Fuel prices, weather shocks, and food prices

Florence Lwiza
Department of Agribusiness and Natural Resource Economics
Makerere University, Uganda
Email: florence.lwiza@mak.ac.ug

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Abstract

To better understand how food prices respond to changes in fuel prices and weather conditions, this research employs a panel vector autoregressive (PVAR) model to estimate the impulse response functions to the changes and also variance decomposition measures to examine their relative importance. Monthly food price data is obtained from 42 markets for the period 2011 to 2022, and it is matched with location-specific weather variables and fuel price data. The results show that changes in fuel prices and weather conditions have both short term and long run effects on food prices. The results also show that the changes food prices are largely explained by fuel prices and that changes in temperature and precipitation have moderate the effect of fuel prices on food prices. These findings indicate that continued increases in weather variability and fuel price changes pose food price risks, and therefore recommends for policies to increase resilience of markets to the price risks.

Key findings

- Increases in temperature and rainfall and fuel prices all have positive and significant effects on the prices for the food products. However, the effects are stronger for the fuel price changes as compared to the weather changes
- The effect of a one period shock persists for approximately two periods for temperature and four periods for precipitation. However, the effects of fuel prices are positive and persist for more than 10 periods.
- Changes temperature and precipitation have a moderate the effect of fuel prices on food prices.

1. Introduction

Food price risks pose a significant and complex challenge to global food security, economic stability and the well-being of households. Food price fluctuations affect consumer spending and access to nutritious and affordable food products. For low-income households and those that are net-buyers of food products, increased prices can have detrimental effects since food purchases comprise a major proportion of their household expenditure (Nsabimana et al. 2020). Agricultural producers and traders also face income volatility due to unpredictable changes in food prices. Climate-related factors such as droughts, and extreme weather events have been found to drive food price volatility through their effect on productivity and market supply (Kakpo et al.2022; Letta et al. 2021; Hill and Habtamu 2019). Gradual shifts in temperature and precipitation, and extreme events influence production decisions, affect crop and livestock productivity (Kumar and Sharma 2022; Schlenker and Roberts, 2009) and market supply. Consistent supply of food products in the food markets can be maintained by using effective transportation and food distribution systems. However, distribution of food products is limited by the limited transport infrastructure and increasing cost of fossil fuels. As fuel prices increase, the cost of production, processing and distribution of food product increases affecting the profitability from production and can be passed on to consumers in form of increased food prices.

Whereas it is evident that fuel prices and weather changes have important implications for food security, little is known about the combined effect of the two shocks on food prices. It is probable that the price effects of arising from changes in fuel prices can be mitigated or exacerbated by the effects of arising from extreme changes in the weather conditions. For example, the reduction in food supply as a result of increased transportation costs arising from changes in fuel prices can be mitigated by the supply from domestic production when weather conditions are conducive. It is therefore imperative to understand the relationship between the two shocks and how they affect food prices. The research questions that I attempt to answer are; (i) Do extreme changes in precipitation, temperature and fossil fuel prices have a significant effect on the prices for food products? Do changes in weather conditions have a moderating effect of fuel prices on food price? The goal is to quantify how multiple factors changes in fuel prices and weather conditions, jointly influence food prices.

Using a panel of monthly food prices for 42 domestic market prices for the period 2011 to 2022, I match food prices with location-specific weather data and retail fuel price data. I therefore exploit the spatial and temporal variability in fuel prices and weather conditions to analyze the effect on the food prices set by the markets. The staple foods considered are maize and beans because of their importance in the diets of households for the different ethnic groups of Uganda (UBOS 2020). The data is therefore an unbalanced panel comprising of 1350 observations and the unit of analysis is the food market. I estimate the causal impact of changes in fuel prices and weather conditions on food prices using a Panel Vector Auto-regression (PVAR) model that is estimated with a generalized method of moments (GMM) framework. Using the lagged regressors as instruments, the PVAR Controls for endogeneity arising from observed heterogeneity, dynamic endogeneity and simultaneity among the key regressors. The PVAR model therefore accounts for heterogeneity for individual food markets, while allowing for estimation of the dynamic relationships between the multiple endogenous variables. The findings show that fuel prices, temperature and precipitation have positive and significant effects on food prices, with the effects persisting for more than 2 periods. The findings also show that the variability in food prices is driven more by changes in fuel prices as compared to the weather variability and that the price response to the two shocks is higher for maize flour as compared to the beans.

