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Food imports, international prices, and violence in Africa

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Abstract

This study examines the effect of food price fluctuations on violence in Africa, using international food prices as a source of exogenous shock weighted by a country's import pattern of major food commodities to create a country-specific food price index. The regression analysis shows that between 1990 and 2011, food price increases are associated with higher levels of violence. Moving from low to high values in the price index corresponds, after controlling for economic, social, and political factors, to an increase in violence intensity of 1.3 incidents. This effect is predominantly driven by imports of low-value-added primary products. Despite the statistically significant results, the predictive power of food prices is relatively low, both in and out of sample. Using 2012 data for out-of-sample forecast shows that food prices are a relatively poor predictor of violence.

JEL classifications: D74, O55, Q17, Q18.

1. Introduction

There is a popular discourse that links the incidence of civil unrest to higher food prices. Accordingly, the increased sense of relative deprivation leads to a higher risk of violent collective action when staple foods become unaffordable for the masses. Although riots and violence linked to food prices have become less common in the 20th and 21st centuries (Taylor, 1996), some recent events that confronted several countries with severe unrest and political instability have been linked to food price levels (Lagi *et al.*, 2011). A prime example is the wave of protests, riots, and sometimes lethal violence that followed the 2007–08 world food price crisis. Developing countries such as Haiti, Bangladesh, the Philippines, and several African countries faced severe unrest after food prices peaked. In a reaction to these events, the FAO warned that the spread of violence would continue if food price levels did not drop and expressed surprise about the fact that this issue was not on the United Nations Security Council's agenda, arguing that these events showed that higher food prices have dire consequences for peace, security, and human rights (Reuters, 2008).[1] Other

1 Since the 2011 meeting of the G20, food security has become a top priority on the agenda.

recent societal upheavals have also been linked to food prices: the Arab Spring, which saw political reforms, ousting of various rulers, and in some cases culminated in civil war, followed after record high prices for major foodstuffs such as cereals in late 2010. Similarly, the escalation of violence in 2012 in Nigeria has also been partially linked to food prices consumers pay, as the removal of the fuel subsidy increased local food prices due to higher transport costs (The Economist, 2012).

Despite anecdotal evidence, the link between food prices and incidence of violence has remained largely speculative due to the paucity of empirical research on this subject. Only recently, a number of studies have started to address this gap in the literature and in general they find support for the hypothesis that higher food prices lead to violence (Hendrix *et al.*, 2009; Arezki and Brückner, 2011; Berazneva and Lee, 2013; Smith, 2014; Weinberg and Bakker, 2015; Bellemare, 2015).

This study expands the existing literature by focusing on the particular foodstuffs that can be linked to violence and examining the predictive power of food prices in terms of forecasting violence levels. The effect of shocks in food prices on violence is measured through a country-specific food price index (FPI) that weights international food prices by a country's import pattern of a basket of basic food commodities. As domestic food prices are potentially endogenous, international food prices are used as they are a source of exogenous shocks. In contrast to much of the existing literature, I account for the fact that the effect of different food commodities is likely not homogeneous and that the correlation between food prices and unrest is driven by import dependence on predominantly the low-value-added basic foodstuffs. Monthly data are used in order to capture within-year variation of both food prices and civil unrest. Civil unrest, in this case, is measured as the number of violent events that occur within a month, thereby capturing lower intensities of violence often not accounted for in the larger conflict literature that focuses on battle-related death thresholds. To examine this relation between food prices, import dependence, and violence, this study focuses on Africa. Africa is a particularly interesting region to study, as the large majority of African countries are net importers of food.[2] Additionally, the average African consumer spends a disproportionally large share of their income on food (Baquedano and Liefert, 2014; Dawe and Maltsoglou, 2014; Tadesse *et al.*, 2013),[3] which makes them vulnerable to the transmission of international food prices to domestic prices, leading to inflation.[4] If there is indeed a link between food prices and civil unrest, then we should be able to observe this in African countries, due to their import dependency and large share of consumers who live at the margin, making these countries very vulnerable to changes in international food price levels.[5]

2 See Fig. A1 in the Supplementary Appendix.

3 See Fig. A2 in the Supplementary Appendix.

4 Despite the relevance of the subject, there is actually little information on the impact of higher food prices on the poor (Ivanic and Martin, 2008).

5 The argument could be made that higher international food prices can actually bring benefits to countries largely dependent on agricultural productivity, as the gains to poor net producers can outweigh the adverse impacts on poor consumers. However, African countries largely depend on the export of cash crops and although food prices have sky-rocketed in the past decade, there was no similar increase in the prices of cash crops, leading to a net loss in welfare. In general, for low-income countries there has been deterioration in the trade balance, where imports increased faster than exports (Ng and Aksoy, 2008).

The regression analysis for 45 countries in Africa between 1990 and 2011 suggests that higher fluctuations of food prices from the long-term trend are associated with higher violence levels. Moving from low to high food prices corresponds to an increase in the log count of violent incidents of about 0.3. The correlation between the outbreak of violence and food prices is predominantly driven by low-value-added primary products such as wheat. Although for the in-sample data the results show that food prices seem to be a strong predictor, examining the predicted values show that larger food price shocks are not associated with higher violence risks. Testing the strength of the model on out-of-sample data for 2012 illustrates this deficiency: individual country forecasts are reasonably accurate compared to observed violence levels, but food prices seem to carry little weight in the assessment. The results from this study therefore seem to add some nuances to the current consensus in the literature, that higher food prices are strongly associated with civil unrest. The study also stresses that the strength of evidence cannot be captured by a single criterion such as the level of statistical significance.

