

Article

Global Market Shocks and Food Riots: The Impact of Energy Prices, Biofuels, and Financial Speculation in Africa

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Abstract

Even though the existing literature has elucidated the domestic causes of riots and the links between global food prices and riots, the relationship between riots and various external factors, such as biofuel production, global crude oil prices, speculation, and the US dollar exchange rate, has yet to be fully analyzed. This study aimed to fill this research gap by examining the associations of these external factors on the occurrence of riots in Africa using the Poisson, negative binomial, and zero-inflated negative binomial models. Our key findings are as follows: (1) U.S. ethanol production and international crude oil prices are positively associated with riot frequency, whereas U.S. biodiesel production is not statistically significant. (2) A higher long share relative to open interest increases riot incidence, while a higher short share reduces it. (3) Both international food prices and African domestic food prices exhibit positive and statistically significant associations with riots. (4) Appreciation of the U.S. dollar is negatively correlated with food riots. Overall, the findings suggest that global energy, financial, monetary, and food price dynamics are systematically linked to food riots in Africa.

Keywords: biofuel; crude oil; riots; food prices; speculation; generalised linear model

1. Introduction

Food riots have historically been closely linked, with scholars tracing the connection between food prices and revolutions over centuries [1]. While food-related uprisings declined in frequency by the mid-nineteenth century, they resurged in the 1970s due to austerity measures imposed under the International Monetary Fund's structural adjustment programs [2]. More recently, the global food crisis of 2007–2008 triggered widespread political instability, affecting 71 middle-income and 74 low-income countries. Spiking commodity prices, particularly in oil and food markets, led to riots in multiple African nations, highlighting the critical role of cross-border factors in exacerbating domestic vulnerabilities [3].

A growing body of literature has explored the causes of food price surges, attributing them to factors such as adverse weather conditions, biofuel production, energy price increases, financial speculation, trade restrictions, inadequate grain reserves, and rising meat consumption in emerging economies [4–8]. Although these studies have deepened our understanding of food price volatility, few have examined the extent to which geographically remote factors influence food riots, particularly in Africa. Existing research has primarily focused on local determinants such as climatic conditions, domestic food production, and



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political regimes, with limited emphasis on global market dynamics and their transmission mechanisms [9,10].

Among the key cross-border factors, biofuel production has attracted considerable attention. Between 2005 and 2019, bioethanol and biodiesel production in the United States increased by 800% and 20,000%, respectively [11]. Given that 39% of US corn production was diverted to bioethanol facilities in 2019 [12,13], concerns have emerged regarding its impact on food prices both domestically and internationally [14,15]. While some policymakers and scholars argue that biofuel expansion exacerbates food insecurity and food riots [8,16], others contend that its role in global price volatility remains unclear [17]. However, the direct link between biofuel production and food riots has yet to be thoroughly quantified.

Another critical driver of food price volatility is financial speculation. The assets managed by hedge funds surged from USD 118 billion in 1997 to USD 2.9 trillion in 2017 [18]. The director-general of the United Nations Food and Agriculture Organization warned of the potential role of speculative activity in amplifying food price fluctuations [19]. While some studies find evidence that speculation increases food prices and contributes to food riots [20–22], others dispute its impact [23]. The mixed findings underscore the need for further empirical investigation.

Additionally, the devaluation of the US dollar may affect food-importing nations in complex ways. While a weaker dollar can lower import costs, it may simultaneously increase commodity prices, creating arbitrage opportunities for investors. Despite extensive research on exchange rate fluctuations and agricultural trade [4,7], few studies have directly examined the relationship between exchange rate movements and food riots.

This paper addresses these research gaps by quantitatively analyzing the impact of geographically remote factors on food riots in Africa. Specifically, we analyze how U.S. bioethanol and biodiesel production, financial speculation measured by long and short shares relative to open interest in grain futures markets, global crude oil prices, fluctuations in the U.S. dollar, and both international and African domestic food prices are associated with food-related social unrest. To this end, we employ count-data econometric models, including Poisson, negative binomial, and zero-inflated negative binomial specifications, using monthly data from January 2007 to April 2015.

By incorporating a comprehensive dataset and rigorous statistical techniques, our study offers novel insights into the complex linkages between global market forces and food riots in developing countries. In doing so, we contribute to a deeper understanding of the structural vulnerabilities that drive food riots, providing a foundation for more effective policy interventions.

The paper is structured as follows: Section 2 reviews the literature on food riots and price volatility. Section 3 describes the dataset used in our analysis, while Section 4 outlines the methodological framework. Section 5 presents the empirical results, followed by a discussion of policy implications in Section 6. Finally, Section 7 concludes with a summary of findings and suggestions for future research.

2. Literature Review

The existing literature on social unrest has evolved from qualitative observations to rigorous quantitative assessments. While a broad spectrum of studies has explored the underlying causes of various types of riots [24–26], research that specifically quantifies the drivers of food-related social unrest remain relatively limited [9].

This section synthesizes the literature by categorizing the determinants into four primary global mechanisms (Biofuels, Oil, Speculation, and the USD) while contrasting them with established domestic factors.

2.1. The Transmission of International Price Shocks (Biofuels and Oil)

The primary nexus between energy markets and social stability lies in how international price fluctuations are transmitted to domestic markets. Previous research identifies international wheat prices as a significant determinant of protests and riots in urban centers, even when controlling for broader economic performance [10].

This relationship is increasingly mediated by the “Food–Energy Nexus.” Environmental and climatic conditions, such as droughts and reduced rainfall, are known to indirectly increase the frequency of riots by tightening commodity markets and inflating prices [27]. Furthermore, agent-based models have been employed to simulate how food insecurity, triggered by price spikes, interacts with political fragility and international trade networks to spark unrest [28].

The Research Gap: Despite these insights, the specific roles of biofuel production (distinguishing between bioethanol and biodiesel feedstocks) and global crude oil prices as direct precursors to riots remain under-analyzed in the current literature.

2.2. Financialization and Market Volatility (Speculation)

A second critical mechanism involves the impact of non-commercial traders and the “financialization” of commodity markets. While the volatility of food prices is sometimes found to be uncorrelated or even negatively correlated with the frequency of riots [9], sudden and extreme price shocks are proven to have a significant impact on urban unrest [29].

Significant academic attention has been paid to how speculative activities and the arbitrage behavior of non-commercial traders contribute to global food price hikes [20–22,30,31]. However, a quantitative bridge connecting these financial market dynamics directly to social uprisings on the ground is still missing. Existing papers often prioritize local factors, leaving the influence of global financial “villains” as a secondary or qualitative consideration.

2.3. Global Integration and Macroeconomic Drivers (USD)

The deepening of global market integration, evidenced by the proliferation of Regional Trade Agreements (RTAs) since the 1980s, has emerged as a driver of social unrest [30]. As nations become more integrated, cross-border factors, including the US dollar (USD) exchange rate, play a more crucial role in the stability of developing countries.

While researchers have identified that keeping domestic food prices low is often less critical for stability than preventing sudden international shocks [29], the specific quantitative relationship between USD fluctuations and the triggering of riots via price transmission has yet to be fully explored.

