inflation typically involve inclusion of alternative measures of weather variation into standard ARIMA-based models (for example, Imnaishvili, 2025). Table 3 provides a high-level summary of the net contribution of controlling for various measures of weather volatility in standard models where the ARMA structure for the food price component of inflation, defined as $ARMA(p,q)$, is augmented by a small set of controls, a vector of stationary seasonal dummy variables and alternative measures of aggregate weather volatility (as defined in Section 3 above). The models are estimated on monthly data over the period from July 2017 to December 2024.[15] The non-weather control variables, designed to reflect the impact of external trade on domestic food and headline prices include the border price of traded food (based on the World Bank’s food price index); the border price of price of energy, from the same source; and the change in the nominal exchange rate.

This table seems to suggest that, as expected, conditioning on measures of weather variability reduces the overall mean square error across a range of standard ARMAX models of aggregate food price inflation. Moreover, this reduction in mean-square error is largest when we use asymmetric measures of weather anomalies that distinguish between positive and negative deviations from the long-run seasonal average rainfall and temperatures (lagged by one quarter).

At least from an historical perspective, the gains from conditioning on these measures of weather variability are limited. This can be seen in Figure 11 which plots fitted values from the ARMA(1,0) model against actual inflation, for the specification with no weather controls (the yellow line) and the ‘Asymmetric Deviation (t=3)’ specification from Table 3. And as shown in Appendix Figure 1, the coefficients on the individual rainfall and temperature anomalies on both headline and food price inflation are imprecisely estimated.

[15] We restrict our attention to models of the log change in monthly prices which are, for the sample considered here, strictly stationary.

Table 3. Improvement in ARIMA Fit Conditioning on Weather Variability

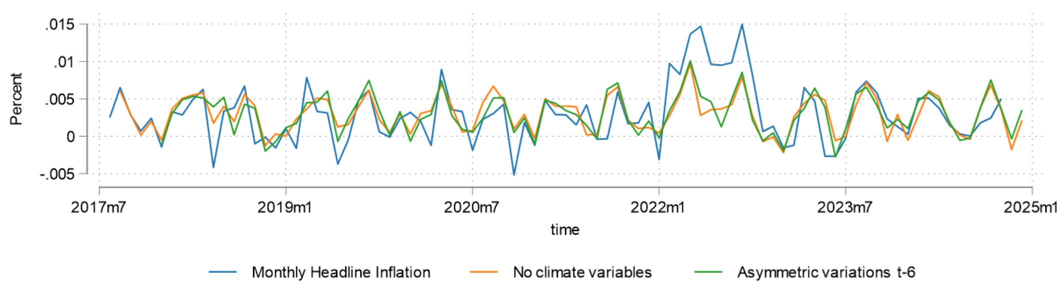
Percentage Reduction in Model Mean Square Error

	ARMA (p,q)									
	(2, 2)		**(2, 0)**		**(1, 1)**		**(1, 0)**		**(0, 1)**	
	Headline	**Food**	**Headline**	**Food**	**Headline**	**Food**	**Headline**	**Food**	**Headline**	**Food**
Baseline MSE										
(no climate anomalies)	0.000013	0.00013	0.000013	0.000131	0.000013	0.000134	0.000013	0.000145	0.0000133	0.000135
Climate anomaly										
Absolute deviation										
t=0	-0.77%	-1.46%	-0.77%	-1.30%	-0.77%	-2.16%	-0.77%	-2.70%	-0.75%	-2.08%
t=1	-0.77%	1.70%	0.00%	-0.23%	0.00%	-0.30%	0.00%	-1.66%	-0.75%	-0.22%
t=3	-6.92%	1.70%	-6.92%	-0.77%	-6.92%	-1.49%	-6.15%	-3.11%	-3.01%	-1.48%
t=6	-6.92%	2.00%	-6.15%	2.30%	-6.15%	1.27%	-6.15%	-1.52%	-7.52%	0.96%
Asymmetric deviation										
t=0	-0.77%	-2.24%	-0.77%	-2.14%	-0.77%	-2.46%	-0.77%	-2.90%	-0.75%	-2.45%
t=1	-1.54%	-0.62%	-0.77%	-0.46%	-0.77%	-0.67%	-0.77%	-2.01%	-0.75%	-0.37%
t=3	-12.31%	-3.47%	-10.77%	-3.37%	-10.77%	-4.55%	-10.00%	-8.99%	-7.52%	-4.60%
t=6	-8.46%	-0.54%	-7.69%	-0.77%	-7.69%	-2.46%	-7.69%	-6.29%	-8.27%	-2.52%
Squared deviations										
t=0	-3.08%	-1.31%	-0.77%	-1.07%	-0.77%	-1.79%	-0.77%	-1.87%	0.00%	-1.78%
t=1	-0.77%	-1.00%	0.00%	-0.84%	0.00%	-1.04%	0.00%	-2.90%	0.00%	-0.82%
t=3	-5.38%	-1.23%	-4.62%	-0.92%	-4.62%	-0.97%	-3.85%	-2.56%	-2.26%	-0.89%
t=6	-3.08%	1.70%	-2.31%	3.14%	-2.31%	3.14%	-2.31%	2.31%	-2.31%	-1.52%

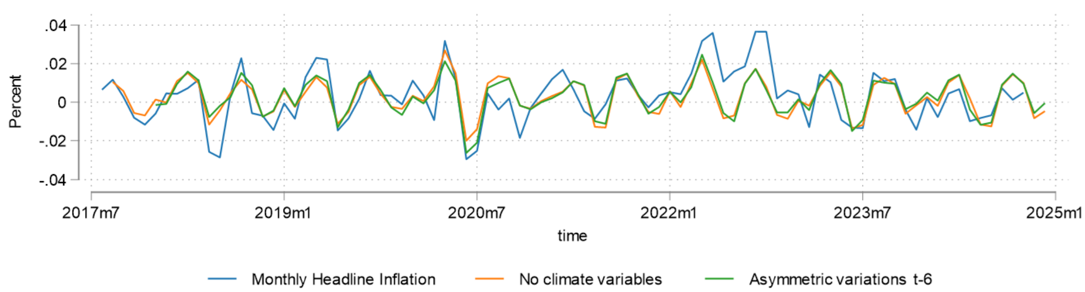
Notes: [1] Cell entries measure percentage reduction in mean square error relative to corresponding ARMAX model with standard controls (see note 3). **[2]** All models estimated on monthly data from July 2017 to December 2024, with dependent variable change in log monthly prices. **[3]** All models include monthly seasonal dummy variables; lagged change in border price of world food price index; lagged change in world energy price index; and lagged change in nominal exchange rate.

Figure 11. Actual vs Predicted Inflation 2017-2024

a. Headline inflation



b. Food inflation



Disaggregation and granularity

We now examine whether a more granular approach to data and modelling provides a stronger basis for assessing the pass-through from weather variability to agriculture and food price inflation. At this stage, following from Section 4, we focus exclusively on the agricultural supply gap and therefore on the relationship between domestically produced food commodities and weather variability.