2. Linking food prices and violence

Throughout modern history, there have been examples of food riots, such as during the Qing dynasty in China (Bin Wong, 1982) or the 1790s in North-West England (Booth, 1977). These food riots were often a reactionary form of collective action: impulsive, communally based, and often local in focus (Taylor, 1996). Although these riots have become less common over time, arguably replaced by other forms of collective action, there has been a recent surge in interest in the effect of food prices on violent collective action. This is partially driven by the events surrounding the 2007–08 world food price crisis, which were remarkably similar to historical examples of food riots. As Bush (2010) argues, these events were likely part of a larger fight against, amongst others, inequality and political oppression. As such, food price spikes provide a political trigger, often signalling other underlying factors of dissatisfaction, for the population to resort to violence. This argument has also been brought forward in relation to the beginning of the Arab Spring, which followed after record high prices for wheat (The Economist, 2012) in 2010. In that particular case, food prices are said to have been the tipping point, leading the population to express their grievances concerning government corruption and economic decline. In this study, I therefore do not exclusively focus on the link between food prices and riots, but account for other types of violence as well.

Besides the risk that riots could escalate into more serious forms of violence, we must also consider the circumstances under which people might actually engage in more costly forms of conflict over food price increases. Based on the wider literature on conflict, it can be argued that higher food prices potentially lead to violence as they (i) present a negative income shock, lowering the opportunity costs of violence (Collier and Hoeffler, 1998), and (ii) can put additional burdens on the government, based on its role in securing food security, reducing its capacity and deterrence (Fearon and Laitin, 2003). The population can feel entitled to the consumption of particular foodstuffs, specifically staple foods, and when these become unaffordable there could be a growing sense that their dignity is being violated, which signals a limit of the hardships that can be accepted under a particular regime. Additionally, food price increases form part of an erosion of the standard of living and are associated with an incapable government (Messer, 2009). Following the work by Fearon and Laitin (2003), if high food prices signal an incapable and weak state, it makes it viable for other agents to contest its power.[6] Of course, the government could take action to curtail the sense of deprivation among the population following high food prices, for example by providing subsidies or implementing other forms of social spending. In this case, the burden of high food prices is simply shifted from the market to the government (Headey and Fan, 2008). And for many cash-strapped African governments, this will produce a real challenge, as they lack the capacity or financial power to apply these measures. The violence in Nigeria following the removal of wasteful fuel subsidies in 2012 serves as an example.

This study is part of the broader literature on food security and conflict (Pinstrup-Andersen and Shimokawa, 2008; Blaydes and Kayser, 2011; Nunn and Qian, 2014; Maystadt *et al*., 2014) and can also be linked to the literature on conflict and commodity prices, which includes a number of studies also using international prices as a source of exogenous shocks (Besley and Persson, 2008; Brückner and Ciccone, 2010; Dube and Vargas, 2013; Bazzi and Blattman, 2014). Within this body of research, there is a small but steadily growing strand dedicated to examining the effect of food prices on unrest.

One of the earliest empirical studies by Hendrix *et al.* (2009) found for a sample of major cities in Asia and Africa that international food prices were a significant determinant of the incidence of protests and riots, an effect contingent on regime type. However, they focused exclusively on wheat prices, which could potentially fail to account for substitution effects between foodstuffs; this is addressed in the current study. A number of studies have followed since, such as work by Berazneva and Lee (2013) on food riots in Africa during the 2007–08 global food price crisis and a global study by Bellemare (2015) on the link between monthly international food prices. In contrast to Berazneva and Lee (2013), I focus on a longer time period to examine if the food–unrest nexus can be generalized. The main shortcoming of the work by Bellemare (2015) is that due to the use of aggregate data, much country-specific information is lost. I overcome this by constructing a price index that captures country-specific food consumption patterns.

The country-specific FPI used in this study is similar to the one in Arezki and Brückner (2011). The main difference with their paper is that this study exploits the relatively high frequency with which data on both food prices and violence are available, using country-month rather than country-year as the unit of analysis. This disaggregated approach moves beyond the crude analysis at the annual level and gives a better understanding of the within-year relation between food prices and violence. Similarly, Weinberg and Bakker (2015) also use the country-year as the unit of analysis. As a measure for food prices they use the consumer tax equivalent rather than for instance international food prices as they argue that international prices are (i) only useful for imports, as exporters will benefit, and (ii) since not all countries consume the same type of food. However, both of these factors are easily accounted for by using a country-specific FPI as is done in the current study, avoiding the use of crude proxies.

This study is probably most closely related to the recent work by Smith (2014), who investigated the effect of changes in domestic prices on urban unrest in Africa.[7] Since

6 Additionally, considering examples in Ethiopia and Zimbabwe, ill-willing governments can actually use access to food as a political weapon. Even if a state was able to intervene and alleviate the inflationary pressure on local populations, it could refuse to do so and thereby antagonize people, which could lead to revolt.

7 The domestic prices cover a broader basket of foodstuffs that reflects local consumption, but can also include alcohol and tobacco.

domestic prices are potentially endogenous, he instruments these using international prices (for wheat, rice, and maize) and estimates the effect on urban socio-political unrest at the extensive margin. Because he uses current imports and exports to calculate his trade-balanced instrument, it is likely endogenous as these trade flows may be determined by the incidence of unrest. In contrast, the FPI that is created is based on the trade balance before the period in which the outcome variable is measured. Additionally, a broader basket of foodstuffs is considered in order to estimate the relative importance of food import dependence, something that is generally not addressed in the literature. Moreover, the effect of food prices on conflict levels are estimated for better insight into the severity of the impact that food prices can have, retaining the full information of the conflict data, which is often lost when using binary measures. There is a growing conflict literature that uses conflict intensity as a measure (Hegre *et al.*, 2009; Costalli and Moro, 2012; Hendrix and Salehyan, 2012; O'Loughlin *et al.*, 2012; Raleigh and Kniveton, 2012; Maystadt *et al.*, 2014).

The biggest departure of this paper relative to the current literature is the analysis provided on the effect of food prices on violence, focusing on predicted outcomes and using a model for out-of-sample prediction. Given recent trends in food prices and the events of the 2007–08 global food price crisis, having a model with predictive power is particularly relevant, especially considering future population growth (Ezeh *et al.*, 2012) as well as the potential harmful effects of climate change on local African agriculture (Schlenker and Lobell, 2010; Seo *et al.*, 2009). This study therefore adds to the relatively small strand in the political instability and conflict literature that uses predictions and forecasts to scrutinize results (Goldstone *et al.*, 2010; Weidmann and Ward, 2010; Gleditsch and Ward, 2013; Blair *et al.*, 2014; Wischnath and Buhaug, 2014).