Previous research has examined the relationship between fuel prices, weather and food prices using macroeconomic variables. Zmami & Ben-Salha (2023), Janda & Kristoufek (2019), Ngare & Derek (2021), Sands et al. (2011) analyzed the effect of global crude oil prices on global and country-level food prices. Their findings show that an increase in crude oil prices has a positive and significant effect on food prices. Letta et al. (2021) and Hill and Habtamu (2019) examined the effect of climate variables on local food markets in India and Ethiopia respectively. Their findings showed that longer drought conditions during the production seasons resulted in higher food prices. These studies show that there are multiple channels through which the food prices can be affected. Disentangling the relative importance of these channels provides information on the vulnerability of the food markets to exogenous changes in climate and fuel price changes in developing economics. The main contribution of this study therefore is the analysis of the simultaneous impact of weather changes and fossil fuel prices, which have been commonly investigated possible but separate drivers of changes in domestic food prices. Similar studies conducted for selected Sub-Saharan countries include Odongo et al (2022), Mawejje (2016) and

Badolo and Kinda (2014) and these used macroeconomic variables to analyze the relationship between climate variables, fuel prices and food prices. While the use of macro-level economic data provides a broad overview of the effects for the economy, it also can result in aggregation bias, where the heterogeneous effects across different groups or markets at the local are obscured (Carpenter et al. 2022). Empirical analyses of food prices at the micro and meso levels are limited. This study fills this gap by undertaking a meso-level analysis and using location-specific food price and weather data. The analysis of the drivers of food price changes is crucial for designing early warning systems and programs to mitigate food price risks. It provides policy implications on enhancing the resilience of food supply networks as shown in section 7 of this paper. The rest of the paper is organized as follows; First we base on economic theory to develop a conceptual framework as presented in section 2. We then describe the data, analytical methods and then present the results in section 3 and 4 respectively. The analysis includes the empirical models and estimations strategies used for the study. In sections 5 and 6, we present and discuss the results.

2. Conceptual framework

We follow the economic theory of price determination under a perfectly competitive market. The analysis follows a short run market supply where the number of firms is fixed and the firms are able to adjust the quantity that they supply to the market. The market supply is represented by the supply relationship is given by $Q_S = S(P, \beta)$ where P is the market price and β is an exogenous factor that shifts the supply such that $\partial S / \partial P > 0$ and $\partial S / \partial \beta = S_\beta$. Exogenous factors include technical changes, prices of inputs, fuel prices and weather conditions among others.

$$\frac{\partial Q_S}{\partial \beta} = \frac{\partial S(P, \beta)}{\partial \beta} = S_P \frac{\partial P}{\partial \beta} + S_\beta \tag{1}$$

In this case, the effect of the exogenous factor on food prices is through its effect on food supply and also through the direct effect S_β. The effect on S_β can be negative or positive depending on what the exogenous parameter represents.

The market demand function is represented by $Q_D = D(P, \alpha)$ where α is a parameter that allows a shift in the demand curve such as consumer income, prices of other goods, or changing consumer preferences and $\partial D / \partial P < 0$. The effect of a small change in the exogenous factors on the market equilibrium, can be obtained by differentiating the demand function, holding α constant. Differentiation of the demand function yields;

$$\frac{\partial Q_D}{\partial \beta} = \frac{\partial D(P,\alpha)}{\partial \beta} = D_P \frac{\partial P}{\partial \beta} \tag{2}$$

In this case, the effect of the exogenous factor on market prices occurs through its effect on demand for the food product. At equilibrium, $Q_D = Q_S$. Therefore, to maintain a market equilibrium, $\frac{\partial Q_S}{\partial \beta} = \frac{\partial Q_D}{\partial \beta}$. The change in equilibrium price will be given as $S_P \frac{\partial P}{\partial \beta} + S_\beta = D_P \frac{\partial P}{\partial \beta}$, implying that

$$\frac{\partial P}{\partial \beta} = \frac{S_\beta}{D_P - S_P} \tag{3}$$

The effect of exogenous factors such as fuel prices and weather variables on the market prices for staple foods depends on the supply response and also the responsiveness of the demand and supply to the food price changes. The demand response depends on the price of the food product, and also the prices for related food products that may be substitutes or complements. For many staple food products, the demand is inelastic given that food is a necessity. The supply response depends on the magnitude of the exogenous factors that include fuel prices and weather variables. The selection of the variables of for the analyses is guided by equation 3.