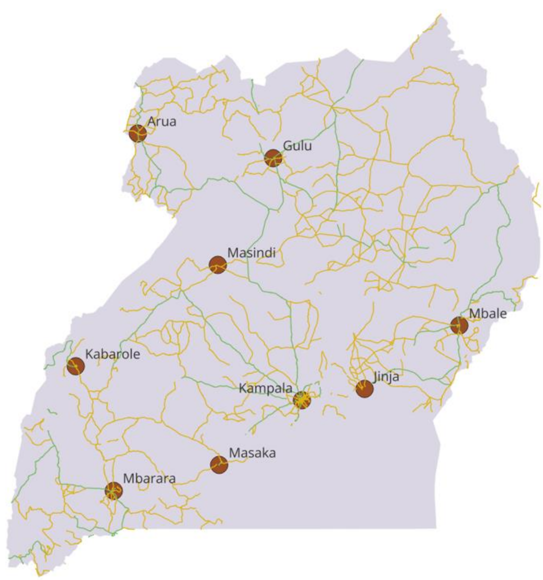
Estimation is based around the following general form:

$$y_{i,t}^{c} = f\left(\boldsymbol{\theta}_{p,s}^{c}; \boldsymbol{X}_{i,p,t-k}^{c}\right) + \varepsilon_{i,t} \quad (4)$$

where the dependent variable $y_{i,t}^{c}$ alternatively measures price inflation, for commodity c consumed at location i, price volatility or the volatility of inflation over monthly, quarterly or annual horizons. We also consider versions of equation (4) in which the dependent variable is the volatility of inflation.

The consumption locations, i, correspond to the CPI data collection points across Uganda while the commodities, c ,are the (relevant) individual components of the consumption basket. The Uganda Bureau of Statistics (UBOS) collects market prices for 106 food products at eight separate locations around the country (see Figure 12). These are in Central Region (low-, middle-, and high-income Kampala plus Masaka); Eastern Region (Mbale and Jinja); Northern Region (Gulu and Arua); and Western Region (Mbarara and Fortportal). We use the detailed price data on food for the period from July 2010 to December 2024 (174 months). [16]

Figure 12. Location of Uganda Bureau of Statistics Price Collection Markets



Notes: [1] Kabarole is the local district around UBOS collection market at Fortportal. [2] the map also includes the centre of the Masindi area, an important growing region in Uganda.

[16] This period spans a re-basing of the CPI in July 2017. While the rebasing resulted in a change in the vector of CPI weights, the principal food products analyzed here were collected on a consistent basis from 2010.

The vector $\boldsymbol{\theta}^{c}_{p,s}$ is the vector of anomalies described in Section 4 above. These are indexed over production locations, p and the lags s relate to the most recent phase in the agricultural cycle by commodity. Thus, for example, $\boldsymbol{\theta}^{c}_{p,g}$ refers to the weather anomalies in the production regions for commodity c during the most recent growing season, g. Subscripts p and h correspond to the most recent planting and harvest seasons. Notice that since the phases of the agricultural cycle are fixed, this generates a variable lag structure within a year for weather anomalies: as time moves forward, each phase recedes further in the past, but since there are two seasons for most crops the weather-effects of the first-season phase will eventually be replaced by those relating to second-season weather conditions.

Finally, $\boldsymbol{X}^{c}_{i,p,t-k}$ is a vector of controls. In addition to location and commodity fixed effects, this vector consists of factors identified in the framework discussed in Section 2, principally those that determine the 'parity band'. Hence, we include the world price of tradable food and energy expressed in local prices (to reflect the landed local cost of imported food).[17] We also include, for each product, cross-border trade volumes and distance to market data.[18] We do not have data on commodity-specific internal trade flows.

Pooling across locations by crop

We first examine the impact of phase-specific weather anomalies on inflation and price volatility for specific commodities across the price collection locations in Uganda.[19] Table 4 reports the results of this exercise in a manner similar to that shown in Table 3. Here we pool price and weather data across collection points and estimate the impact of weather anomalies on commodity-level inflation using a two-way-fixed effects estimator as in equation (5) for inflation and (5') for inflation volatility for the six principal core domestically produced food commodities, c (beans, cassava, maize, matoke, millet and sorghum) and where the index on the weather anomalies denotes the three phases of the agricultural cycle, planting, harvesting and growing, $s = \{p, g, h\}$.

$$\pi^{c}_{i,t} = \mu_i + \lambda_t + \boldsymbol{\beta}'\boldsymbol{\theta}^{c}_{p,s} + \boldsymbol{\gamma}'\boldsymbol{X}^{c}_{i,p,t-k} + +\varepsilon_{i,t} \tag{5}$$

$$\sigma^{c}_{\pi\, i,t} = \mu_i + \lambda_t + \boldsymbol{\beta}'\boldsymbol{\theta}^{c}_{p,s} + \boldsymbol{\gamma}'\boldsymbol{X}^{c}_{i,p,t-k} + +\varepsilon_{i,t} \tag{5'}$$

where $\pi^{c}_{i,t} = \Delta\ln\left(p^{c}_{i,t}\right)$ for commodity c at CPI collection location i and $\sigma^{c}_{\pi\, i,t}$ is the six-month moving standard deviation of $\pi^{c}_{i,t}$. Controls for trade effects are as defined above, while μ_i and λ_t denote location and time-specific dummy variables.

[17] World Bank monthly commodity price series for 'food' and the average price of oil at https://www.worldbank.org/en/research/commodity-markets.

[18] Trade data at the commodity level is sourced from the World Bank *World Integrated Trade Solution* database (https://wits.worldbank.org/). Distances from each market location to the principal border crossing points with Rwanda (Gatuna), DRC (Bwera) and Kenya (Busia) are computed using Google Earth.

[19] We employ a simple moving standard deviation measure of volatility at present, although this may be augmented by a formal GARCH-X approach as described by Francq, C., and Le Quien (2019).

Table 4 presents a high-level summary of the central results where we report only the results for the 'asymmetric deviation' measure of weather anomalies (for both temperature and rainfall) for a static version of the model ($j = 0$) and a dynamic version. While we explored a range of dynamic specifications for this model, the table reports only a fraction of the results, in this case the most basic form in monthly inflation and volatility with phase-specific lags for weather variables and one-period lags on the non-climate control variables.[20]

As indicated by the reduction in the within-sample mean square error, the evidence in the top half of Table 4 points to a significant role for phase-related weather anomalies in improving the forecast accuracy of short-term forecasting models relative to a baseline model that excludes climate anomalies. The weather anomalies are jointly significant determinants of the price movements in all the principal home-produced commodities in Uganda, with the exception of Sorghum.[21] This is true for both inflation and for the volatility of inflation.