3. Estimation framework

The regression analysis is based on time-series cross-sectional data from 1990–2011 for all African countries with a population of at least 1 million.[8] The results from the model estimation are then used to predict the outcome in 2012. Monthly data are used for the outcome and the main explanatory variable in order to capture within-year variability. If there is indeed a strong correlation between food prices and violence, then it is likely that this relationship can be observed in a relatively short time. For the outcome variable, the count of the total number of violent events in a given country-month is used. In the sample data, the distribution of violence is slightly over-dispersed; of the 12,326 country-months, 20.7% are non-zero ($\mu = 0.37$, $\sigma = 0.97$).[9] To model the over-dispersion adequately, a negative binomial (NB) model is used (Hausman *et al.*, 1984; Cameron and Trivedi, 1986; Allison and Waterman, 2002; Lloyd-Smith, 2007).[10] In general, Poisson models are preferred when estimating a model where the outcome variable is a count, but since the conditional mean exceeds the conditional variance, such a model would fit the data poorly as it does not account for over-dispersion. The NB model is more flexible in this respect.

8 This restriction is due to the availability of data for the outcome variable.

9 The data cover 47 countries over 21 years, with the exception of Eritrea, which is covered from 1993. South Sudan is not included.

10 The variance of the NB model is given by $\sigma^2 = \mu(1 + \mu/\theta)$, where θ is the dispersion parameter (decreasing θ correspond to higher levels of dispersion). This model allows the variance to exceed the mean, in contrast to Poisson distribution.

To account for unexplained variation over time and across countries, country and year fixed effects are included in some of the model estimations (Angrist and Pischke, 2008) as well as country-specific time trends. I follow Allison and Waterman (2002) and use an unconditional NB regression with indicator variables to represent the fixed effects, which is similar to the models used by Hendrix and Salehyan (2012) and O'Loughlin *et al.* (2012).[11] The year fixed effects also control for any possible bias in the outcome variable, as the reporting of civil unrest in the earlier stages of the period covered might have been sparser compared with more recent years.

The NB dispersion parameter is estimated using maximum likelihood.[12] A generalized linear model is used where the outcome and explanatory variables are linked with a standard link function (i.e. log) to the linear predictor:

$$\eta : P(Y = y|X) = \mu = g(\eta) \tag{1}$$

This linear predictor is a function of the country-specific FPI and the explanatory variables:

$$\eta_{ct} = X'\beta + F_{ct}\gamma \tag{2}$$

where X' is a vector of explanatory variables and the intercept while F_{ct} is the country-specific FPI.[13] β is a vector of coefficients associated with the matrix of explanatory variables and γ is the parameter of interest measuring the effect of the FPI on the incidence of violence. Due to the use of time-series cross-sectional data, the model might exhibit heteroscedasticity; therefore, to assess the statistical significance of the results, robust standard errors are used clustered at the country level.

To account for possible serial autocorrelation in the data, as current violence might depend on past violent levels (Beck and Katz, 2011), I follow the recent literature and construct an outcome variable that measures the outbreak of violence (see Brückner and Ciccone, 2010; Bazzi and Blattman, 2014).[14] Outcome variable Y_{ct} is the count of the number of violent incidents in a country-month. If $Y_{c,t-1}$ is not equal to zero, the outcome variable is not defined.

4. Data and measurement

4.1 Food price index

Time-series data on food prices are taken from the Global Economic Monitor (GEM) Commodities, which is a collection of monthly commodity prices of the major traded commodities from 1960 to present (World Bank, 2013a).[15] International rather than domestic

11 See also Blundell *et al.* (1995) on issues with estimating an NB model with fixed effects.

12 The dispersion parameter θ is estimated in R using the MASS package.

13 Data and measurement are discussed in Section 4.

14 Angrist and Pischke (2008) note that estimates from a model with both fixed effects and lagged outcome variable will be biased. Beck and Katz (2011) show that if T is sufficiently large, there are no serious issues concerning the bias in OLS. It is not known, however, whether these results also apply to NB models.

15 Since the data are given in nominal US dollars, the Manufactures Unit Value Index (MUV) (World Bank, 2013b) is used to deflate and calculate real prices. Values are available from 1960 to 2009; all later years are projections. The MUV is also used by the FAO to calculate their monthly FPI.

food prices are used as they are a source of exogenous variation. The literature on price transmission shows that domestic food prices are responsive to international food prices (Demeke *et al.*, 2009; Minot, 2011; Verpoorten *et al.*, 2013; Ianchovichina *et al.*, 2014) and can respond instantaneously (Kalkuhl, 2014). Using domestic prices could introduce endogeneity into the model, as civil unrest could also impact the level of local food prices.[16] Like most economic time series, food prices exhibit a trend over time that needs to be taken into account in order to estimate the effect as a result of real level differences (Gilbert and Morgan, 2010). To detrend the food prices, a penalized spline method is applied to estimate the trend in the data. This method uses a generalized additive model that accounts for the autocorrelation of the data and the error structure, in contrast to other more commonly used detrending methods (Claeskens *et al.*, 2009; Rosales and Krivobokova, 2012).[17] For robustness checks, I also report results of the estimation using price data that are not detrended.

The effect of food prices on civil unrest will probably largely depend on the type of foodstuffs that are consumed in a country.[18] To account for these cross-country differences, a country-specific FPI is constructed based on the country's net import pattern, where net imports are the difference between the imports and exports of a specific commodity. This country-specific index is calculated as:

$$F_{ct} = \sum_{i=1}^{N=9} P_{it}\lambda_{ci} \tag{3}$$

where P_{it} is the price series of commodity i in month t and λ_{ci} is country c's net import share of commodity i relative to its GDP in 1989.[19] Net imports are used to model the wealth effect of trade, net imports of food measure the vulnerability through the trade balance, whereas the share of GDP measures the potential impact of prices through income (Headey and Fan, 2008). A fixed weight is used rather than periodic shares, as short-term changes in the import pattern could reflect socio-political conditions leading to endogeneity (Arezki and Brückner, 2011). The food commodities included in the index are the main staples, such as the major cereals, as well as sugar and oils. These commodities are the dominant traded agricultural crops (Nelson *et al.*, 2010) and make up the bulk of total food imports.[20] Most other price indices contain food items that are of little relevance to the poor (Kalkuhl, 2014), such as meat. Other studies (see, e.g., Hendrix *et al.*, 2009) use individual

16 Gil-Alana and Singh (2015) found no strong evidence for the effect of violence on local food prices in a study on Kenya. It is unclear, however, if this result generalizes to the whole of Africa.