3. Data

The data was collected from a variety of sources, with the unit of analysis being the domestic food markets. The retail food price data was obtained from the database of the World Food Program accessible at https://data.humdata.org/dataset/wfp-food-prices-for-uganda?force_layout=desktop and this was collected for 42 markets and these representative of the food markets in the Northern, Eastern, Western and Central regions of Uganda. The list of markets considered for the study is attached in appendix 1. We focus on maize flour and beans as the major food product, given their dominance in the household diets and is consumed in all regions of the country. UBOS (2020) show that the average per capita consumption of maize flour and its products is 48.2 KG per year. The prices for maize flour and beans are estimated per kilogram. Other staple food products such as millet, sorghum and bananas are consumed by specific ethnic groups and were therefore not considered for this study. Bananas are a staple food for the Central and Western regions of the country. For each of the markets, monthly food price data is used for a period of 11 years from April 2011 to December 2022. The panel is unbalanced and comprises 1350 observations. The selection of the sample and the starting and end dates was based the availability of data. However, the period coincides with the time where there were large fluctuations in the prices of fuel and food products.

The food price data was merged with fuel price data and weather data. The weather data was matched with the districts where the food markets were located. The weather data was obtained from the USAID Climate links. Monthly fuel price data was collected from the Uganda Bureau of Statistics database and it comprises the retail prices of fuel at the pump. The common fuel used are diesel and gasoline. However, given the high collinearity between diesel and gasoline, gasoline is selected as the representative fuel.

4. Empirical strategy

We estimate the causal impact of fuel prices and weather variables on the retail food prices for maize flour and beans as the major staple food products. We therefore explore the variability in food prices, weather conditions and fuel prices by locations and over time. Given the dynamic nature of the food prices, autocorrelation is a challenge that can yield inconsistent and biased results (Abrigo and Love 2016). The dynamic interactions between food prices, fuel prices and weather variables are therefore analysed using a Panel Vector Auto-regression (PVAR). The PVAR is an extension of the Vector Auto-regression (VAR) model that is used to accommodate data time-series observations for multiple cross sectional units. The panel VAR therefore analyses dynamic relationships between variables within and across the units by jointly modeling multiple observations of several units. This is important for this analysis given that the prices for food products are related and also that the changes in fuel prices and weather conditions can have simultaneous effects on the prices of the different food types. The PVAR model is also applicable given that the panel data is unbalanced for the different markets Therefore, given N markets indexed $i = 1, \dots . N$ and $t = 1, \dots \dots T,$ the model is defined as follows;

$$X_{it} = \mu_i + \Phi\ (L)X_{it} + \varepsilon_{it} \tag{4}$$

Where the vector X_{it} comprises of endogenous stationary variables, and $X_{it} = [F_{it}, Temp_{it}, Prec_{it}, M_{it}, B_{it}]'$ where, $Temp_{it}$ is the monthly average temperature observed in market i at a time t, F_t represents the gasoline fuel prices, and $prec_{it}$ is the monthly average precipitation. Other variables are the prices for food products that include; Maize (M_{it}), beans (B_{it}). $\Phi\ (L)X$ is a matrix polynomial in the lag operator lag L , μ_i is the vector of time-invariant market effects, and ε_{it} is the error term that accounts for all other factors not included in the model. The model is estimated using the generalized method of Moments (GMM) framework, with the means difference transformation following Love and Abrigo (2016). I also estimate the effects using standard error clustered at the market level to account for correlation of observations within the cluster. For robustness checks, the robust standard errors are also clustered at the market level. The coefficients of interest are the Φs that are associated with the fuel prices and weather variables respectively. Weather variables and fuel prices are exogenous and therefore not influenced by other control variables in the model.

5. Results

5.1 Descriptive analysis

The descriptive statistics presented in table1 show the distribution for the food prices, fuel prices, and weather variables. The prices for the food products varied for the different markets and also varied over time. The average prices for beans was the highest estimated at 0.80 USD per kilogram. The average price of maize, millet and sorghum is 0.37 USD, 0.65USD and 0.44USD respectively. The average price for petrol is 1.29 USD with a minimum of 0.93 and maximum of 1.71. It can be observed that the average price of fuel is higher than the average price for all the staple food products. The mean temperatures are 21.64 with a minimum of 19.20 and a maximum of 26^{o}C. The average precipitation was 124 millimeters although it differed for different locations with a minimum of 11 millimeters and maximum of 269 millimeters.