Table 4. Conditioning on Weather Anomalies at the Commodity Level

	Percentage Reduction in Mean Square Error *July 2010 to December 2024* Commodity					
Two-way Fixed Effects	**Beans**	**Cassava**	**Maize**	**Matoke**	**Millet**	**Sorghum**
MSE Baseline model (no climate anomalies)						
Inflation	0.0811	0.0905	0.0707	0.1040	0.0567	0.1171
Volatility	0.0317	0.0330	0.0270	0.0399	0.0274	0.0389
Model with climate anomalies						
Inflation	-2.59%	-3.76%	-6.22%	-0.38%	-0.53%	-1.88%
Volatility	-3.94%	-4.90%	-3.91%	0.00%	-4.20%	-16.52%
F-stat on climate anomalies [p-value]						
Inflation	39.90	57.23	86.95	7.26	98.36	5.12
	[0.000]	[0.000]	[0.000]	[0.009]	[0.000]	[0.1634]
Volatility	216.77	32.03	4.20	4.40	23.65	4.15
	[0.000]	[0.000]	[0.029]	[0.036]	[0.000]	[0.210]
Number of observations	1463	1463	1463	1463	1463	431

Notes: [1] Cell entries in lower half of the table measure the percentage reduction in mean square error relative to corresponding ARMAX model with standard controls as reported in top block. **[2]** All models are estimated on monthly data from July 2010 to December 2024. **[3]** The dependent variables are inflation (= the change in log monthly prices by commodity) and inflation volatility (= six month moving standard deviation of inflation). **[4]** Models estimated by two way fixed effects and include monthly seasonal dummy variables; time and location fixed effects; plus controls for external and domestic trade (see text for details).

[20] This is only a subset of the potential specifications we have explored; the full set of results will be available in the full data and results appendix.

[21] It is not yet clear why this is so, but it is worth noting that sorghum only enters the CPI basket in Arua and Gulu but not at the other collection points in the country.

Table 4 reports the results for only a single representation of the underlying ARIMA model and for the case where we consider only the asymmetric deviations of temperature and rainfall from their long-run seasonal means over the various phases of the growing cycle. Similar exercises can be undertaken for alternative dynamic specifications and alternative representations of weather volatility. These are not reported here but Table 5 provides a high-level summary of the effects of varying the representation of climate volatility. Using a simple 'minimum within-sample MSE' criterion, it is clear that allowing for asymmetry in the impact of weather variation delivers the lowest MSE across models for both inflation and inflation volatility for the principal food commodities in Uganda.

Table 5. Comparison of Alternative Representations of Weather Anomalies

	Percentage Reduction in Mean Square Error *July 2010 to December 2024* Commodity					
Two-way Fixed Effects	**Beans**	**Cassava**	**Maize**	**Matoke**	**Millet**	**Sorghum**
Inflation						
Absolute deviation	0.0794	0.0876	0.0682	0.1037	0.0565	0.1158
Percent deviations	0.0791	0.0875	0.0663	0.1039	0.0564	0.1151
Asymmetric deviations	0.0790	0.0871	0.0663	0.1036	0.0564	0.1149
Squared deviations	0.0795	0.0877	0.0683	0.1039	0.0565	0.1167
Volatility						
Absolute deviation	0.0324	0.0335	0.0274	0.0401	0.0277	0.0408
Percent deviations	0.0320	0.0336	0.0276	0.0399	0.0281	0.0448
Asymmetric deviations	0.0317	0.0330	0.0270	0.0398	0.0274	0.0389
Squared deviations	0.0323	0.0335	0.0273	0.0401	0.0278	0.0422

Notes: [1] Cell entries report the MSE for estimated models under different characterisations of climate anomalies, with highlighted cells indicating lowest MSE by climate anomaly and crop. **[2]** All models are estimated on monthly data from July 2010 to December 2024. **[3]** The dependent variables are inflation (= the change in log monthly prices by commodity) and inflation volatility (= six month moving standard deviation of inflation). **[4]** Models estimated by two way fixed effects and include monthly seasonal dummy variables; time and location fixed effects; plus controls for external and domestic trade (see text for details).

The impact of individual anomalies

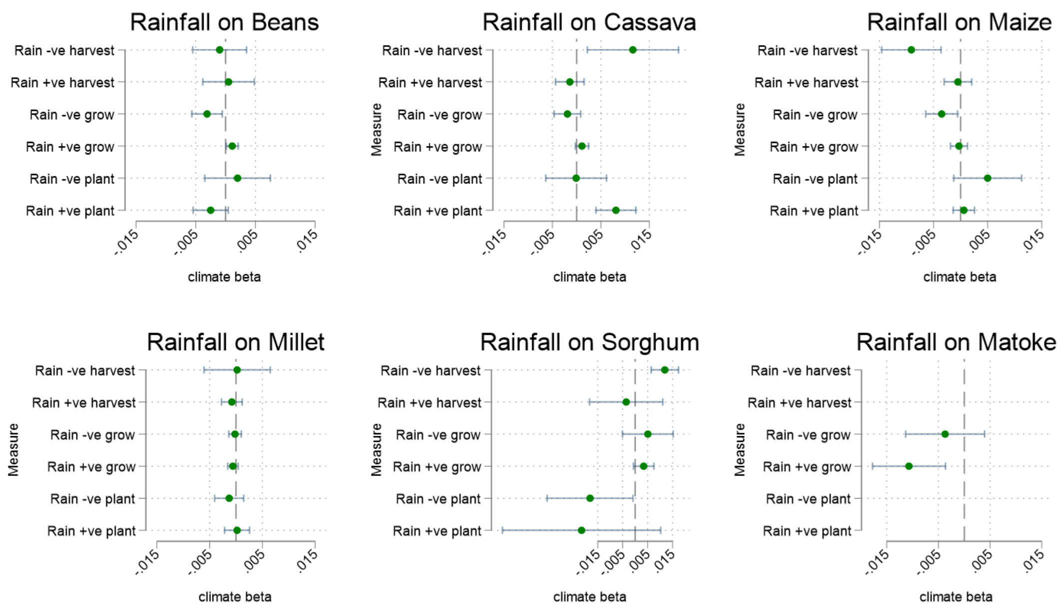
The next step in the analysis is to unpick the vector of estimated effects of weather anomalies on inflation, i.e. the values of the $\hat{\boldsymbol{\beta}}$ vector in Equation (5). Figures 13(a) and 13 (b) report the marginal effects for the cumulative (positive and negative) deviations of rainfall and temperature in the crop-specific production locations across the phases of the agricultural cycle. Recall that each coefficient measures the effect *on current prices* of the realized deviation from the long-run mean in the most recently experienced phase in the cycle. For example, the coefficient on '*rain -ve harvest*' measures the marginal impact of a shortfall in rainfall during the most recent harvest season *for the specific crop*.

The most striking feature of these figures is the apparent lack of precision in the estimates – few of the individual effects are statistically significant – while, at the same time, no strong patterns are apparent between anomalies and price effects.