17 For commodity *i*, the long-term trend between 1960 and 2011 is estimated and subtracted from the data. The resulting price series is shifted upwards with a constant to avoid negative values, which would distort the country-specific price index when multiplied by negative values due to the use of net imports.

18 To estimate the impact of higher food prices, we must consider that the effect will depend on (i) the commodities involved, (ii) the pattern of income and expenditure, and (iii) government policy response. Points (i) and (ii) are modelled by the FPI; however, (iii) is not accounted for due to a paucity of data. There are also seemingly no close proxies available for this factor.

19 For Eritrea, this is the year of independence (1993).

20 Food imports make up 10–25% of total merchandise imports. Cereals make up the majority of food imports (48.7%) followed by oils and fats (15.8%), and sugars (10.4%). Included food commodities are barley, maize, palm oil, rice, sorghum, soybeans, soybean oil, sugar, and wheat.

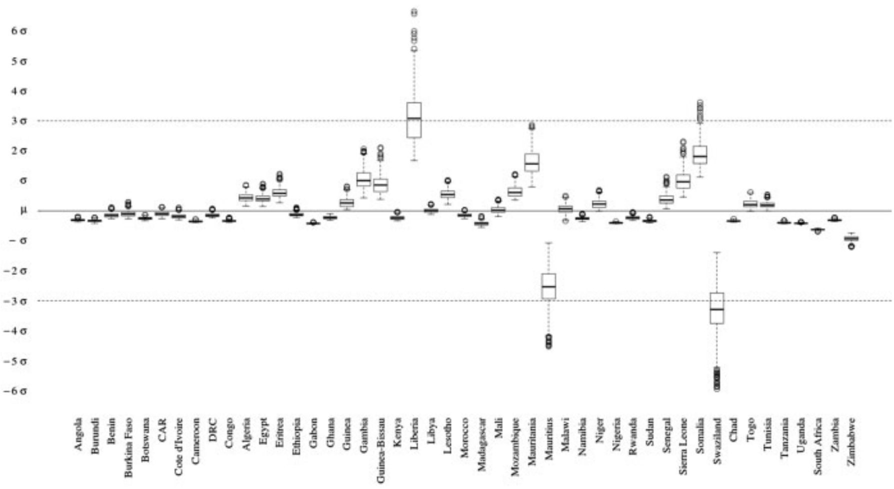

Fig. 1. Distribution of values of the country-specific food price index for each country in the sample.
Sources: FAOSTAT, GEM Commodities, and World Bank.

crop prices rather than a price index. However, this could potentially lead to incorrect results as it neglects possible substitution effects, for example between cereals. Data on food trade are taken from FAO Statistical Division (2013).

Figure 1 provides a visual summary of the FPI per country and illustrates the large variation in index values across countries.[21] To account for this between-country variation and to capture the monthly variation, I follow the climate–conflict literature and use anomalies as a measure for shocks to food prices.[22] Anomalies are measured as the monthly standardized FPI deviation from the mean for a given country:

$$\frac{FPI_{ct} - \bar{FPI}_c}{\sigma_c} \tag{4}$$

where FPI_{ct} is the current FPI level, FPI_c is the mean for country c, and σ_c is the standard deviation of the FPI for country c.[23]

4.2 Violent events

Data on civil unrest in Africa from 1990 to 2012 are taken from the Social Conflict Analysis Database (SCAD) (Hendrix and Salehyan, 2013). SCAD covers a wide range of civil unrest and includes low-intensity conflict events such as protests, riots, and intercommunal violence. The data come from media sources and are human coded with information coming from the news wires from Agence France Press and Associated Press, containing detailed information about the actors and location of the events for a total of around 10,000 events.[24] The focus of this study is on violent events such as riots, inter-

21 Descriptive statistics per country are provided in Table A1 in the Supplementary Appendix.

22 See, e.g., Hendrix and Salehyan (2012).

23 Figure A3 in the Supplementary Appendix shows this measure per country over time.

24 As mentioned in the previous section, year indicators are included in some specifications to control for possible reporting bias over the years. Bias resulting from over- or under-reporting of particular events is discussed in the relevant results section. See Weidmann (2015, 2016) for a discussion on the accuracy of media-reported conflict event data.

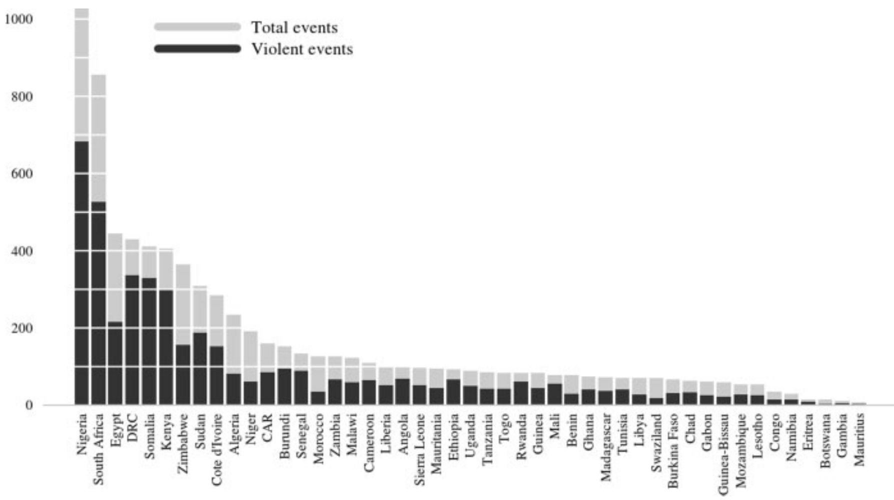

Fig. 2. Number of total and violent social conflict events for African countries, 1990–2011.
Source: SCAD 3.0.

communal violence, and civil conflict.[25] Figure 2 illustrates per country the number of violent events relative to the total number of events for 1990–2011.