2.4. Contrast with Domestic and Structural Determinants

To understand these global mechanisms, they must be weighed against domestic variables. Historical data from African cities suggests that while international prices are key [10], local conditions such as the Human Poverty Index, urban agglomeration, and civil liberties significantly influence riot incidence [3].

Risk Factors: Low coastal access (exposure to global markets) and political fragility exacerbate the likelihood of unrest [3,28].

Mitigating Factors: Higher domestic food production indices and robust political rights can reduce the probability of food riots, particularly in sub-Saharan Africa [3].

Spatial Factors: Contemporary armed conflicts are also linked to structural issues like ethnic diversity, travel time to markets, and specific climate conditions [32].

2.5. Summary of Contributions

In summary, while most existing papers identify local factors such as domestic production and political regimes, only a few have quantitatively explored international determinants [9,10]. This study addresses these gaps through three primary contributions:

Cross-border focus: We provide the first quantitative analysis focusing on biofuel production, non-commercial speculation, oil prices, and USD exchange rates as direct drivers of riots.

Biofuel Distinction: We differentiate between bioethanol and biodiesel production to evaluate the trade-offs between climate change policies and food security.

Speculative Impact: We test the impact of financial transactions by non-commercial traders on social uprisings, contributing to the ongoing debate regarding financial market regulation [20–22,30,31].

2.6. Theoretical Framework and Hypotheses

US Ethanol Production: We expect a positive relationship with food riots. As a significant portion of US corn is diverted to bioethanol (36–39% in recent years), this reduces global food supply and increases corn prices, which are a staple in many African diets. * **International Crude Oil Price:** We expect a positive relationship with food riots. Rising oil prices increase the cost of agricultural inputs and transportation, thereby raising local food prices and eroding the purchasing power of low-income populations.

Grain Speculation (Long and Short Positions): * **Long Positions:** We expect a positive relationship with food riots, as “buying” positions reflect optimism and can drive global grain prices upward. * **Short Positions:** We expect a negative relationship with food riots, as “selling” positions represent a wager against price performance, potentially suppressing excessive price hikes. * **US Dollar (USD) Index:** We expect a negative relationship with food riots. Since global commodity prices are typically denominated in USD, a depreciation of the dollar (a lower index value) makes commodities more expensive in international markets, increasing import costs for African nations.

3. Data

The empirical analysis investigates the linkages between social unrest and its trans-boundary determinants from January 2007 to April 2015, a period dictated by the availability of the dependent variable. We utilized the Food Riot Radar dataset provided by the World Bank, specifically filtering for “food-related” protest and riot events within the African continent. This dataset provides granular incident-level data, including precise dates, event classifications, and severity metrics such as fatalities and arrests.

For the explanatory variables, monthly bioethanol production volumes in the United States were obtained from the USDA Economic Research Service (ERS) Feed Grains Database [12], while biodiesel production data were retrieved from the U.S. Energy Information Administration (EIA) Monthly Energy Review [11]. Macroeconomic conditions were proxied by the U.S. Dollar Index (DXY) monthly closing prices obtained from Investing.com. Long and short position data, as well as open interest data, for grain commodities (i.e., wheat, corn, and rice) held by non-commercial traders were obtained from the Chicago Board of Trade (CBOT). To address concerns regarding identification and potential omitted-variable bias, we extend the baseline specification by including international food prices and African domestic food prices. Since our proposed mechanism operates through a food price transmission channel, excluding these variables could confound the estimated effects of global macroeconomic factors. By explicitly controlling for both international and domestic food prices, we are better able to isolate the independent effects of the core explanatory variables and reduce the likelihood that the results simply capture broader global shocks

correlated with both commodity prices and unrest. The inclusion of IFP and AFP therefore strengthens the identification strategy and enhances the credibility of the empirical analysis. International food price indices were obtained from the IMF Commodity Price Database and deflated by the U.S. consumer price index from Federal Reserve Economic Data (FRED). The African food price index was deflated using the African consumer price index, both obtained from FAOSTAT. Table 1 summarizes the symbols, detailed definitions, specific data sources, and units of measurement for all variables used in the estimation.

Table 1. Definitions of the variables in the analysis.

Variable	Symbol	Definition	Source	Unit
Riot in Africa	RA	Number of riots that have occurred in Africa	The World Bank Food Riot Radar	Case
USD index	USD	US dollar index (1973 = 100)	Investing.com	Index
US ethanol	USEN	US ethanol production	USDA	1000 gallons
US diesel	USDS	US biodiesel production	EIA	1000 barrels
Crude oil price	COP	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob UK.	IMF Commodity Prices	USD/barrel
Grain short	GS	Grain futures short positions held by non-commercial traders.	CBOT	Contracts
Grain long	GL	Grain futures long positions held by non-commercial traders.	CBOT	Contracts
Open interest	OI	Total open interest in grain futures held by non-commercial traders.	CBOT	Contracts
International food price	IFP	The real food price index comprises cereals, vegetable oils, meat, seafood, sugar, and other food products.	IMF Commodity Prices	Index
African food price	AFP	Real food price index for Africa.	FAOSTAT	Index

To address cyclical fluctuations, we adjusted the variables USEN, USDS, GS, and GL using the X-13-ARIMA (autoregressive integrated moving average) method developed by the US Census Bureau. Table 2 presents the summary statistics for each variable. Notably, the mean value for the dependent variable RA stands at 0.32, with a median of zero. Skewness, a measure of distribution asymmetry, offers valuable insights. A normal distribution, inherently symmetrical, possesses a skewness value of zero. However, in the case of RA, a skewness value of 2.69 was observed, indicating a right-skewed (positively skewed) bias within the distribution. A high kurtosis suggests a distribution with sharp peaks and a fat tail, implying numerous outliers compared to the normal distribution. Conversely, a low kurtosis suggests more rounded peaks and a lighter tail. For a normal distribution, the kurtosis is zero. However, in the case of RA, the kurtosis value was 6.61, indicating sharp peaks and a fat tail. The Jarque–Bera test assesses the normality of a distribution with a null hypothesis of normal distribution. As RA rejects normality, it indicates a right-skewed long tail in its distribution. Given these outcomes, employing a generalized linear model (GLM) to form estimations was appropriate.

Table 2. Summary statistics for variables.

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque–Bera Test
RA	0.320	0.000	0.815	2.730	9.809	317.43 ***
ln USD	4.390	4.386	0.059	0.806	4.444	19.522 ***
ln USEN	6.874	6.997	0.262	−1.332	3.609	31.133 ***
ln USDS	7.306	7.283	0.497	−0.324	1.856	7.205 ***
ln COP	4.478	4.573	0.284	−0.808	2.736	11.171 **
GS/IO	0.169	0.146	0.068	1.060	3.198	18.903 ***
GL/IO	0.287	0.292	0.068	0.007	2.903	0.040
ln IFP	3.897	3.914	0.100	−0.203	1.940	5.375 *
ln AFP	4.565	4.578	0.034	−0.896	2.644	13.903 ***
Observations	100					

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Prior to the estimation, we performed a consistent data transformation pipeline: (1) seasonal adjustment for USEN, USDS, GS, and GL using the X-13-ARIMA method; (2) log-transformation for all continuous variables (except ratios) to calculate elasticities; (3) first-differencing for non-stationary series (USD, USEN, USDS, COP, IFP, and AFP) to ensure stationarity as confirmed by ADF-GLS and KPSS tests; and (4) lagging explanatory variables based on the highest cross-correlation functions (CCFs) to account for price-transmission delays and mitigate endogeneity.