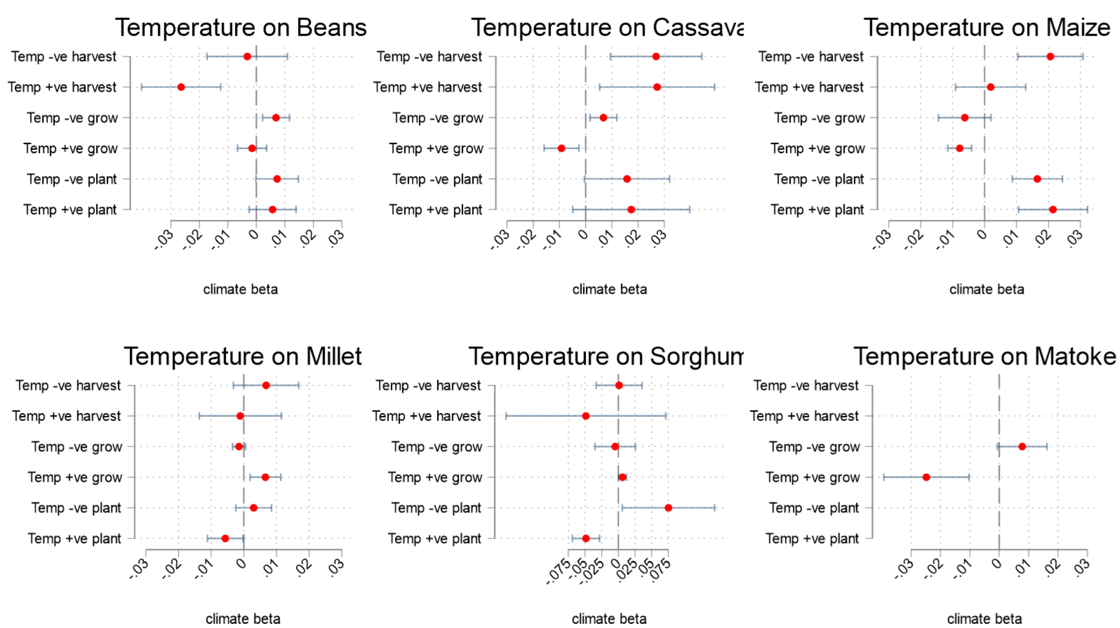
One source of concern is that by distinguishing between temperature and rainfall anomalies, across multiple seasonal phases, and allowing anomalies to be asymmetric, potential collinearity across the vector of measures may weaken the signal extraction process.

Figure 13. Coefficient Estimates of Weather Impacts

a. Rainfall impacts (TWFE with controls and time FE)



b. Temperature impacts (TWFE with controls and time FE)



Notes: See notes to Tables 4 and 5.

Covariate shrinkage using LASSO-Elastic Net

The construction of the weather anomalies in Section 4 above generates a very large set of potential (exogenous) covariates, with measures of weather volatility varying across locations, crops and seasons. One potential approach to aid model selection for NTF models is to use standard machine-learning method for model selection. In this section we employ standard machine learning (ML) techniques to explore the potential to shrink the vector of anomalies in order to derive a more meaningful and interpretable vector of results. Specifically, we employ a standard variant of the LASSO method for variable selection to re-estimate equation (5) where the non-weather control variables described above are always included in the model (i.e. they are un-penalised by the LASSO algorithm).

More specifically, we employ the Zhou and Hastie (2005) Elastic Net which has been shown to be more robust in the context of correlated covariates. By choice of parameter, the Elastic net balances the shrinkage properties of the standard LASSO algorithm with a ridge regression which is known to be robust in circumstances where regressors are highly collinear.[22]

Table 6 reports the results of re-estimating the TWFE model (5) following the LASSO / Elastic Net shrinkage.[23] It is at this stage we now begin to see some patterns emerge from the data. There are clearly variances across crops, and some surprisingly large estimated effects, but what appears to be the case is that weather volatility across the growing season has some significant impact on commodity price inflation. For beans, cassava, maize and matoke rainfall shortages during the growing season raise prices following that year's harvest, *ceteris paribus.* Excess rainfall and warmth in the growing season ("good rains and warmer days"), by contrast, appears to have a favorable (but generally weaker) effect on price dynamics. Again, however, the quantitative size of these effects is modest. Take, for example, the impact of a negative rainfall shock during the growing period for maize. The standardized beta coefficient implies a one standard deviation increase in negative rainfall shocks in the growing period is associated with a 0.0835 standard deviation increase in monthly inflation. The standard deviation of the former is approximately 1.4 *mm* and the latter is around 7.5 percent per month. Hence a negative rainfall shock of *5 mm* across a dry growing season might be expected to increase monthly maize price inflation by around 2.2 percentage points, other things equal.[24]

[22] Relative to the LASSO estimator, the Elastic Net adds a second penalty term (α) to the standard least squares objective function. Specifically, the (penalised objective function) is of the form

$$Q = \frac{1}{2N}\sum_{i=1}^{N}(y_i - \beta_0 - \boldsymbol{x}_i\boldsymbol{\beta}')^2 + \lambda\sum_{j=1}^{p}\left(\frac{1-\alpha}{2}\beta_j^2 + \alpha|\beta_j|\right)$$

where $\boldsymbol{\beta}$ is the full vector of covariates and β_j constitute the subset of climate anomalies that are candidates for shrinkage. The estimated $\boldsymbol{\beta}$ are those values that minimize Q subject to the LASSO penalty terms λ, and the second penalty term, α. When $\alpha = 1$ the elastic net reduces to a standard LASSO and when $\alpha = 0$ it converges on a standard ridge regression. In the results reported, we set $\alpha = 0$ and use a 10-fold cross validation method. These parameter settings do require robustness checking.

[23] To compare the strength of relative effects across anomalies, recognizing that temperature and rainfall are measured in different scales, we report standardized-beta coefficients such that $\beta_{j,SE} = \hat{\beta}_j(\frac{\sigma_{Xj}}{\sigma_Y})$.

[24] (5/1.4)*0.0835*0.075 = 0.022.

Table 6. Summary Model Shrinkage

		Coefficient Estimates from Elastic Net Reduction (standardised-beta coefficients)					
		Beans	**Cassava**	**Maize**	**Matoke**	**Millet**	**Sorghum**
Elastic net penalty parameters							
alpha		0.5	0.5	0.5	0.5	0.5	0.5
Retained Climate Anomalies							
		4	9	4	3	5	5
Phase							
Planting							
	Rain +ve	-0.0395		-0.1099		-0.0201	-0.101
		[1.11]		[4.58]		[0.79]	[1.85]
	Rain -ve		0.0059				
			[0.15]				
	Temp +ve		0.0497				
			[1.02]				
	Temp -ve	0.514	0.0313				0.2041
		[1.50]	[0.87]				[2.24]
Growing							
	Rain +ve		-0.0219	-0.0043	-0.0686	-0.0228	
			[0.57]	[0.14]	[2.88]	[0.83]	
	Rain -ve	0.0527	0.0526	0.0835	0.0192		
		[1.93]	[1.31]	[2.81]	[0.67]		
	Temp +ve		-0.1339		-0.0767	0.0847	-0.1004
			[3.04]		[2.68]	[2.13]	[1.36]
	Temp -ve						0.0248
							[0.35]
Harvest							
	Rain +ve		-0.0304	-0.1254		-0.0098	
			[0.93]	[4.71]		[0.29]	
	Rain -ve		0.1009				0.0688
			[2.37]				[1.37]
	Temp +ve	-0.0987	0.1663				
		[2.84]	[3.72]				
	Temp -ve	0.0261				0.0506	
		[0.75]				[1.80]	
N		1439	1407	1439	1463	1439	417
R2		0.2429	0.0474	0.1864	0.3375	0.0401	0.2692
MSE		0.0797	0.0877	0.0676	0.1037	0.0561	0.1135

Notes: [1] All models estimated by TWFE and include full set of controls (time and location fixed effects, seasonal dummy variables, controls for external and domestic trade as described in text). **[2]** Reported coefficients are standardised-beta coefficients with robust t-statistics in parentheses.