4.3 Other explanatory variables

To account for other factors that are commonly associated with instability and conflict, a number of other explanatory variables are included in the model. Violent civil unrest could spread between countries due to spillover or demonstration effects. Therefore, I follow Braithwaite *et al.* (2015) and include a variable that measures the percentage of countries in the sample that experienced violent unrest in the previous month. Civil unrest can also be linked to broader issues of political neglect, poverty, and low living standards; therefore, measures for regime type and income shocks are included. Regime type is measured using the categorical measure of Goldstone *et al.* (2010), classifying regimes based on the openness of executive recruitment and the competitiveness of political participation using data from the Polity IV Project (Marshall *et al.*, 2013).[26] GDP per capita growth, taken from the World Development Indicators (World Bank, 2012), is included to control for income shocks.[27] Since larger populations are more difficult to control (Fearon and Laitin, 2003) and increase food demand, the natural log of total population is included.[28] Note that the explanatory variables for regime type, income shocks, and population are only available annually. To

25 This entails all observations coded as 3,4,7,8,9,10 for either *Etype* or *Escalation*. It also includes some events from the Uppsala Conflict Data Program dataset on conflict, which are included in the SCAD dataset and coded as −9.

26 Note that in addition to the 5-point scale of Marshall *et al.* (2013), I recode regimes in transition to 0.

27 Measured in purchasing power parity exchange rates in order to compare across countries.

28 The natural log is used due to scale differences between countries: the smallest country in the dataset has a population around 1 million (Swaziland) whereas the largest country's (Nigeria) population numbers 160 million (the average population is 8.7 million).

Table 1. Descriptive statistics

Variable	Mean	SD	Median	Minimum	Maximum	N
Outbreak violent unrest	0.16	0.50	0	0	8	11,097
Violent unrest	0.37	0.97	0	0	15	12,326
Violent unrest$_{(t-1)}$	0.36	0.97	0	0	15	12,326
Violent unrest$_{(C-i)}$	0.20	0.07	0.21	0.02	0.40	12,326
Food price index	−0.06	0.98	−0.20	−2.64	4.07	12,326
Δ GDP per capita$_{(y-1)}$	0.01	0.07	0.02	−0.50	0.93	11,645
Regime type$_{(y-1)}$	2.17	1.14	2	0	5	12,326
Population$_{(y-1)}$ (log)	15.99	1.20	16.08	13.63	18.89	12,326

account for potential endogeneity issues, through reverse causality, all these variables are lagged by 1 year. Descriptive statistics for the main variables are given in Table 1.

4.4 Exploratory data analysis

I start the analysis by looking at trends in the data that possibly provide descriptive evidence for a link between food prices and civil unrest. Figure 3 shows the total number of violent events for each month along the monthly time series for the country-specific food prices and the more generic FAO FPI. The figure illustrates that the trends in violence and food prices are, in general, not very strongly related to each other. Although, there are some trends observable across certain sub-periods. Between 1990 and 1998 there seems to be a pro-cyclical movement between the price indices and violence, a trend that also seems to manifest itself in 2011. In both of these cases, higher food prices correspond to higher counts of violence. An example is the large spike in food prices around 2010–11, which seems to coincide with the large increase of violence around that time.[29]

Interestingly, a similar spike in prices during 2007–08, as a result of the world food price crisis, does not materialize in a noticeable increase in violence levels. As opposed to the years 2007–2008, between 1999 and 2005 the time series seem to exhibit a counter-cyclical movement. A period when food prices increase, but the number of violent events across Africa stabilizes at around 20 incidents per month. Although information is lost due to the level of aggregation, this exercise does provide some interesting initial insights. Based on these data, there does not seem to be a clear pattern between fluctuations in food prices and violence levels in Africa.For deeper understanding, I consider the timing of the effect. For each country-month, I examine the violence levels in the 10 months preceding and following a shock to the FPI at time t ($N = 11{,}912$). The results for which are shown in Fig. 4, which plots the average for all country-months (dotted line) as well as the top 10% of shocks to the FPI (solid line). Focusing on the average, we can see that over time there is a slight increase in the levels of violence, seemingly regardless of the time of the food price shock. In comparison, for the top 10% there seems to be a much stronger and sudden increase in violence in the months from $t = 0$ onwards.[30] This provides some preliminary evidence for a link between food prices and violence.

29 This period corresponds to the start of the Arab Spring, which occurred across a number of North African countries.

30 On average, violence levels are already higher in these countries. Nonetheless, the sharp increase from $t = 0$ onwards is remarkable.

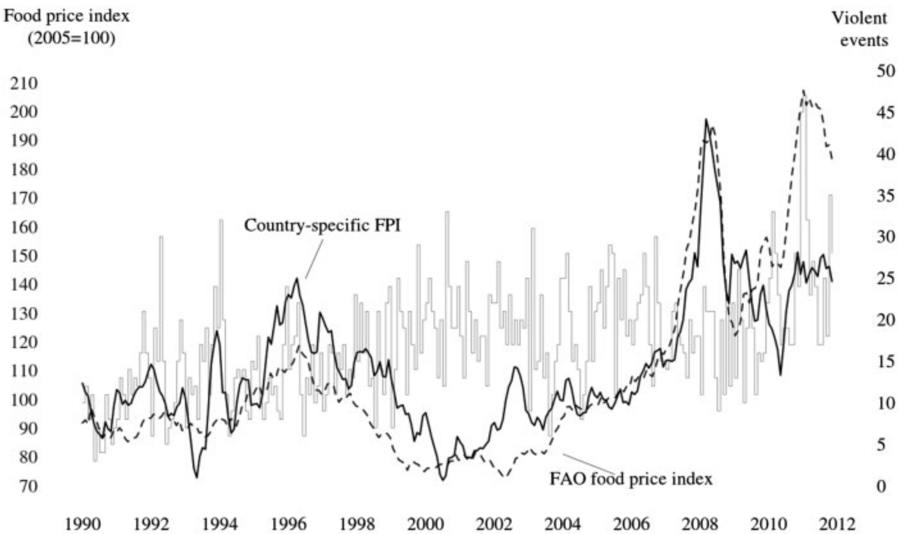

Fig. 3. Food prices over time plotted against the violence incidence level in each month between 1990 and 2011.
Sources: FAO Food Price Index, GEM Commodities, and SCAD 3.0.