Table 1: Descriptive statistics

Variable	**Mean (n=1350)**	**Standard Deviation**	**Minimum**	**Maximum**
Beans price (USD)	0.80	0.18	0.36	1.53
Millet price (USD)	0.65	0.20	0.27	1.41
Maize price (USD)	0.37	0.12	0.00	0.79
Sorghum price (USD)	0.44	0.20	0.11	1.08
Gasoline price (USD)	1.29	0.22	0.93	1.71
Precipitation (Millimeters)	124.30	59.22	11.00	269.00
Average temperature (^{o}C)	21.64	1.14	19.20	26.00

5.2 Estimation of PVAR model

The results for the estimation of the relationship between food prices, fuel prices and weather variables are summarized in table 2 and disaggregated for the staple food products. The coefficients of interest are those associated with the price of gasoline fuel, temperature and precipitation. The findings from the GMM estimation with clustered standard errors shows that the effect of fuel prices and weather variables is positive and significant for both the maize and beans prices. Holding other factors constant, a unit increase in the fuel prices result in an increase in the food prices by 75.6 and 13.9 percent for maize and beans respectively. and the results are significant at 1 percent level. This result shows that the relationship between the food prices and fuel process is inelastic given that the coefficients are less than 1. On the other hand, an increase in temperature and precipitation result in an increase in the prices for all the food products. For robustness check, the estimation is done with robust standard errors and also without and the findings are presented in appendix 3. The results remain consistent for the GMM estimation with robust standard errors but the standard errors are larger. The magnitude of the coefficients and significance of the variables is much lower with the GMM estimation with non-robust standard errors.

To examine whether the changes in weather variables have an intervening effect on fuel prices, the PVAR model was estimated with interaction terms included and the results are also presented in table 2. The interaction terms between fuel price and precipitation shows a negative effect on the prices of maize and beans. This implies that the positive and significant effects of changes in fuel prices on food prices are partially mitigated by an increase in the precipitation. Also the coefficient of the interaction term between temperature and precipitation was only significant for influencing the price for maize.

It is important to note that whereas the findings show that changes in temperature and precipitation have significant effects on food prices, the extent of the impact depend on the magnitude of the changes, and can differ base on the geographic regions. When estimated by geographic region, the results show that the effects of price changes for fuel are significant for the central, western and northern Uganda but not the eastern region.

However, the coefficients of the reduced form PVAR cannot be interpreted as causal without imposing identifying restrictions on the parameters. Therefore, the stability of the model was tested using the Eigen values as shown in appendix 2. The graphical presentation shows that all Eigen values lie within the unit circle. This indicates that the estimated PVAR model is reliable and unbiased for inference with optimal lag length of 1 and can be used to conduct other causality tests such as the impulse response functions and error variance error decomposition.

Table 2: Regression output for PVAR estimation

	Estimation with no interaction terms		Estimation with interaction terms	
Variables	Log Maize price	Log Bean price	Log Maize price	Log Bean price
L. Log maize price	0.713	0.012	0.648	-0.035
	(13.07)**	(1.02)	(12.92)**	(2.84)**
L Log beans price	0.207	0.824	-0.082	0.725
	(3.91)**	(29.28)**	(1.89)	(20.82)**
L. Log precipitation	0.056	0.044	4.668	2.755
	(3.33)**	(3.66)**	(2.52)*	(1.71)
L. Log fuel price	0.314	0.160	42.255	24.344
	(5.48)**	(4.83)**	(6.35)**	(7.79)**
L. Log temperature	0.811	1.051	9.409	6.440
	(2.98)**	(5.47)**	(3.51)**	(2.66)**
L. Log fuel*Log precipitation			-0.730	-0.276
			(6.37)**	(5.43)**
L. Log fuel * Log precipitation			-12.539	-7.464
			(6.24)**	(7.84)**
L. Log temperature * Log precipitation			-1.441	-0.848
			(2.42)*	(1.63)
N	1,350	1,350	1,350	1,350

Standard errors in parentheses

* p<0.05; ** p<0.01

5.3 Impulse response functions

Impulse response functions are estimated to show how a one-time change or shock in the fuel prices and weather variables influence the behavior of other variables over time and these are presented in figure 1. The results show that the responses for the food prices to changes in temperature and precipitation are nonlinear. A change in temperature results in a positive price response within the first 2 time periods, beyond which the effect reduces and eventually tends to zero. Also the response of the price of maize to changes in temperature is higher than the response for the price of beans. On the other hand, the negative effect of precipitation is realized in the first 4 periods and thereafter, the response increases and becomes zero. The response of food prices to changes in fuel prices are positive and persist up to the 10^{th} period as shown in the figure 1.