VI. Conclusions and Next Steps

The analysis presented above represents a preliminary assessment of the returns to exploiting highly granular earth-observation climate data to examine the impact of spatial and temporal variability in rainfall and temperature on the short-run price dynamics of domestically produced staple food crops in Uganda. First, whilst Uganda has not been immune to the effect of weather change, with an increase in the frequency of extreme events – most commonly localized flooding, leeching and mudslides associated with increased intensity of rainfall – at an *aggregate* level changing patterns of rainfall have been relatively modest and to the extent they have occurred, they have done so relatively slowly. As a consequence, it is unsurprising that conventionally measured weather variation appears to have a relatively modest impact on food prices in aggregate and at the commodity level. Second, and building on this first point, the analysis in this paper has not sought to exploit specific low-frequency extreme weather to identify climate-to-food price linkages. Rather the intention is to assess whether it is possible to establish an operationally useful relationship between patterns of weather variability and food prices and to determine whether this relationship is sufficiently robust that it can be integrated into routine near-term forecasting of food prices. Third, while we were able to identify some systematic relationships between weather variability across the agricultural cycle and short-term price determination, the estimated effects remain fragile and relatively small. Thus, while a failure to reflect these effects in near-term forecasting is unlikely to lead to significantly larger forecast errors in the short run, weather-related impacts are highly likely to strengthen over time as the pace of weather change accelerates and it will become increasingly important for central banks to embed data collection and analysis procedures such as those described here in their day-to-day operations.

A number of tasks remain outstanding and provide the basis for extensions of this work. First, the dimensionality of the empirical analysis is substantial and this paper has explored only a subset of the potential dynamic and spatial model specifications. Further work can be done to refine the dynamic specification of the underlying forecasting model and to refine the characterization of rainfall anomalies. Finally, more detailed work is also required to reflect non-weather determinants of local food prices. In this paper we control for the potentially price-stabilizing and price-transmitting effects of *cross-border* international and regional trade in food commodities, controlling also for distance-to-market frictions. But we are unable to control for *internal* trade between locations, which in principle could also transmit or modify local food production shocks, including those arising from localized weather variation. The reason is simple: high-frequency time-series data on internal market-to-market commodity trade are typically not regularly collected, either in Uganda or in most other similar countries. To the extent that such data are available they are likely to emerge from occasional cross-sectional survey data or possibly from district-level local government sources. Exploration of such sources may be important.

Appendix I

Table I.1. Construction of Product-Specific Prices

Commodity	UBOS CPI Line	UBOS Description	Weight in national food CPI
Maize	01.1.1.1.1	Whole grain maize	5.6%
	01.1.1.2.1	Maize Flour	
Sesame	01.1.1.1.2	Simsim Grains	0.6%
Sorghum	01.1.1.1.3	Sorghum Grains	0.2%
Millet	01.1.1.2.2	Millet Flour	0.9%
Matoke	01.1.6.1.6	Banana, short finger (Ndiizi)	7.6%
	01.1.6.1.7	Banana, Standard (Bogoya)	
	01.1.7.5.4	Cooking Bananas (Matoke)	
	01.1.7.5.5	Matooke (Cluster)	
	01.1.7.5.6	Matooke (Heap)	
Groundnuts	01.1.6.8.1	Groundnuts (unpounded)	2.6%
	01.1.6.9.1	Groundnuts (roasted)	
	01.1.6.9.2	Groundnuts (Pounded)	
Beans	01.1.7.3.1	Fresh Beans	6.5%
	01.1.7.6.1	Beans	
	01.1.7.6.2	Cowpeas	
	01.1.7.6.3	Peas	
Cassava	01.1.7.5.2	Whole Cassava	4.2%
	01.1.7.7.2	Cassava Dried	
	01.1.7.9.1	Cassava Flour	
Yam	01.1.7.5.3	Yams	0.0%
Sweet Potatoes	01.1.7.5.7	Sweet Potatoes	2.0%
	01.1.7.7.1	Dried Sweet Potatoes	

Notes: The location-specific price for each Commodity in column [1] is the weighted sum of the price series for the component items, where the weights are the location- and time-specific weights assigned by UBOS.

Figure I.1. Estimated Marginal Effects of Weather Variation on Aggregate Headline and Food Inflation