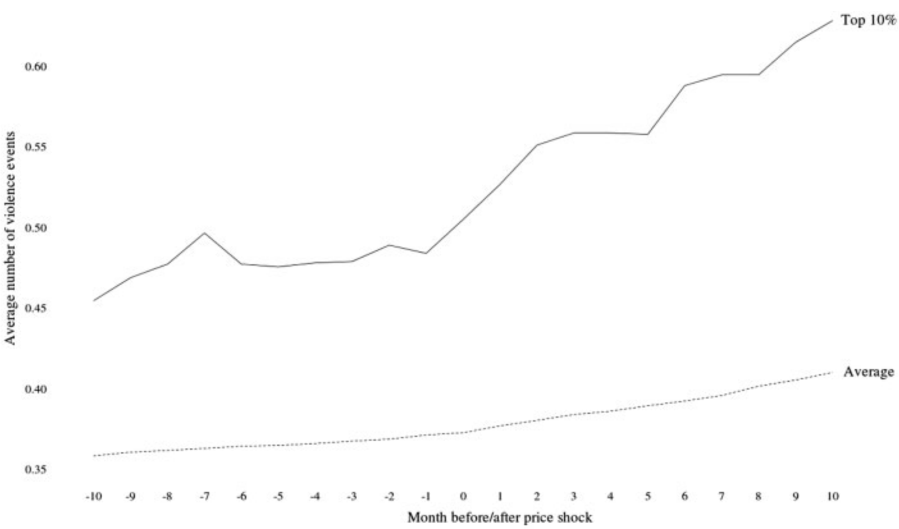

Fig. 4. Average violence levels before/after food price index.
Sources: FAO Food Price Index, GEM Commodities, and SCAD 3.0.

4.5 Main regression results

Table 2 presents the main regression results using an NB regression to estimate the effect of shocks in food prices on violent unrest. The variable FPI here indicates standardized shocks to the country-specific FPI as discussed in the section 4.1 and the outcome variable is the number of violent events in a country-month contingent on the absence of violence in the previous month. Note that for all the regression results, all input variables are placed on a

Table 2. Results of negative binomial regression: effect of food prices on violence, 1990–2011 ($N = 10{,}585$)

	(1)	(2)	(3)	(4)
Specifications	Simple model	Including FE	Other explanatory variables	Full model
FPI	0.14	0.2	0.11	0.29
	(0.06)**	(0.1)**	(0.06)*	(0.08)***
Violence$_{(C-i)}$			0.08	−0.18
			(0.08)	(0.07)**
ΔGDP pc$_{(y-1)}$			−0.1	0.03
			(0.1)	(0.05)
Regime type$_{(y-1)}$			−0.2	−0.26
			(0.1)	(0.10)**
Population$_{(y-1)}$			1.1	−4
			(0.2)***	(2)
AIC	9298.185	8680.135	8964.42	8702.227
AUC	0.5120	0.7194	0.6454	0.7057
Country FE	–	Yes	–	Yes
Year FE	–	Yes	–	Yes
Country-specific time trend		Yes	–	–

Notes: Robust standard errors, clustered at country level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. FPI, country-specific food price index; AIC, Akaike information criterion; AUC, area under the curve; FE, fixed effects.

common scale, centred around the mean and divided by two standard deviations, in order to facilitate easier comparison (Gelman, 2008). As such, they can be interpreted as the effect of moving from low to high values.

I start with a simple model (column 1) regressing the level of violence on the FPI and find that positive fluctuations correspond to higher violence levels ($e^{0.14} = 1.15$ relative risk ratio).[31] However, the model has a relatively poor fit. Using the area under the curve (AUC) of the receiver operating characteristic curve shows that at 0.512, the model is barely better than random in matching cases of violence with higher fitted values.[32]

I proceed by including various indicators to account for some of the unexplained variation (column 2). The country fixed effects account for time-invariant country characteristics such as colonial heritage, while the country-specific time trends capture country-specific year shocks such as local droughts. The year indicators account for common time shocks as well as potential reporting bias over the years in the outcome variable. As a result of including these measures to capture unobserved influences, the estimated effect of food prices on violence increases by about 43% while the AUC statistic increases by 41%

31 The log relative risk is assumed to be normally distributed.

32 As an alternative measure of significance, the AUC is used, which measures the overall prediction accuracy of the model based on the effect of each variable (Fawcett, 2006). The AUC statistic is measured on a 0–1 scale with the threshold based on the true and false positives ratio. Values closer to one indicate a better prediction rate. Normally, the AUC is used for logit models, so non-zero values are truncated to one in order to calculate the AUC statistic and determine the predictive power of the model.

compared with the baseline model in column 1.[33] One drawback of solely including indicators to account for unobserved factors that influence the outcome variable is that it eliminates other possible explanations for violence (O'Loughlin *et al.*, 2014). Estimating the baseline model with a set of explanatory variables upholds the result that food prices are linked to violence.[34] However, the fit of this model is relatively poor, as illustrated by both the Akaike information criterion (AIC) and the AUC statistic, in comparison with the fixed-effects model. Therefore, the preferred model (column 4) is specified with the full set of explanatory variables along with the country and year indicators. The estimation shows that higher food prices increase the risk of violence after controlling for economic, social, and political factors.[35] Moving from low to high values on the country-specific FPI corresponds to a 0.29 increase in the log of expected counts (the standard deviation of the log of the outcome variable is 0.27).