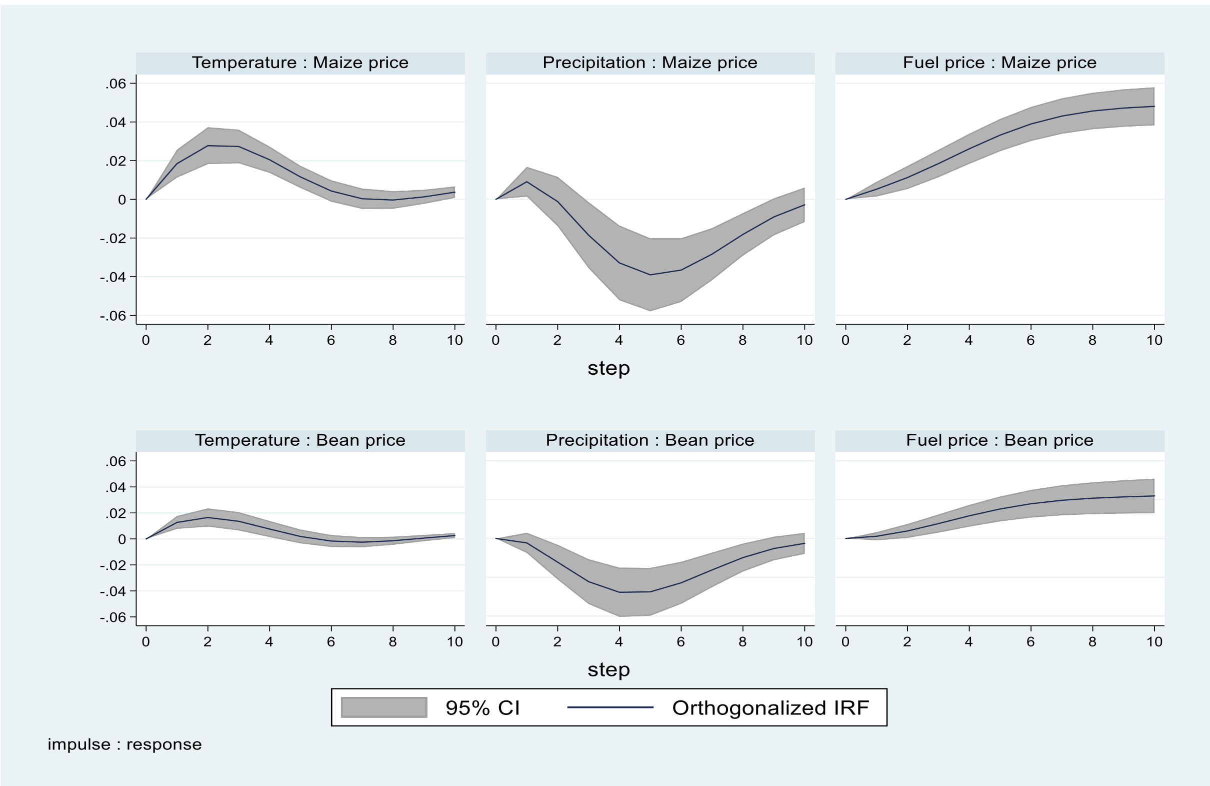

Figure 1. Graph for the impulse response functions

5.4 Granger causality tests

A Granger causality test was conducted to assess the nature of relationship between the excluded variables which is the food price and the included variables that are the lagged values for the independent variables. The results show that the p-value for the price of gasoline fuel is significant for both the maize and bean prices 1 percent level. This implies that the null hypothesis that there is no granger causality between the excluded and included variables is rejected. There is therefore evidence to show that the lagged prices for gasoline fuel contain information that can be used to predict the future values of the prices of beans and maize flour. The p-values for temperature and precipitation were significant for maize and beans at 1 percent level. This implies that temperature and precipitation variables granger cause the prices for maize and beans. The findings also show the joint significance of the variables in predicting food prices. The excluded variables jointly granger cause the equation variables and the results are significant for all the food products.

Table 3. Results for granger causality tests

	Equation variables	
Excluded variables	**Maize**	**Beans**
Log fuel price	40.837***	22.00***
Log precipitation	22.31***	6.76***
Log temperature	26.78***	21.00***
Log beans price	22.06***	
Log of maize price		5.34**
All variables	98.89***	52.86***

*** p<0.01, ** p<0.05, * p<0.1

5.5 Variance Decomposition

Although the impulse response functions provide details of trend of the effects over time, it does not show the magnitude and extent of the impacts. The PVAR Error Variance Decomposition (FEVD) solves this problem. The FEVD results involves analyzing the contribution of different shocks to the forecast error variances of variables in a PVAR model. This analysis helps identify the shocks are more influential in explaining the variability of food prices over time. The findings show that the lagged prices for the food products explain the largest variability in the food prices but the effect reduces with the fuel price and weather shocks. The effect also reduces over time in appendix 3.