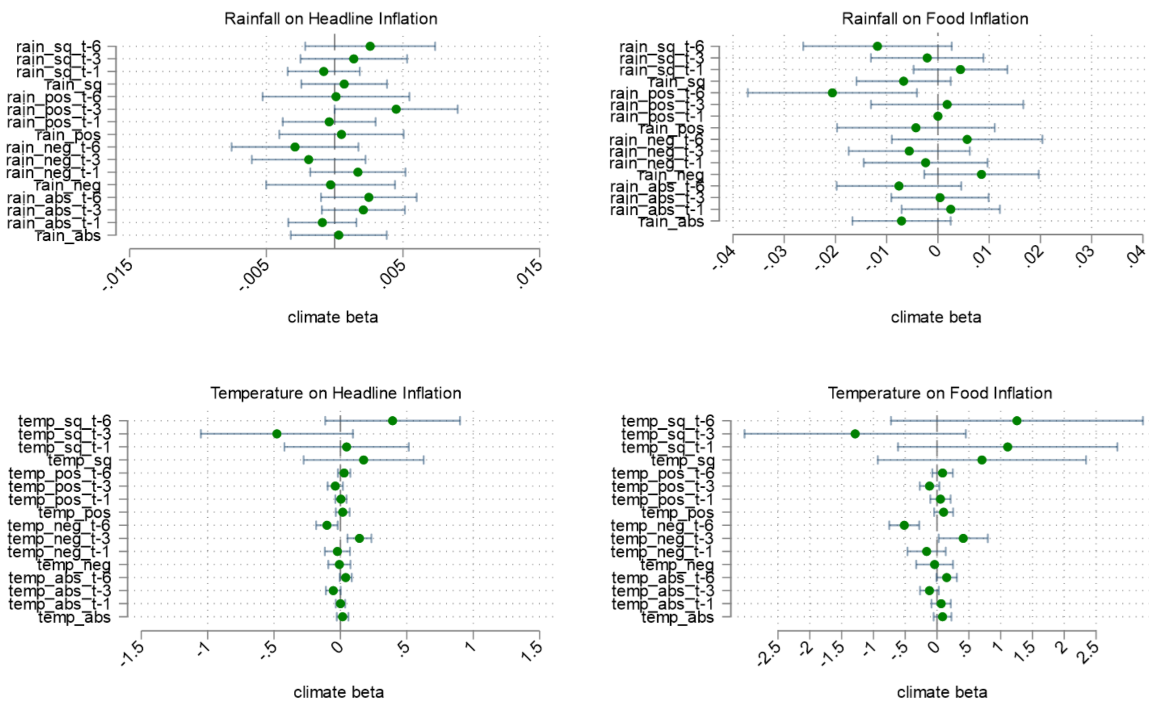
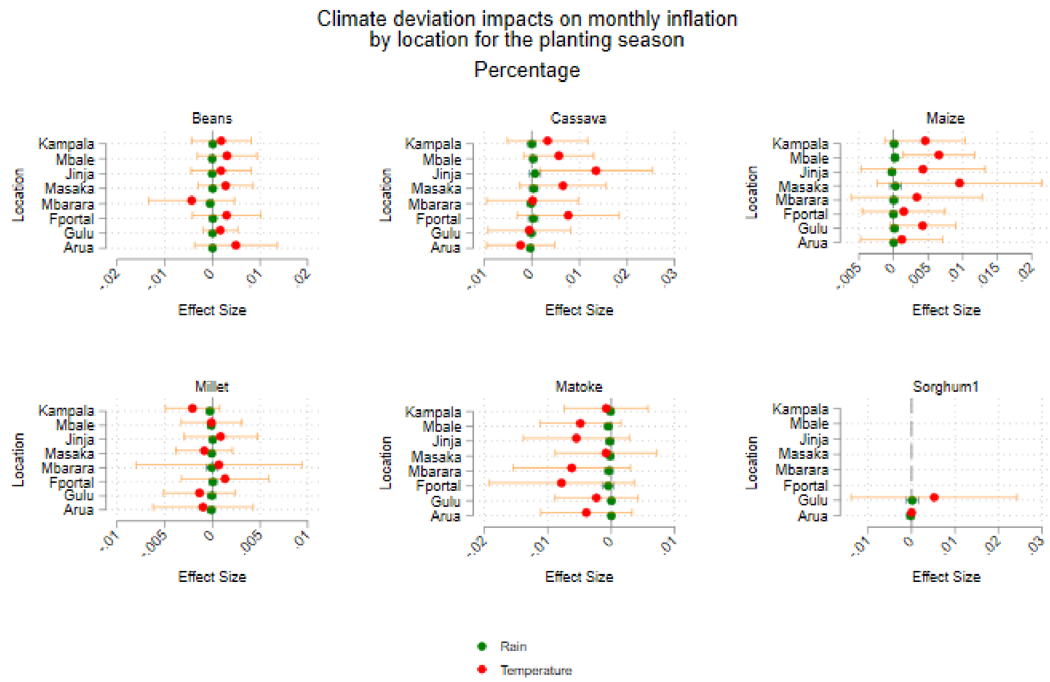
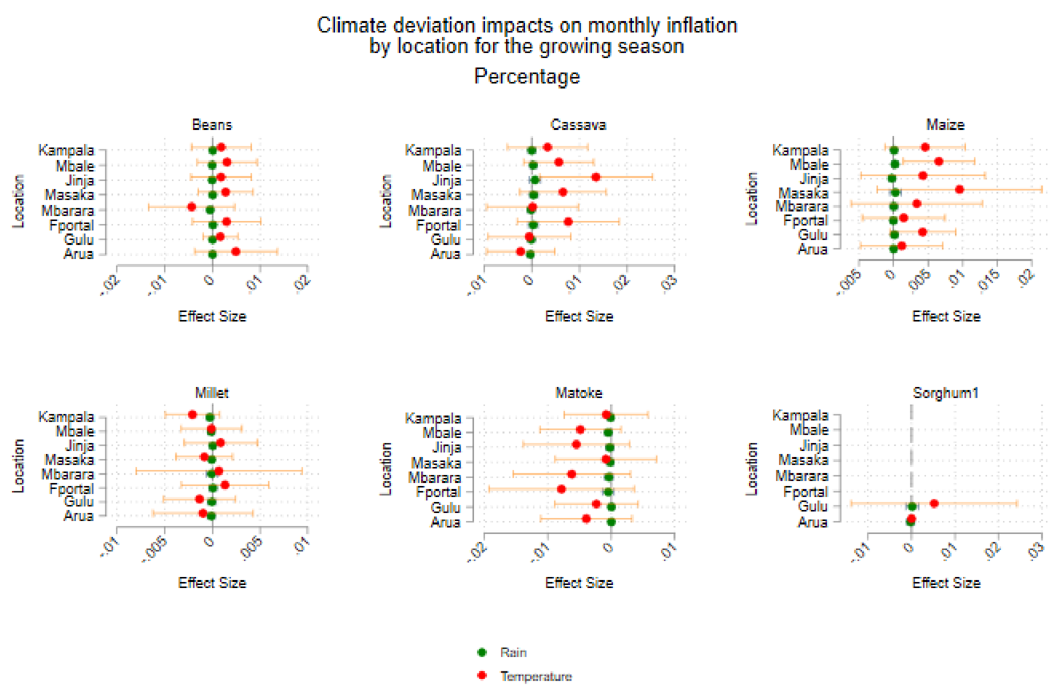