To address concerns that futures positions may reflect non-price factors, institutional conditions, or overall market expansion rather than directional speculation, we replace gross long and short positions with measures scaled by total open interest (GS/IO and GL/IO). This normalization captures speculative intensity relative to total market activity and reduces the mechanical comovement between gross positions and aggregate market growth. By expressing positions as a share of open interest, we distinguish directional exposure from changes in market size, liquidity, or participation. While we do not assume that futures positions are fully exogenous, this specification more closely aligns the empirical measure with the proposed price-pressure mechanism and strengthens the interpretability of the estimated relationships. From Table 2, GS/IO has a lower mean (0.169) and displays a right-skewed distribution (skewness = 1.060), with the Jarque–Bera test indicating a significant departure from normality. In contrast, GL/IO has a higher mean (0.287), is approximately symmetric (skewness ≈ 0), and does not reject normality, suggesting a more stable and near-normal distribution.

All explanatory variables, except for GS/IO and GL/IO, are expressed in logarithmic form. The mean and median values are positive for all variables, with USDS exhibiting the highest value and IFP the lowest. USDS also has the largest standard deviation, indicating greater volatility relative to the other variables, whereas AFP displays the smallest standard deviation. Regarding skewness, USD is positively skewed, while the remaining variables exhibit negative skewness, indicating left-tailed asymmetry. In terms of kurtosis, USD has the highest value, suggesting a more peaked distribution, whereas USDS shows the lowest kurtosis, indicating a flatter distribution relative to the normal benchmark. The Jarque–Bera tests reject normality for all logged explanatory variables at conventional significance levels.

Additionally, it is imperative to establish the stationarity of all explanatory series before proceeding with the analysis. The outcomes of the augmented Dickey–Fuller generalized least squares (ADF-GLS) unit root test [33] and the KPSS stationarity test [34] are presented in Table 3.

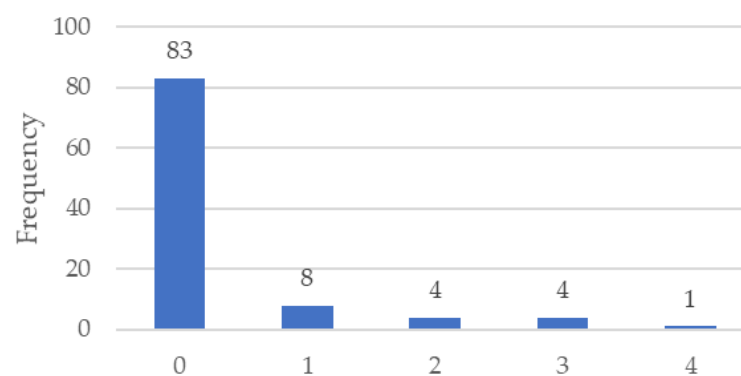
Table 3. Unit root tests for explanatory variables.

	ADF-GLS			KPSS				
	Levels	Lag	First Differences	Lag	Levels	Lag	First Differences	Lag
USD	−1.754	0	−4.305 ***	2	0.144 *	4	0.044	3
USEN	−0.592	2	−2.630 *	6	0.461 ***	4	0.140	3
USDS	−2.224	0	−3.781 ***	4	0.170 **	4	0.050	3
COP	−2.312	1	−4.496 ***	1	0.153 **	4	0.055	3
GS/IO	−4.885 ***	1	−7.232 ***	2	0.138	6	0.040	6
GL/IO	−3.002 *	1	−7.282 ***	0	0.092	8	0.047	1
IFP	−2.370	1	−6.065 ***	0	0.118 *	8	0.052	4
AFP	−0.735	0	−9.484 ***	0	0.292 ***	8	0.091	9

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. The model for the test includes a constant and trend term. The test statistics are shown in the table. Specifically, the ADF-GLS pertains to the augmented Dickey–Fuller unit root test with GLS detrending, while the KPSS refers to the Kwiatkowski, Phillips, Schmidt, and Shin stationarity test. To determine the appropriate lag order p , a testing procedure was performed downward from the maximum lag order of 12 months. This procedure is based on the modified Akaike information with the Perron-Qu [35] method for ADF-GLS. For KPSS, truncated lags (bandwidth) are selected by $\text{integer} \left[4 \left(\frac{T}{100} \right)^{\frac{1}{4}} \right]$, resulting in a choice of four lags. Consequently, when we take the difference, the count reduces to three lags.

The unit root test results indicate that all variables, with the exception of GS/IO and GL/IO, exhibit non-stationarity in levels. However, after taking first differences, all series become stationary. Accordingly, first-order differences are applied to USD, USEN, USDS, COP, IFP, and AFP to ensure stationarity. In contrast, GS/IO and GL/IO are found to be stationary in levels, as confirmed by the unit root tests, and are therefore included in their level form. Overall, the unit root diagnostics ensure that all variables used in the econometric analysis satisfy the stationarity requirement prior to estimation.

Figures 1 and 2 provide an overview of the data, presenting the histogram of riot occurrences and the time-series plots of the variables, respectively. As shown in Figure 1, the dependent variable RA takes non-negative integer values (0, 1, 2, 3, and so forth), confirming its nature as count data. Accordingly, count-data models such as Poisson regression are appropriate [36]. Moreover, descriptive statistics indicate that the monthly Africa-wide riot count is heavily zero-inflated, with at least 75% of observations equal to zero. In addition, the variance (0.66) substantially exceeds the mean (0.32), suggesting the possibility of overdispersion. These characteristics may violate the equidispersion assumption of the Poisson model and justify the use of more flexible count-data specifications, such as quasi-Poisson, negative binomial, and zero-inflated models, which explicitly account for excess zeros and overdispersion.

**Figure 1.** Histogram of riots in Africa.

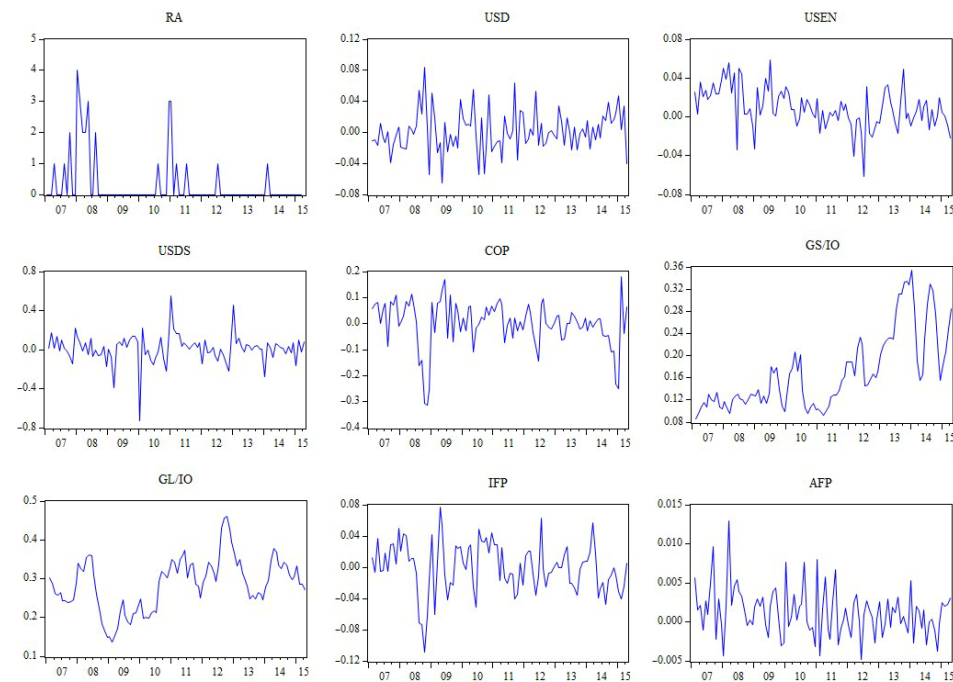


Figure 2. Time series plot of each variable. Note: USD, USEN, USDS, COP, IFP, and AFP are included in first-log-difference form, whereas GS/IO and GL/IO are specified in levels.