The relative importance of the shock was examined by analyzing the cumulative contributions of each variable to the prices for the food products as shown in table 4. The findings show that shocks in the lagged prices are the most important in influencing the prices of maize and bean prices. When comparing the effect of exogenous shocks, the effect is greater for fuel prices as compare to the changes in weather variables. Also, the cumulative effect of the fuel price and weather shocks is higher for the maize price as compared to the bean price.

Table 4. Results for the cumulative error variance decomposition

	Log maize price	Log beans price	Log fuel price	Log Temperature	Log precipitation
Maize	6.0819	0.2114	2.1490	0.3703	1.1875
Beans	0.7273	8.3999	0.4178	0.2082	0.2468

6. Discussion of findings

6.1.1 Impact of fuel prices on food prices

The results for the PVAR estimation, granger causality tests, impulse response functions and the error variance decomposition all show that changes in the prices of fossil fuels such as gasoline have a positive and significant effect on the prices of the food products and that the effects vary over time. Where markets are not autarkic, changes in fuel prices affect the transportation costs of the food products, and inputs to the different markets. Dillon and Barret (2016) show that one of the channels through which fuel prices affect food prices is by disrupting the distribution of food supply. However, given that the biofuel industry is undeveloped, the main channels through which this can be realized is by increasing the transportation and food processing costs of food products. Based on the selected staple food products, the main channel is by affecting transportation costs since they form a significant proportion of the overall production and distributional costs. With increased costs of production, traders can pass on the cost to the consumers inform of higher food prices.

6.1.2 Impact of temperature and precipitation on food prices

The results for the different estimations also show that precipitation and temperature have a positive and significant effects on the prices of food products. However, the effect of temperature is stronger than the effect of precipitation, based on the magnitude of the coefficients and the confidence intervals for the impulse response functions. The findings show that an increase in the temperature leads to an increase in food prices for all the staple food products and this can be through several channels. Exposure of crops to excessive heat during the critical growing period can lead to lower crop yields (Schlenker and Roberts 2009) and physical damage of crops resulting in a reduced supply of food commodities, driving up the food prices. Nguru and Mwongera (2023) show that warmer temperatures create favorable conditions for pests, diseases and invasive weeds to thrive thereby lowering crop productivity. For locations with seasonal water sources, excessive warming can exacerbate water scarcity by increasing evaporation rates and reducing the availability of water sources for irrigation.

The findings show that an increase in the precipitation has a positive and significant effect on the prices of for the food products. Precipitation from rainfall provides moisture to support the crop growth processes. However, excessive rains or poorly timed rainfall can have negative effects on crop production and yields, and consequently food prices. Excessive rainfall leads to flooding and water logging, that can cause physical damage crops, soil erosion, leaching of nutrients and also render agricultural land unusable. Increased rainfall during the harvest seasons can also damage crops, reduce the quantity and quality of the food products. For example, grains can become moldy or contaminated with aflatoxins due to prolonged exposure to damp conditions, reducing the marketability of the crop products. Prolonged rainfall can also damage agricultural infrastructure including roads, bridges, storage facilities that disrupt the transportation and distribution systems for the food products (Godde et al. 2021). Letta et al. (2021) show that changes in weather patterns can impact food prices through market speculation by traders. As the impacts of extreme weather changes become more significant, traders may anticipate future disruptions in food supply. These speculative activities can drive food prices even where food supply shortages may be minimal.

6.1.3 The combined effect of fuel prices and weather variables on food prices

The coefficients for the interaction terms between fuel price and the weather variables were negative and significant for both the maize and bean prices This suggests that holding other factors constant, the effect of fuel price on the food prices is reduced when precipitation levels are higher. Likewise, the effect of fuel prices on food prices is partially mitigated by increases in temperature. Therefore, the effect of fuel price changes on food prices in not uniform across different levels of precipitation and temperature. This finding is important for policy as it implies that supporting the food production sector to be resilient against changes in weather conditions is one way maintaining sufficient food production and supply to the markets, to moderate the effect of unprecedented increases in fuel prices.