Additionally, we see that the measure to capture spillovers and demonstration effects is statistically significant and has a negative relation with the outbreak of violence. Thus, as violence levels increase across Africa in the preceding month, a country will likely see decreases in its own violence levels. Although this seems slightly counter-intuitive, it does correspond to the results by Danneman and Ritter (2014), who found that states use preemptive repression in response to the possible spread of conflict. The variable to account for different regime types is also statistically significant and has the hypothesized sign, linking more democratic states to lower risk of violence outbreaks.[36] Despite differences in the goodness of fit, based on the AIC and AUC statistics, the NB model seems to be sufficient as the dispersion parameter θ is larger than one (1.5 based on model 4 in Table 2), indicating that the data are not highly over-dispersed (Lloyd-Smith, 2007).[37] I also consider other estimation methods to model the data-generating process: Poisson, quasi-Poisson, and a log-linear model estimated using OLS, as well as logit, rare event logit, and a linear probability model, using a binary outcome variable to account for possible reporting bias. In all cases, the results indicate a positive relation between shocks in food prices and violent unrest.[38] The results also hold when subjected to a number of robustness checks accounting for different measurements of the outcome variable, additional control variables, and sample selection as well as different specifications of the FPI (these results are discussed in the Supplementary Appendix). In general, the results suggest that the link between food prices and violence is driven by imports of the major traded food commodities such as wheat.

The main model specification assumes that the effect of shocks in food prices on violence is instantaneous, similar to the research design by Bellemare (2015). However, as illustrated in Fig. 4, there may be a lagged effect or, possibly, violence might occur because higher food prices are anticipated. To test this, I estimate a model with country and year

33 See also Table C1 in the Supplementary Appendix for permutations of the included indicators.

34 All annual explanatory variables are lagged by 1 year to prevent endogeneity issues due to reverse causality.

35 $e^{0.26} = 1.33$ relative risk ratio.

36 Hendrix *et al.* (2009) found that the food–unrest nexus was largely contingent on regime type. Political heterogeneity is discussed in more detail in the Supplementary Appendix.

37 The distribution of the outcome variable is slightly more over-dispersed than the general distribution of violence across country-months as 12% of the observations are non-zero ($\mu = 0.15$, $\sigma = 0.48$).

38 Results are available in the Supplementary Appendix.

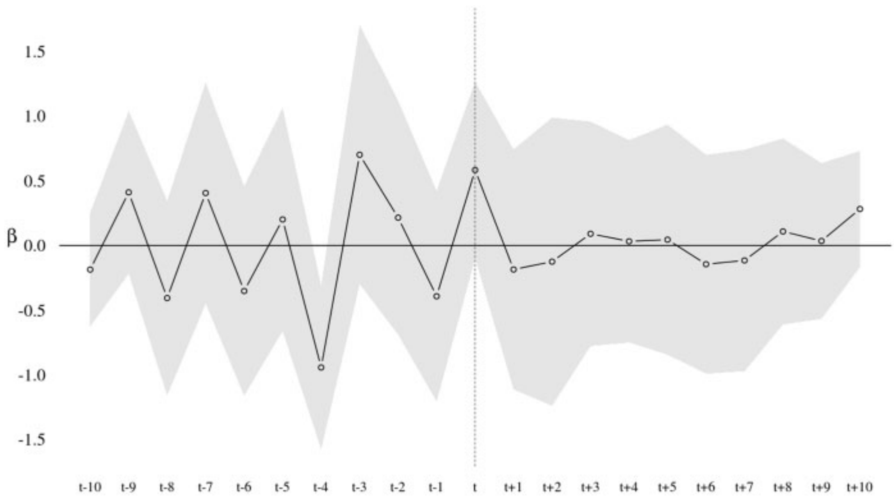

Fig. 5. Timing of the effect of food prices on violence. The figure shows the estimated effect of the lags and leads of the food price index on the outbreak of violence in month *t*. Shaded area indicates the 95% interval.

indicators along with the standardized FPI and 10 lags and leads of this index. Figure 5 shows the results, plotting the coefficient for each variable along with its 95% interval. As the figure shows, it is unlikely that violence is a response to anticipated food price increases as future shocks to the FPI seem to have no effect on current violence levels. For the current and lagged effects, we see that although current shocks to food prices are positively associated with the outbreak of violence, in the subsequent month the correlation is negative. Most of these shocks are not statistically significant within the traditional boundaries, except for t (10%) and $t - 4$ (1%). It could be that rather than food price shocks, the growth rate between months could help explain the outbreak of violence.[39] Testing this, I do find that current and lagged growth rates are positively associated with the outbreak of violence, where moving from low to high values increases the log country by 0.42 in the current month and another 0.42 in the next month. Using a 5-month growth rate, the estimated effect is close to zero.[40]

4.6 Predicting violent events

So far, the estimation results and its various robustness checks have shown that in general there seems to be a positive effect of food price shocks on violent civil unrest. These results mirror those in the recent literature. However, following Ward *et al.* (2010), we should be cautious about relying too much on *p*-values for determining the strength of a particular model, as the strength of the evidence cannot be captured by a single criterion such as the level of statistical significance. Therefore, in this section I will focus on the predictive power of the model, looking at how the variable on food prices contributes to accuracy in the

39 The effects of food prices are likely not transitory. See Ciccone (2011, 2013) for a discussion.

40 See Supplementary Appendix B for the results and a discussion.

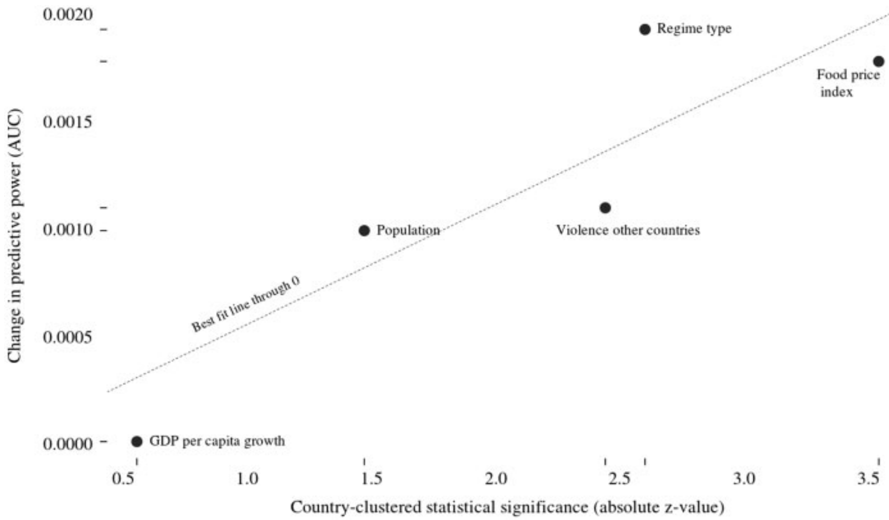

Fig. 6. Comparison of statistical significance (absolute *z*-value) versus predictive power of the variable (ΔAUC), based on the model in Table 2 (column 4).