In Figure 2, the dependent variable RA was prominently observed in 2008 and 2011. The $\Delta \ln \text{USD}$ (first log-differenced USD) mirrors fluctuations characterized by notable oscillations, particularly after its pronounced volatility in late 2008. In contrast, the $\Delta \ln \text{USEN}$ showcases significant fluctuations during 2008 and 2009, followed by yet another period of flux in 2012. The $\Delta \ln \text{USDS}$ witnesses notable spikes in January 2011 and January 2013, in addition to a significant drop in January 2010. The $\Delta \ln \text{COP}$ rises after experiencing a moderate decline between June and November 2008 before rising again between July 2014 and January 2015. The GS/IO ratio exhibits a substantial upward trend after July 2009, followed by pronounced fluctuations between 2012 and 2015. In contrast, the GL/IO ratio declined from June 2008, subsequently increased, and reached its peak in October 2012. Finally, it is evident that the IFP (first log-differenced) and AFP (first log-differenced) exhibit pronounced fluctuations between 2007 and 2008, coinciding with the 2007–2008 global commodity price spike and the global financial crisis.

Table 4 presents the correlation matrix of the explanatory variables. The results indicate that most pairwise correlations are moderate and do not suggest severe multicollinearity. However, the correlation between the IFP and COP exceeds 0.5, showing a relatively strong association between these variables. Including both variables simultaneously in the same regression specification may, therefore, raise multicollinearity concerns, potentially inflating standard errors and reducing the precision of coefficient estimates. To address this issue and enhance the robustness of the empirical findings, IFP and COP are not included jointly in the same specification. Instead, they are incorporated separately across alternative model specifications to isolate their respective effects while mitigating potential collinearity bias.

Table 4. Correlation matrix of the explanatory variables.

	USD	USEN	USDS	COP	GS/IO	GL/IO	IFP	AFP
USD	1							
USEN	−0.153	1.000						
USDS	−0.181	0.085	1.000					
COP	−0.369	0.052	0.146	1.000				
GS/IO	0.002	−0.172	0.143	0.120	1.000			
GL/IO	0.118	−0.239	−0.073	−0.154	0.037	1.000		
IFP	−0.415	0.057	0.106	0.550	0.087	−0.237	1.000	
AFP	−0.132	0.171	−0.119	0.176	−0.058	−0.161	0.094	1

Note: USD, USEN, USDS, COP, IFP, and AFP are included in first-log-difference form, whereas GS/IO and GL/IO are specified in levels.

Subsequently, we calculated the sample cross-correlation functions (CCFs) between the dependent variable and the explanatory variables to ascertain the lag order of each explanatory variable. We pinpointed the lags that exhibited the highest correlations. It is important to note that fluctuations in each of the variables contributing to the occurrence of riots do not immediately trigger the riots themselves. Instead, there tends to be a lag of several months between the shifts in these variables and the onset of riots. As a result, we posit that people are more likely to riot a few months after changes in each variable have occurred. According to this premise, we identified the optimal lag as the point in time when the correlation coefficient between the explanatory variables and the occurrence of riots reached its highest magnitude. The rationale behind this selection is rooted in the understanding that the explanatory variations that hold the most significant correlation with riot occurrences correspond to the optimal lag timeframe. The formulation of the CCFs can be described as follows:

$$CCF = \frac{\frac{1}{T} \sum_{t=1}^T (y_t - \bar{y}_t)(x_{t-h} - \bar{x}_{t-h})}{\sqrt{\frac{1}{T} \sum_{t=1}^T (y_t - \bar{y}_t)^2} \sqrt{\frac{1}{T} \sum_{t=1}^T (x_{t-h} - \bar{x}_{t-h})^2}} \quad (1)$$

Equation (1) calculates the correlations between x_{t-h} and y_t , for $h = 0, \pm 1, \pm 2, \pm 3, \dots$. Here, a negative value for h is a correlation between explanatory variables x (cross-border factors) at a time before t and dependent variable y (riots) at time t . The t -value for the CCF is calculated as $T = \frac{CCF\sqrt{n-2}}{\sqrt{1-CCF^2}}$, where n is the sample size. Given that the sample size was 100, we opted for a lag of six months. The outcomes of Equation (1) are presented in Table 5. The results indicate that USD exhibits a lag of four months, while USEN and USDS display a one-month lag. COP is associated with a five-month lag, and IFP with a two-month lag. In contrast, no statistically meaningful lag is detected for GS/IO, GL/IO, or AFP, suggesting that domestic food prices and speculative intensity exert contemporaneous effects on riot occurrences.

Moreover, to examine potential structural breaks in the riot series, we conducted a Bai–Perron multiple structural break test using the log-transformed dependent variable, defined as $\ln(RA + 1)$. The results identify a statistically significant breakpoint in October 2008. This timing corresponds to the peak of the global financial crisis, spanning approximately September 2008 to March 2009. Given the economic significance of this period and its potential influence on social unrest, we introduce a crisis dummy variable that equals one during September 2008–March 2009 and zero otherwise. This dummy variable is included in the baseline regression specification to account for the macroeconomic disruptions associated with the global financial crisis. Controlling for this structural shift enables us to isolate the effects of the explanatory variables from crisis-related changes in riot dynamics.

Table 5. Correlation coefficient functions of the series used for estimation.

	CCF Value	Lag (Month)
USD	−0.204 * (0.056)	−4
USEN	0.309 *** (0.000)	−1
USDS	0.217 ** (0.023)	−1
COP	0.204 ** (0.034)	−5
GS/IO	−0.320 ** (0.019)	0
GL/IO	0.214 *** (0.000)	0
IFP	0.292 *** (0.000)	−2
AFP	0.342 *** (0.000)	0

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. *p*-values are in parentheses. USD, USEN, USDS, COP, IFP, and AFP are included in first-log-difference form, whereas GS/IO and GL/IO are specified in levels.