7. Conclusions and recommendations

In this paper, I use a PVAR mode to estimate the functional relationship that exists between fuel prices, weather variables and food prices using 10 years of monthly panel data, and the unit of analysis is the food markets. The estimation accounts for serial correlation in food prices that occurs when error terms for the cross section correlated. The results reveal a non-linear relationship between the weather variables and food prices as well as a positive relationship between fuel prices and food prices. The results also reveal that the effects of the shocks are experienced immediately and can continue even in the subsequent periods. Given that the government intervention in both the food and fuel markets is minimal, the results are not likely to biased by confounding factors.

The results therefore highlight the importance of weather changes and fuel prices as possible drives of food price changes. The key implication of the findings is that increasing the resilience of the agricultural sector to changes in weather variables is one way of moderating the effect of fuel prices on food prices. Uganda’s agricultural sector is experiencing gradual changes in temperature and rainfall patterns, and more frequent extreme weather events such as droughts and floods Therefore, the focus for policy should go beyond being reactionary in responding to periodic food price shocks but also focus on building resilience to gradual changes in the climatic conditions and fuel prices. This can be done by developing and promoting technologies to improve resilience of crop production to gradual and extreme weather changes and also invest in in the development of early warning systems to enable farmers and traders to plan and manage production and market risks. The government should also focus on the development of alternative renewable fuels to reduce on the reliance on fossil fuels.

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APPENDIX 1: List of Markets

No	Market	
1	Adjumani	25
2	Arua	6
3	Bidibidi	25
4	Busia	10
5	Fort Portal	10
6	Gulu	45
7	Hoima	15
8	Iganga	37
9	Imvepi	25
10	Jinja	17
11	Kaabong	44
12	Kapchorwa	42
13	Karenga	4
14	Karita	25
15	Kasese	15
16	Kiryandongo	25
17	Kotido	40
18	Kyaka II	25
19	Kyangwali	25
20	Lira	45
21	Lobule	25
22	Makaratin	38
23	Masaka	10
24	Masindi	18
25	Mbale	38
26	Mbarara	44
27	Moroto	11
28	Mukono	10
29	Nabilatuk	5
30	Nakivale	25
31	Namalu	37
32	Napak	4
33	Oruchinga	25
34	Owino	45
35	Palabek	23
36	Palorinya	25
37	Rhino Camp	25
38	Rwamwanja	25
39	Soroti	13
40	Tororo	17
41	Wakiso	10

APPENDIX 2: Diagnostic tests

i. Panel Unit root tests

The time properties of the variables used are tested with panel unit root tests. Given that there were gaps in the data, the Augmented Dickey-Fuller (ADF) Fisher is used. All the variables are transformed and expressed in their logarithm form as the estimation level The results for the Modified inverse chi-square shows that the p-values for all the variables were significant at 1% and 5% levels, indicating that the variables were stationary or do not have unit roots. Stationary at I(0) implies that the variables do not require differencing.

Variables	Fisher Phillips-Perron	Fisher Augmented Dickey-Fuller (ADF)
	I(0)	I(0)
Fuel price	1.6562**	5.799**
Temperature	12.8649***	46.4255***
Precipitation	12.4168***	59.8513***
Price of beans	9.1858 ***	7.2358***
Price of maize	9.6326***	8.4734***

*** p<0.01, ** p<0.05, * p<0.1

ii. Stability

The stability of the PVAR model was tested based on the Eigen value stability condition. The results show that significant of the p-values, the null hypotheses of no stability was rejected at 1 percent level. The graphical presentation shows that all Eigen values lie within the unit circle. This indicates that the estimated PVAR Granger causality model is reliable and unbiased for inference with optimal lag length of 1.