Figure I.2a. Estimated Anomaly Impact by Location and Crop—Percentage Anomalies

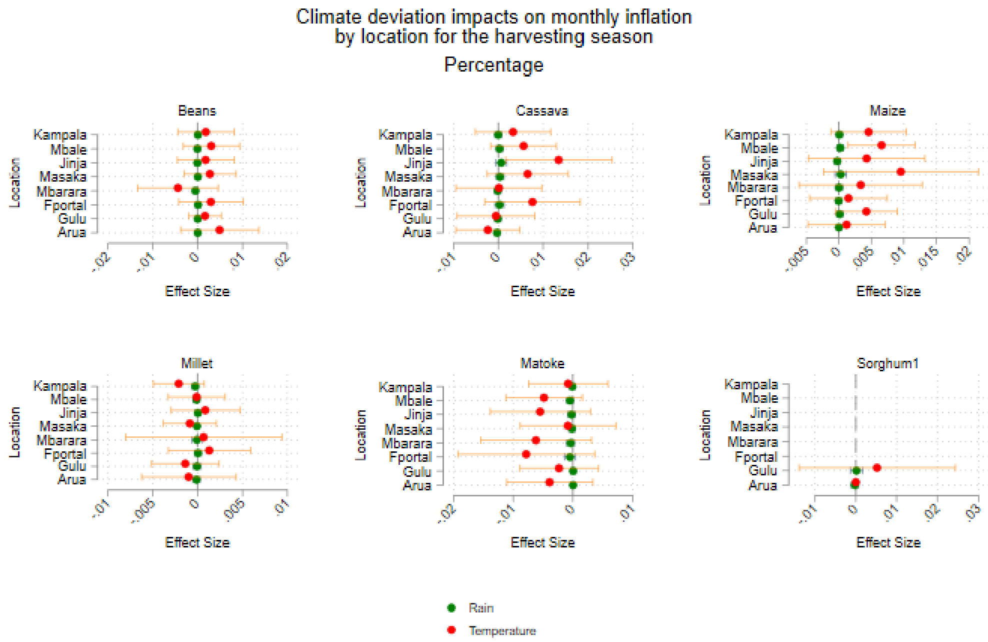


Dots: point estimates, bars: 95% CI



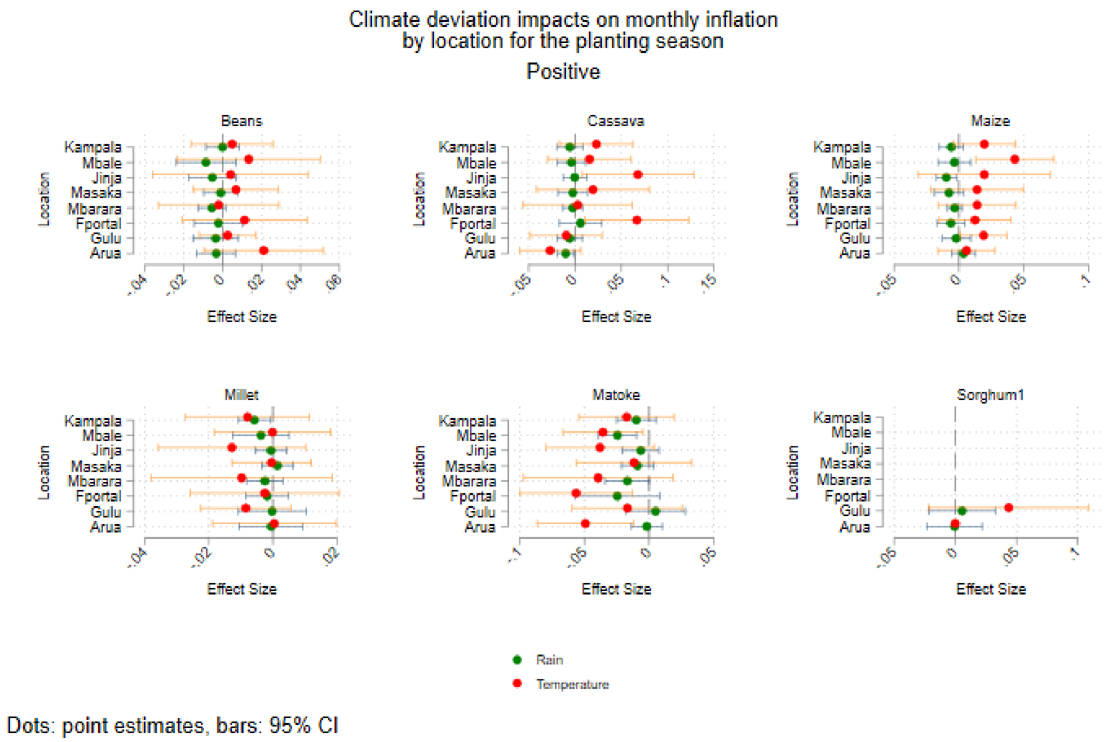
Dots: point estimates, bars: 95% CI

Figure I.2a. (Continuation)



Dots: point estimates, bars: 95% CI

Figure I.2b. Estimated Anomaly Impact by Location and Crop—Asymmetric Anomalies



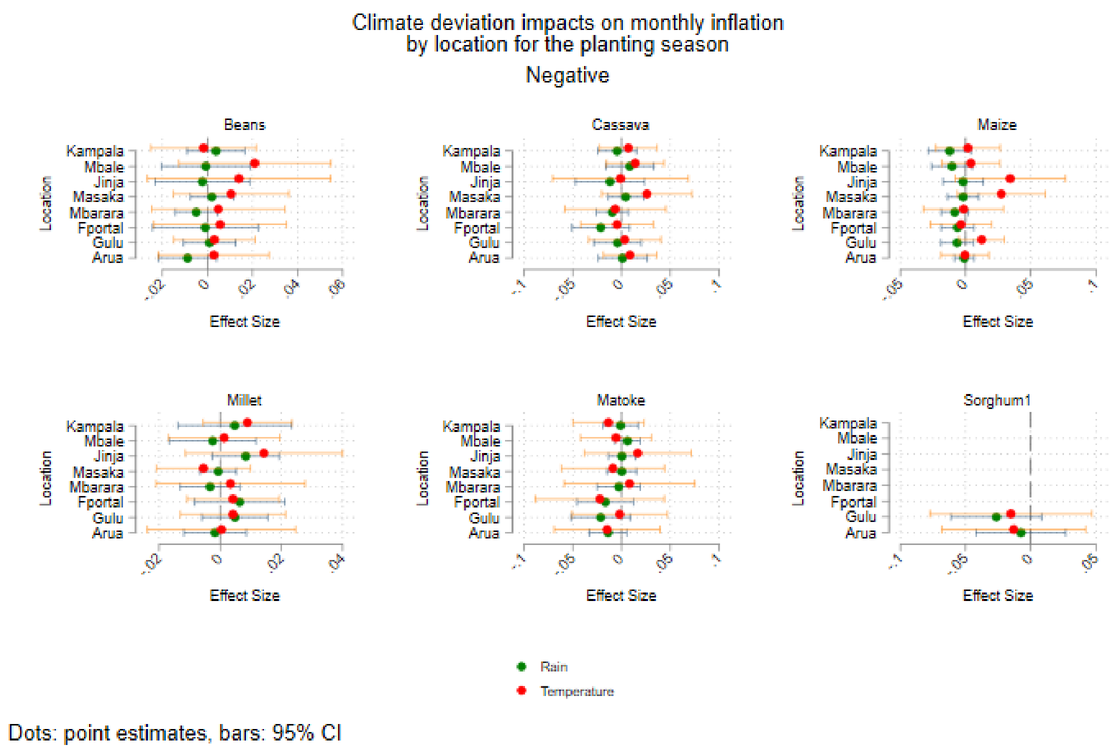
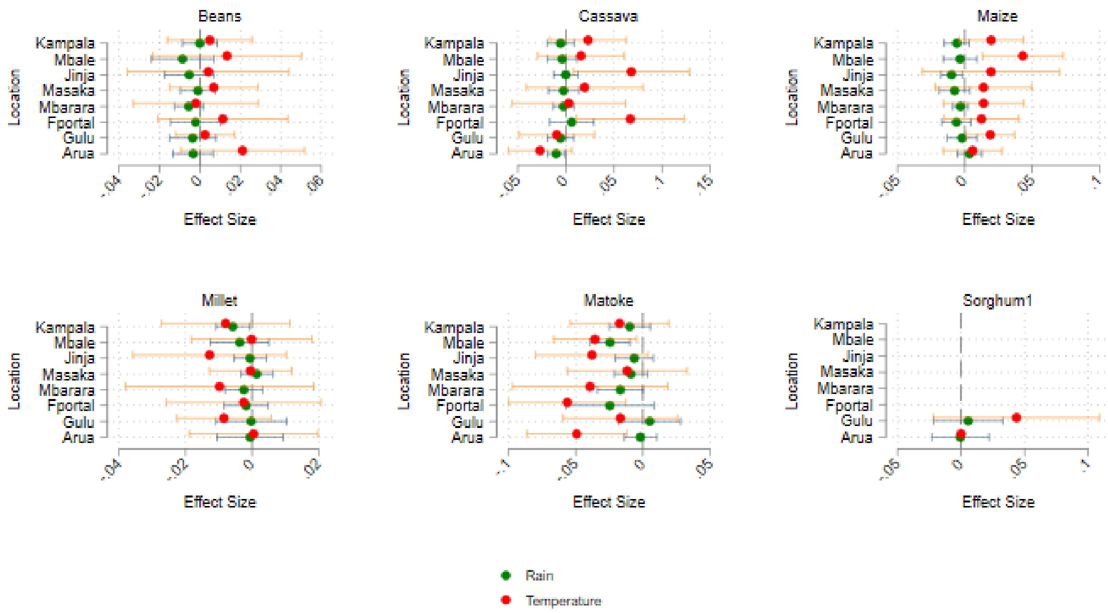