4. Methodology

This section outlines the empirical methods employed in the study, focusing on the econometric tools used to analyze riot occurrences. Because the dependent variable measures the number of riot events, it consists of non-negative integers and is appropriately modeled using count-data techniques. We begin with the Poisson regression model, which assumes equidispersion—i.e., that the conditional mean equals the conditional variance. Preliminary diagnostics indicate the presence of overdispersion in the riot data, suggesting that the variance exceeds the mean. To address this issue, we estimate a quasi-Poisson model, which allows the variance to be proportional to the mean, and a Poisson model with robust standard errors to ensure valid inference under potential variance misspecification. We also employ a negative binomial model, which explicitly accounts for overdispersion through an additional dispersion parameter. Given the substantial number of zero observations in the sample, we further estimate a zero-inflated negative binomial model to test for the presence of a structural zero-generating process. Accordingly, our empirical analysis relies on quasi-Poisson, robust Poisson, negative binomial, and zero-inflated negative binomial specifications to ensure robust inference and appropriate modeling of count data.

When considering GLMs [37,38], we assumed an independent and identically distributed (IID) random variable y_t , $t = 1, 2, \dots, T$ that follows an exponential family of distributions. Under the linear model specification, the conditional expectation is $E[y_t|x_t] = \mu_t$, and the variance is $V[y_t|x_t] = v(\mu_t)$.

In the Poisson model, the mean is $E[y_t|x_t] = \mu_t$, and the variance is $V[y_t|x_t] = v(\mu_t) = \mu_t$ and the same. The mean is expressed as $\mu_t = \exp(x_t'\beta)$, where β is a parameter and x_t is an explanatory variable, both in vector. However, in many cases, the variance from the actual data is often greater than that expected in Poisson regression: $V[y_t|x_t] > E[y_t|x_t]$. This is a so-called overdispersion, and it occurs when there is unobserved heterogeneity, such as:

$$\exp(x_t'\beta + \varepsilon_t) = \exp(\varepsilon_t) \exp(x_t'\beta) \neq \exp(x_t'\beta) \quad (2)$$

In Equation (2), ε_t is an unobservable random variable. In this case, although the estimated coefficients β are not biased, the variance exceeds the mean. To address this overdispersion, several approaches can be adopted [36,39].

To relax the assumption that the mean and variance are equal in the Poisson model, we considered the following relationship using the shape parameter τ [40,41]:

$$V[y_t|x_t] = \tau\mu_t, \tau > 1 \quad (3)$$

Equation (3) is referred to as the quasi-Poisson regression. An alternative approach to address the issue of overdispersion is the robust Poisson regression. Cantoni and

Ronchetti [42,43] underscore the lack of robustness in the quasi-Poisson regression and introduce a more robust technique using quasi-likelihood estimation. To maintain consistency in the ordinal Poisson method, this robust estimation technique involves down-weighting and recentering high leverage points. Another alternative for addressing overdispersion is the negative binomial regression [44]. For this, we assumed a Poisson distribution but allowed the mean μ_t to vary due to the heterogeneity of each observation t . To ensure the randomness of μ_t , we relaxed the assumption of the Poisson model and added heterogeneity to the conditional expectation, as shown in Equation (4) [44,45]:

$$\begin{aligned} E[y_t|x_t] &= \exp(x_t'\beta) \\ V[y_t|x_t] &= \mu_t + \alpha\mu_t^2 \end{aligned} \quad (4)$$

Unlike in the ordinary least squares (OLS) method, the interpretation of our estimated GLMs is not straightforward. The average marginal effect (AME) commonly represents marginal effects in GLMs [36,39]. Furthermore, given the substantial proportion of zero observations in the dataset, we estimate a zero-inflated negative binomial (ZINB) model. The ZINB framework assumes that riot counts may arise from two latent processes: one generating structural zeros and another following a negative binomial distribution. This approach enables us to test whether excess zeros reflect a distinct zero-generating mechanism rather than stochastic variation alone.

Notably, endogeneity concerns are present. For example, riots in Africa could potentially stimulate ethanol or biodiesel production, thereby affecting the grain positions taken by non-commercial traders. To mitigate this, we incorporated lags into our explanatory variables. As a result, the present state remains uninfluenced by future riots, enabling us to circumvent the need to address endogeneity.

5. Results and Interpretation

5.1. Empirical Results

We validated the hypothesis that riots in Africa can be attributed to cross-border factors such as the US dollar index, ethanol and biodiesel production in the US, the global crude oil price, and the long or short positions taken by non-commercial traders in the grain market. The estimated outcomes derived from the quasi-Poisson, robust Poisson, and negative binomial regressions are presented in Table 6. Alternative specifications that include international food prices instead of crude oil prices are reported in Table 7.

Across the four models, the estimated coefficients display broadly consistent signs and significance patterns, with the exception of USD. Specifically, USD is negative and statistically significant in the robust Poisson, negative binomial, and ZINB models, but not significant in the quasi-Poisson specification. For most variables, both the magnitude and statistical significance of the coefficients are similar across models. However, the robust Poisson model generally yields larger coefficient estimates and stronger statistical significance compared to the quasi-Poisson and negative binomial models. Although a formal comparison using the Akaike Information Criterion (AIC) is not applicable across all specifications, econometric considerations lead us to treat the robust Poisson results as the preferred baseline specification.

Our empirical results yield several noteworthy findings.

First, USEN exhibits a consistently positive and statistically significant association with riot incidence across all model specifications, whereas USDS is not statistically significant. This contrast suggests that bioethanol production may exert a stronger linkage to African social unrest than biodiesel production.

Second, COP display a robust and positive effect in all models, underscoring the central role of global energy price dynamics in shaping unrest in Africa.

Table 6. Estimated impact of cross-border factors on riot incidence in Africa (including COP, excluding IFP).

Dependent Variable: RA				
	Quasi-Poisson Regression	Robust Poisson Regression	Negative Binomial Regression	ZINB Regression
USD	−15.781 (0.112)	−15.781 * (0.066)	−15.781 * (0.066)	−15.780 * (0.066)
USEN	27.882 *** (0.003)	27.882 *** (0.004)	27.882 *** (0.004)	27.882 *** (0.004)
USDS	2.221 (0.193)	2.221 (0.206)	2.221 (0.206)	2.221 (0.206)
COP	5.687 (0.182)	5.687 ** (0.050)	5.687 ** (0.050)	5.687 ** (0.050)
GS/IO	−25.289 ** (0.038)	−25.289 ** (0.037)	−25.289 ** (0.037)	−25.286 ** (0.037)
GL/IO	17.231 *** (0.001)	17.231 *** (0.002)	17.231 *** (0.002)	17.231 *** (0.002)
AFP	90.107 ** (0.045)	90.107 ** (0.019)	90.107 ** (0.019)	90.109 ** (0.019)
GFC dummy	2.228 ** (0.025)	2.228 ** (0.012)	2.228 ** (0.012)	2.228 ** (0.012)
Constant (count)	−4.461 * (0.058)	−4.461 (0.124)	−4.461 (0.124)	−4.462 (0.124)
Constant (inflate)				−18.979 *** (0.000)
α			0.000	0.000
Pseudo R ²	0.528	0.528	0.420	
Observations	94	94	94	94

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. *p*-values are in parentheses. There is no correct likelihood function in the case of quasi-Poisson regression and robust Poisson regression, which is based on quasi-likelihood; therefore, one cannot evaluate the models using AIC or maximum log-likelihood.