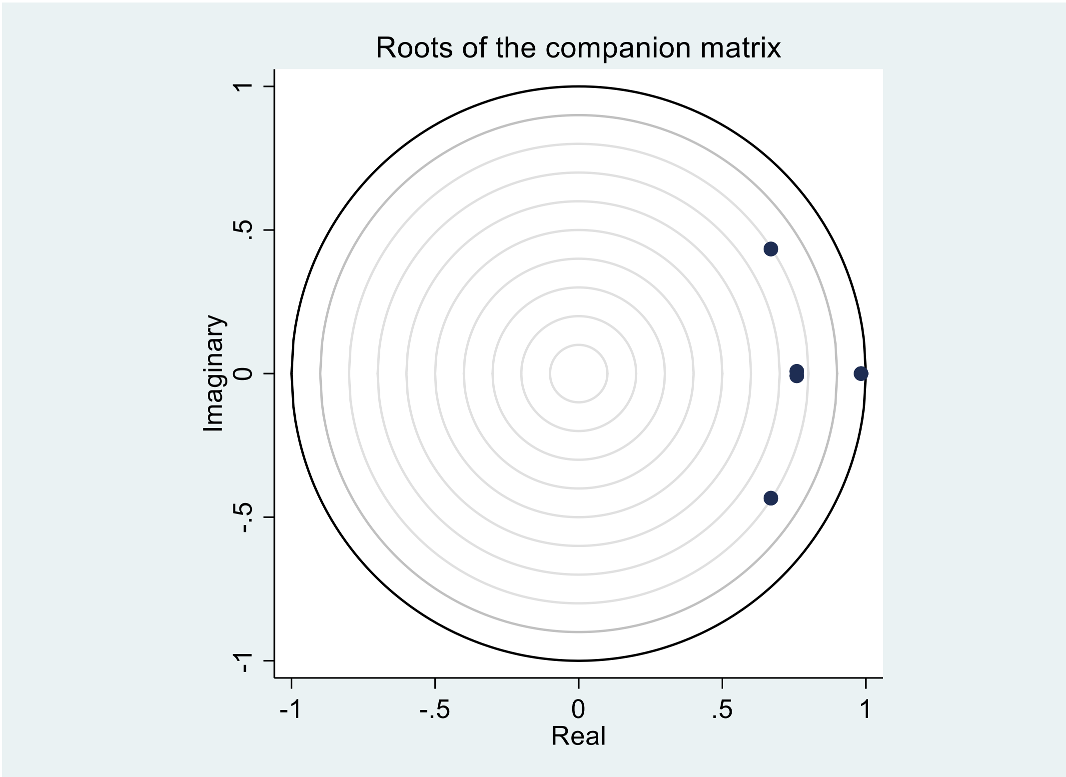

Figure 2. The Panel Granger Causality Model stability test.

APPENDIX3: Regression output for PVAR estimation

		GMM with non-robust standard error	GMM with Robust standard error	GMM with Clustered standard errors
Log maize price	L. Log maize price	0.462	0.756	0.756
		(2.90)**	(19.90)**	(17.12)**
	L. Log fuel price	0.355	0.289	0.289
		(3.44)**	(6.39)**	(6.17)**
	L. Log precipitation	-0.243	0.061	0.061
		(1.60)	(4.72)**	(4.58)**
	L. Log temperature	-4.833	1.059	1.059
		(1.67)	(5.17)**	(4.88)**
	L Log beans price	0.335	0.165	0.165
		(2.50)*	(4.70)**	(5.60)**
Log beans price	L Log beans price	0.790	0.820	0.820
		(26.17)**	(30.90)**	(24.55)**
	L. Log fuel price	0.097	0.139	0.139
		(2.51)*	(4.69)**	(4.23)**
	L. Log precipitation	-0.052	0.027	0.027
		(0.84)	(2.60)**	(3.20)**
	L. Log temperature	-0.691	0.767	0.767
		(0.63)	(4.58)**	(4.72)**
	L. Log maize price	0.031	0.026	0.026
		(1.93)	(2.31)*	(1.95)
N		1,350	1,350	1,350

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 4: Error Variance Deomposition

lusdmaize	lusdmaize	lusdbeans	lusdpetrol	ltemp	prec
0	0.0000	0.0000	0.0000	0.0000	0.0000
1	1.0000	0.0000	0.0000	0.0000	0.0000
2	0.9197	0.0089	0.0039	0.0183	0.0492
3	0.7882	0.0157	0.0900	0.0350	0.0711
4	0.6480	0.0190	0.2399	0.0337	0.0594
5	0.5490	0.0228	0.2968	0.0286	0.1027
6	0.4994	0.0286	0.2721	0.0260	0.1740
7	0.4702	0.0316	0.2833	0.0268	0.1881
8	0.4335	0.0295	0.3287	0.0404	0.1679
9	0.3974	0.0272	0.3265	0.0684	0.1806
10	0.3764	0.0281	0.3077	0.0932	0.1946
lusdbeans					
0	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0623	0.9377	0.0000	0.0000	0.0000
2	0.0827	0.9102	0.0013	0.0022	0.0036
3	0.0860	0.8918	0.0012	0.0081	0.0129
4	0.0802	0.8745	0.0122	0.0149	0.0182
5	0.0736	0.8490	0.0414	0.0192	0.0168
6	0.0687	0.8219	0.0669	0.0212	0.0213
7	0.0665	0.8034	0.0715	0.0229	0.0357
8	0.0680	0.7891	0.0696	0.0272	0.0461
9	0.0701	0.7709	0.0753	0.0374	0.0463
10	0.0691	0.7514	0.0785	0.0550	0.0459