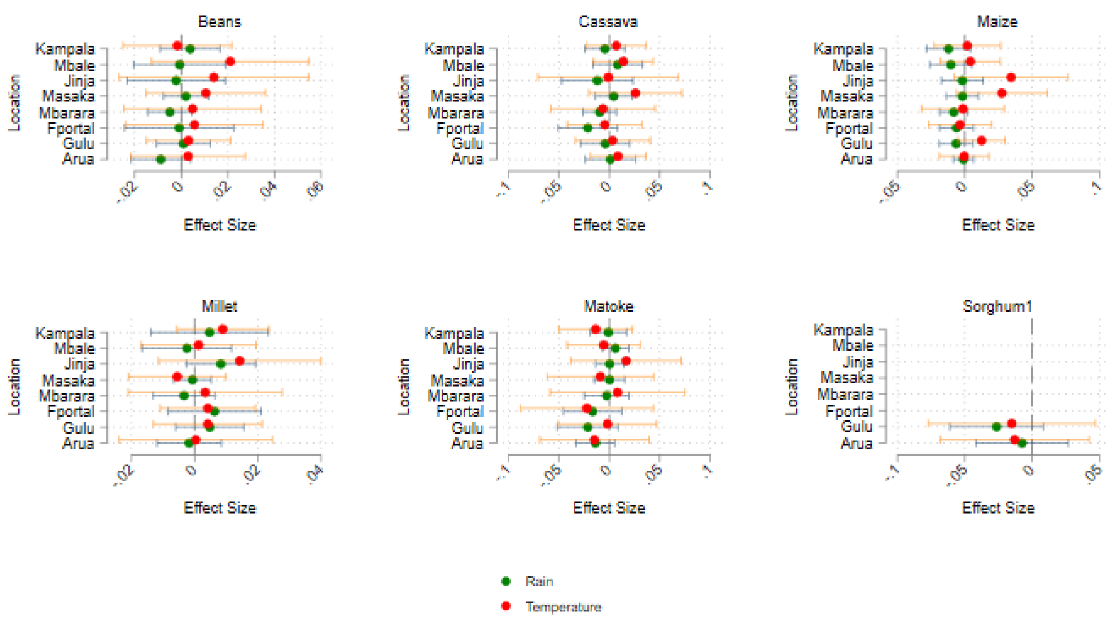
Figure I.2b. (Continuation)

Climate deviation impacts on monthly inflation
by location for the growing season
Positive



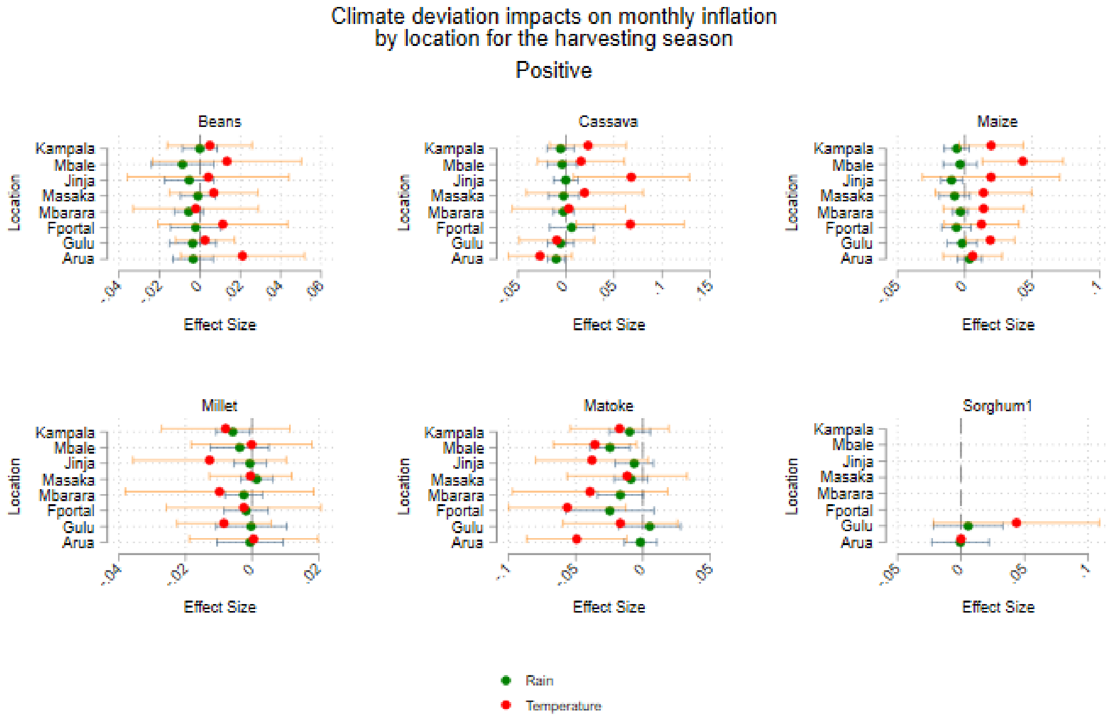
Dots: point estimates, bars: 95% CI

Climate deviation impacts on monthly inflation
by location for the growing season
Negative



Dots: point estimates, bars: 95% CI

Figure I.2b. (Continuation)



Dots: point estimates, bars: 95% CI

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