Third, speculative positioning in grain futures markets reveals asymmetric effects: GL/IO are positively and significantly associated with riot incidence, while GS/IO exhibit a significant negative relationship. This pattern suggests that greater speculative intensity on the long side coincides with higher unrest, whereas increased short exposure is associated with lower riot frequency. Furthermore, both AFP and IFP carry positive and statistically significant coefficients, indicating that rising domestic and global food prices contribute to higher riot incidence. The magnitude of the AFP coefficient is the largest, implying that domestic food price pressures exert the most direct and substantial influence on social instability. Finally, the positive and significant coefficient on the GFC dummy indicates that the 2008 global financial crisis amplified social unrest in Africa. The following subsection elaborates on the mechanisms underlying these findings.

To evaluate the sensitivity of our results to lag specification, Table 8 presents a series of robustness checks. Rather than relying exclusively on lag selection based on cross-correlation functions (CCFs), we estimate alternative specifications using a uniform distributed-lag structure that includes contemporaneous terms and up to two lags for all regressors. We also examine a more parsimonious distributed-lag model and report cumulative effects over the specified horizon. The findings show that the signs and economic magnitudes of the key coefficients, particularly those related to speculative positioning and energy-related price variables, remain broadly consistent with the baseline models based on CCF-selected lags (Tables 6 and 7). Although statistical significance varies slightly across specifications, the substantive conclusions are robust. These exercises alleviate concerns

that the results are driven by data-dependent lag selection and provide further support for the proposed transmission mechanisms.

Table 7. Estimated impact of cross-border factors on riot incidence in Africa (including IFP, excluding COP).

Dependent Variable: RA				
	Quasi-Poisson Regression	Robust Poisson Regression	Negative Binomial Regression	ZINB Regression
USD	−16.909 * (0.075)	−16.909 ** (0.036)	−16.909 ** (0.036)	−16.909 ** (0.036)
USEN	24.886 ** (0.016)	24.886 ** (0.027)	24.885 ** (0.027)	24.886 ** (0.027)
USDS	1.620 (0.331)	1.620 (0.336)	1.620 (0.336)	1.620 (0.336)
GS/IO	−24.963 ** (0.040)	−24.963 ** (0.030)	−24.963 ** (0.030)	−24.963 ** (0.030)
GL/IO	13.868 *** (0.004)	13.868 *** (0.005)	13.868 *** (0.005)	13.868 *** (0.005)
IFP	13.702 (0.191)	13.702 * (0.065)	13.703 * (0.065)	13.701 * (0.065)
AFP	113.638 ** (0.011)	113.638 *** (0.001)	113.643 *** (0.001)	113.634 *** (0.001)
GFC dummy	2.276 ** (0.026)	2.276 ** (0.010)	2.276 ** (0.010)	2.276 ** (0.010)
Constant (count)	−3.454 * (0.087)	−3.454 (0.137)	−3.454 (0.137)	−3.454 (0.137)
Constant (inflate) α				−16.259 *** (0.000)
Pseudo R ²	0.526	0.526	0.417	0.000
Observations	94	94	94	94

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. *p*-values are in parentheses. There is no correct likelihood function in the case of quasi-Poisson regression and robust Poisson regression, which is based on quasi-likelihood; therefore, one cannot evaluate the models using AIC or maximum log-likelihood.

Table 8. Lag-Structure robustness checks: parsimonious distributed-lag specifications and cumulative effects on riot incidence in Africa.

Dependent Variable: RA		
	Robust Poisson Regression (Including COP, Excluding IFP).	Robust Poisson Regression (Including IFP, Excluding COP).
USD	−8.607 (0.875)	−0.975 (0.971)
USEN	44.374 *** (0.000)	55.565 ** (0.003)
USDS	8.275 (0.874)	8.186 (0.336)
COP	1.439 ** (0.037)	
GS/IO	−21.948 * (0.052)	−28.354 * (0.067)
GL/IO	17.152 * (0.066)	13.859 ** (0.014)
IFP		9.914 (0.632)
AFP	248.378 ** (0.038)	245.012 * (0.063)
GFC dummy	3.533 ** (0.011)	0.419 (0.880)
Constant	−6.013 * (0.028)	−4.803 (0.137)
Pseudo R ²	0.612	0.621

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. *p*-values are in parentheses. The reported coefficients represent cumulative effects, calculated as the sum of the contemporaneous and lagged coefficients (lags 0–2). Standard errors for these cumulative effects are computed using the delta method, which accounts for the covariance among the estimated lag coefficients.

To further examine the marginal effects of each explanatory variable, we conducted an AME analysis utilizing GLMs, the outcomes of which are presented in Tables 9 and 10. Among the statistically significant variables, AFP exhibits the largest effect (approximately 28–36), indicating that increases in domestic African food prices substantially raise riot incidence. USEN, GL/IO, and IFP also show sizeable positive marginal effects, highlighting the roles of U.S. bioethanol production, long speculative positioning, and global food prices in shaping unrest. In contrast, GS/IO displays a comparatively large negative effect, suggesting that greater short positioning is associated with fewer riots. The U.S. dollar index has a moderate negative association, while crude oil prices (COP) show a positive but smaller effect. U.S. diesel prices (USDS) remain statistically insignificant. Overall, domestic food prices, bioethanol production, and speculative intensity exert the strongest quantitative influence on riot incidence in Africa.

Table 9. Marginal effects of cross-border factors on riot incidence in Africa (including COP, excluding IFP).

Dependent Variable: RA				
	Quasi-Poisson Regression	Robust Poisson Regression	Negative Binomial Regression	ZINB Regression
USD	−5.036 (0.127)	−5.036 * (0.058)	−5.036 * (0.058)	−5.036 * (0.058)
USEN	8.898 *** (0.009)	8.898 *** (0.004)	8.898 *** (0.004)	8.899 *** (0.004)
USDS	0.709 (0.205)	0.709 (0.190)	0.709 (0.190)	0.709 (0.190)
COP	1.815 (0.194)	1.815 ** (0.032)	1.815 ** (0.032)	1.815 ** (0.032)
GS/IO	−8.071 * (0.052)	−8.071 * (0.052)	−8.071 * (0.052)	−8.070 * (0.052)
GL/IO	5.499 *** (0.005)	5.499 *** (0.001)	5.499 *** (0.001)	5.499 *** (0.001)
AFP	28.758 * (0.059)	28.758 ** (0.020)	28.758 ** (0.020)	28.760 ** (0.020)
GFC dummy	0.711 ** (0.038)	0.711 *** (0.005)	0.711 *** (0.005)	0.711 *** (0.005)

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. *p*-value are in parentheses.

Table 10. Marginal effects of cross-border factors on riot incidence in Africa (including IFP, excluding COP).

Dependent Variable: RA				
	Quasi-Poisson Regression	Robust Poisson Regression	Negative Binomial Regression	ZINB Regression
USD	−5.396 * (0.090)	−5.396 ** (0.032)	−5.396 ** (0.032)	−5.397 ** (0.032)
USEN	7.942 ** (0.028)	7.942 ** (0.026)	7.942 ** (0.026)	7.943 ** (0.026)
USDS	0.517 (0.338)	0.517 (0.327)	0.517 (0.327)	0.517 (0.327)
GS/IO	−7.967 * (0.054)	−7.967 ** (0.041)	−7.967 ** (0.041)	−7.967 ** (0.041)
GL/IO	4.426 ** (0.012)	4.426 *** (0.006)	4.426 *** (0.006)	4.426 *** (0.006)
IFP	4.373 (0.203)	4.373 * (0.071)	4.373 * (0.071)	4.373 * (0.071)
AFP	36.268 ** (0.021)	36.268 *** (0.002)	36.269 *** (0.002)	36.267 *** (0.002)
GFC dummy	0.726 ** (0.039)	0.726 *** (0.008)	0.726 *** (0.008)	0.726 *** (0.008)

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. *p*-value are in parentheses.

To enhance economic interpretability, Tables 11 and 12 reports predicted riot incidence evaluated at the 25th and 75th percentiles of each explanatory variable, holding other covariates constant. The results show that GL/IO has the largest positive effect, increasing predicted riot incidence by approximately 0.37–0.47 across specifications. In contrast, GS/IO is associated with a substantial decline (around −0.30). Among price variables, USEN and IFP display notable positive effects (approximately 0.15–0.18), while AFP show a moderate increase (around 0.08–0.10). The USD consistently exhibits a negative association (about −0.14 to −0.15), and USDS have a relatively small positive effect. These findings are consistent with the estimated average marginal effects and reinforce the economic

significance of speculative positioning and energy–food price dynamics in shaping riot incidence in Africa.

Table 11. Predicted riot incidence at the 25th and 75th percentiles of explanatory variables (including COP, excluding IFP).

Dependent Variable: RA			
	Predicted Riots (25th Percentile)	Predicted Riots (75th Percentile)	Change (75th – 25th)
USD	0.359	0.221	−0.138
USEN	0.175	0.351	0.176
USDS	0.241	0.316	0.074
COP	0.217	0.377	0.160
GS/IO	0.342	0.039	−0.304
GL/IO	0.118	0.582	0.465
AFP	0.229	0.310	0.081

Note: The results are estimated using a robust Poisson regression model.

Table 12. Predicted riot incidence at the 25th and 75th percentiles of explanatory variables (including IFP, excluding COP).

Dependent Variable: RA Robust-Poisson Regression			
	Predicted Riots (25th Percentile)	Predicted Riots (75th Percentile)	Change (75th – 25th)
USD	0.369	0.219	−0.150
USEN	0.179	0.333	0.154
USDS	0.258	0.314	0.056
GS/IO	0.339	0.039	−0.300
GL/IO	0.142	0.513	0.371
IFP	0.179	0.334	0.154
AFP	0.216	0.317	0.101

Note: The results are estimated using a robust Poisson regression model.

In conclusion, this analysis offers important insights into the complex relationship between cross-border factors and riot incidence in Africa. The results highlight the significant roles of U.S. bioethanol production, the U.S. dollar index, crude oil prices, and speculative positioning in grain futures (GS/IO and GL/IO) as key determinants of social unrest. In addition, both domestic African food prices and international food prices emerge as crucial drivers, underscoring the central importance of food price dynamics in understanding riot activity. Overall, these findings emphasize the need to account for both global market forces and domestic price conditions when analyzing and mitigating social instability, thereby providing a foundation for future research and evidence-based policy design.

5.2. Interpretation and Validation of the Results

We found that bioethanol production can potentially aggravate the occurrence of riots in Africa, consistent with historical data on grain consumption per capita from the Food and Agriculture Organization [13]. These data indicate that corn accounts for the largest share of calorie intake among primary food commodities—corn, wheat, rice, sorghum, and cassava—in seven African countries that experienced food riots during the examined period. For example, in Zambia, which encountered food riots in May 2008, the consumption of corn was as much as 714 kilocalories per capita per day in 2018, equivalent to 38% of the total daily calorie intake. By contrast, the production of biodiesel in the United States does not appear to influence the likelihood of food riots in Africa, a trend corroborated by historical records. First, in the 18 nations where social upheaval occurred during the

sample period, the average calorie intake of soybeans and soybean oil amounted to only 3.8 and 65.1 kilocalories in 2018, equivalent to 0.2% and 2.3% of the total daily calorie intake, respectively. The small proportions of calories derived from soybeans suggest that a high soybean price is less likely to trigger food protests in the region. Second, the feedstock used for biodiesel production is significantly smaller in scale than the feedstock used for bioethanol production in the US. For instance, in 2014, 853 million bushels of soybean were used for biodiesel production, equivalent to 22% of the country's soybean production of that year, while in the same year, 36% of US corn production was consumed in bioethanol production. These two sets of historical data provide further support for the findings pertaining to US biofuel production.

Furthermore, we found that the long and short positions of cereal goods held by non-commercial traders were positively and negatively correlated with riots, respectively. These coefficient signs align with our hypothesis—that long positions potentially drive up grain prices while short positions have the potential to drive them down. This finding suggests that speculative activities in the US have the capacity not only to trigger spikes in food prices but also to ignite uprisings in remote geographical regions. As mentioned earlier, hedge funds are now more prominent in today's markets than in the past few decades. This growing presence of speculation underscores its increasing significance as a causal factor behind food riots.

Our findings also indicate that fluctuations in international crude oil prices (COP) are a root cause of food riots in Africa, with three out of four models—Robust Poisson, Negative Binomial, and ZINB—showing statistical significance. In low-income countries, the majority of individuals allocate a substantial portion of their income to food and energy commodities. While previous research suggests that international oil prices influence local corn prices primarily through transportation costs, our empirical results—specifically the positive and statistically significant coefficients for both COP and African domestic food prices (AFP)—demonstrate that rising global energy costs and domestic food price spikes act as simultaneous stressors. Notably, the average marginal effect (AME) of AFP is the largest among all variables, ranging from 28.7 to 36.3, which implies that while high energy prices erode purchasing power through fuel and transport costs, the direct pressure from domestic food price inflation remains the most potent driver of social unrest. Consequently, the convergence of energy and food price shocks creates a critical threshold of economic grievance that triggers protests and rebellions in the region.

Another important observation is that the US dollar index can play a key role in protests. The index displays a consistently negative coefficient across three of the four models, signifying that the depreciation of the US dollar could increase the likelihood of food riots due to the resultant increase in commodity prices. However, the causal link is relative, as demonstrated by the fact that one of the models does not reveal statistical significance. Nevertheless, we hypothesized that commodity prices in the local currencies of importing countries might enhance the purchasing power of importers, thus stimulating commodity demand and leading to upward price pressures. Additionally, given that the global prices of many commodities are denominated in US dollars, international commodity prices may well increase with the devaluation of the US dollar.

6. Discussion

This study examines the impact of cross-border economic factors on the occurrence of food riots in Africa. Specifically, it analyzes how US biofuel production, fluctuations in crude oil prices, speculative activities, and the US dollar index influence food riots. The key findings are as follows: (1) US ethanol production is significantly associated with an increased likelihood of riots in Africa, whereas biodiesel production does not exhibit a

statistically significant effect. (2) Rising international crude oil prices contribute to the occurrence of food riots. (3) Long positions in the grain market increase the likelihood of food riots, while short positions tend to suppress riots. (4) A depreciation of the US dollar may increase the probability of food riots.

6.1. US Biofuel Policy and Food Riots in Africa

Our findings suggest a strong correlation between US biofuel policy and food riots in Africa. In particular, the consistently positive and highly significant association ($p < 0.01$) between ethanol production and riot occurrences is noteworthy. Our analysis shows that US ethanol production has a substantial average marginal effect of approximately 7.9 to 8.9, suggesting it is a major transboundary driver of unrest. This result aligns with the high proportion of US corn used for biofuel—reaching 36% in 2014—and the heavy dependence of African countries on corn as a staple food. According to FAO data, corn was the primary source of dietary calories in at least seven African countries that experienced food riots, such as Zambia, where corn consumption accounted for 38% of total daily calorie intake. In contrast, biodiesel production did not show a statistically significant relationship with riots, likely due to the smaller scale of production and the minimal share of soybeans in African caloric intake. These findings highlight the need to reconsider the balance between food security and climate change policies, suggesting that using staple crops like corn as biofuel feedstock could be a contributing factor to social unrest in low-income countries. As a policy alternative, non-food crops should be prioritized to mitigate these negative externalities.

6.2. The Predominant Role of Domestic Food Prices in Riot Incidence

Furthermore, this updated analysis explicitly incorporates international food prices (IFP) and African domestic food prices (AFP) as explanatory variables to better capture the price-transmission mechanism. Our findings reveal that both variables are positively and statistically significantly correlated with the occurrence of food riots. Notably, the average marginal effect (AME) of AFP is the largest among all variables, ranging from 28.7 to 36.3 across the models. This suggests that while global market shocks—such as US biofuel policies and crude oil prices—act as fundamental drivers, the direct and most potent trigger for social unrest is the inflation of food prices within local African markets. The results underscore that the volatility of international commodity markets eventually culminates in domestic price surges, which immediately erode the purchasing power of vulnerable populations and lead to uprisings.

6.3. Speculative Activities and Food Riots

The results of this study indicate that speculative activities in the grain market significantly influence the occurrence of food riots. Specifically, long positions (buying) increase the probability of riots, while short positions (selling) tend to suppress their occurrence. Our predicted incidence analysis reveals a stark asymmetry: an increase in long positions (GL/IO) from the 25th to the 75th percentile raises the predicted riot incidence by approximately 0.37 to 0.47, the largest positive effect among all variables, whereas a similar increase in short positions (GS/IO) is associated with a substantial decline of around 0.30. This finding suggests that speculative buying drives up grain prices, reducing consumers' purchasing power, whereas short positions play a role in stabilizing excessive price hikes. The policy implications of speculative activities are significant. For example, the introduction of a financial transaction tax (commonly known as the Tobin tax) has been proposed as a mean to curb speculation and stabilize markets. However, previous research suggests that such a tax could reduce market efficiency, and its effectiveness remains uncertain. Based on the findings of this study, taxing long positions might help mitigate food riots, while excessive restrictions on short positions could weaken the market's price adjustment function.

6.4. International Crude Oil Prices and Food Riots

This study finds that international crude oil price increases the likelihood of food riots, with three of the four models—Robust Poisson, Negative Binomial, and ZINB—indicating statistical significance. This result suggests that energy prices are closely linked to food prices and significantly impact purchasing power in low-income countries. In many African nations, food and energy expenditures account for a large share of household budgets, making them particularly vulnerable to rising oil prices. Dillon and Barrett [46] found that international crude oil prices influence local corn prices primarily through increased transportation costs in African countries. The findings of this study support this conclusion, indicating that rising energy costs can trigger food riots by reducing disposable income. Furthermore, our results show that the average marginal effect of African domestic food prices (AFP) is the largest among all variables, suggesting that the transmission of energy price shocks into domestic food price inflation remains a critical and potent trigger for social unrest in the region.

6.5. Fluctuations in the US Dollar Index and Food Riots

This research suggests that a depreciation of the US dollar may increase the likelihood of food riots, with three of the four models—Robust Poisson, Negative Binomial, and ZINB—showing statistically significant negative coefficients. Our average marginal effect (AME) analysis confirms this moderate negative association, indicating that a decline in the USD index corresponds to an increase in riot incidence. This finding aligns with Baumeister and Kilian [47], who suggest that correlations between commodity prices are often driven by shared macroeconomic factors. A weaker US dollar increases international commodity prices, reducing the purchasing power of food-importing countries. Since food prices are denominated in US dollars, currency depreciation leads to higher food import costs, potentially exacerbating food riots. While one model (quasi-Poisson) did not reveal statistical significance, the consistent results across the other robust specifications reinforce the role of the USD as a key transboundary determinant. Although a weaker dollar could also theoretically enhance the purchasing power of some countries through alternative channels, our empirical evidence primarily supports the price-transmission mechanism as a driver of social unrest.

7. Conclusions

The primary contribution of our analysis to the existing literature lies in the identification of both transboundary and domestic elements that influence food riots in Africa. While previous studies have often separated local determinants from international food prices, this study is the first to quantitatively test a comprehensive set of global drivers—including biofuel production, crude oil prices, financial speculation, and the US dollar index—alongside domestic price dynamics.

Our main findings are as follows:

- (1) **Impact of Biofuel Production:** US bioethanol production significantly increases the likelihood of riots in African nations, whereas biodiesel production does not show a statistically significant effect. This reflects the high sensitivity of African markets to corn, a primary feedstock for ethanol.
- (2) **Role of Energy and Food Prices:** Global crude oil prices and international food prices are significant determinants of food riots. Crucially, African domestic food prices (AFP) exert the most direct and potent influence, exhibiting the largest average marginal effect among all tested variables.

- (3) **Speculative Intensity:** Speculative activities in grain futures markets show a clear asymmetry; long positions held by non-commercial traders are positively associated with riot incidence, while short positions exhibit a negative, stabilizing relationship.
- (4) **Macroeconomic and Structural Drivers:** The fluctuation of the US dollar index is a key determinant, with its depreciation generally increasing the risk of unrest. Additionally, the 2008 global financial crisis was found to have significantly amplified social instability across the continent.

One limitation of this study is the temporal scope of the data, which spans from 2007 to 2015 due to the availability of the World Bank Food Riot Radar—the most specialized database for food-specific unrest. While this period precedes more recent climate policy frameworks such as the Paris Agreement and subsequent net-zero targets, it remains a uniquely critical era for analyzing the structural impacts of early-stage biofuel expansion and the financialization of commodity markets. Future research could extend this analysis by incorporating more recent datasets as they become available, potentially testing the effects of updated climate policies. Additionally, while our study focused on the frequency of riots to ensure statistical robustness, future investigations could explore other dimensions of unrest, such as the severity (e.g., fatalities or duration), to provide a more granular understanding of how global shocks manifest as local violence.

When considering avenues for future research, it is worth noting that only a limited number of academic studies have attempted to identify the determinants of food riots by utilizing quantitative methodologies. Furthermore, most research efforts have focused on domestic elements while largely ignoring cross-border factors. Given the contemporary landscape of a highly integrated global economy characterized by RTAs, an unexplored realm of cross-border influences warrants deeper investigation. In addition, while the World Bank riot dataset provides useful data on the number of instances of food riots, the range of its data is ultimately limited. While Bellemare [9] applied a method whose favorable traits made it possible to determine the severity of protests, our findings could be reinforced by regressing this web search result with cross-border variables such as biofuels, speculation, the US dollar index, and global crude oil price.

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