generated forecasts. To assess the in-sample predictive power of the model, I will focus on the change in the AUC statistic as a result of different model specifications omitting one variable at a time and re-estimating the model. The results of this exercise are shown in Fig. 6, which plots the variables' level of statistical significance against the changes in the AUC curve when omitting them from the model. Following the best-fit regression line through 0, the predictive power of most variables is where we would expect it to be, based on the level of statistical significance. At face value, regime type seems to be the best predictor of violence levels in this sample. The variable for the FPI performs reasonably well, but as the values on the *y*-axis show, omitting it from the model results in a loss in predictive power that is not very large. The AUC of the main model is 0.7057 compared with 0.7039 when excluding the FPI.

To get a better understanding of the effect that food prices have on the probability of violence in each individual country, the fitted values for each country are aggregated and plotted against the observed levels of violence as is shown in Fig. 7(a). Looking at this aggregate, the model seems to provide a good fit as the predicted values correspond very closely to the observed levels of violence. Using dispersed count data, there is always the worry that possible excess zeroes are not accounted for (Bagozzi, 2015), but there seems to be very little reason for concern here. One issue that does occur is that due to the coding of the outcome variable, to capture the outbreak, the fitted values do not really follow an NB distribution, which can be deduced from the overview given in Fig. 7(b). This figure plots, for each country, the distribution of fitted values and shows that the model is very conservative in fitting high levels of violent events. This means that the model does not really account for intensity differences in violence for specific country-months, but it does seem to capture differences in violence levels across countries, comparing this figure with Fig. 2. There is an additional interesting observation to make relating to the relation between food prices and violence. Take the case of South Africa and Senegal, for example. South Africa has relatively high fitted values, which is not surprising since it registered 526

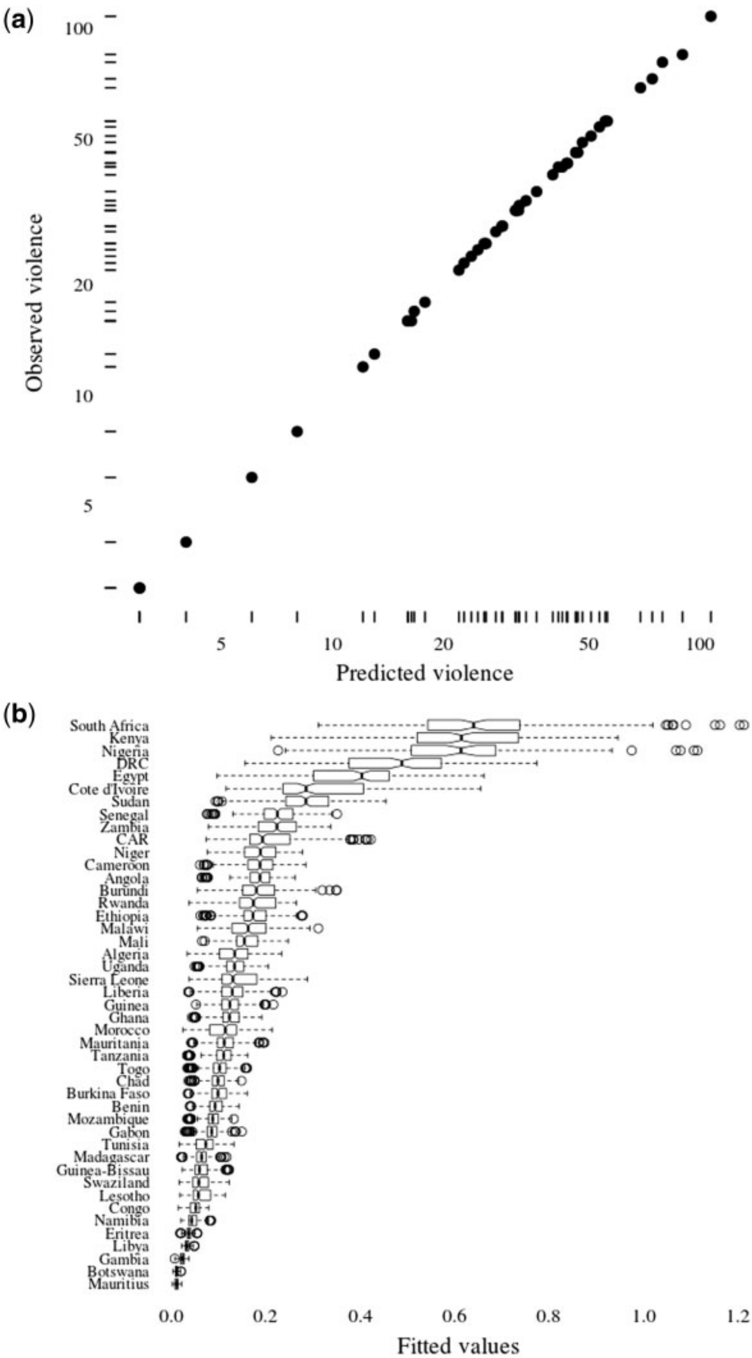

Fig. 7. Summary of fitted values per country. Panel (a) plots aggregated predicted levels of violence for each country against the aggregate observed levels of violence. Panel (b) plots the distribution of fitted values for each individual country.

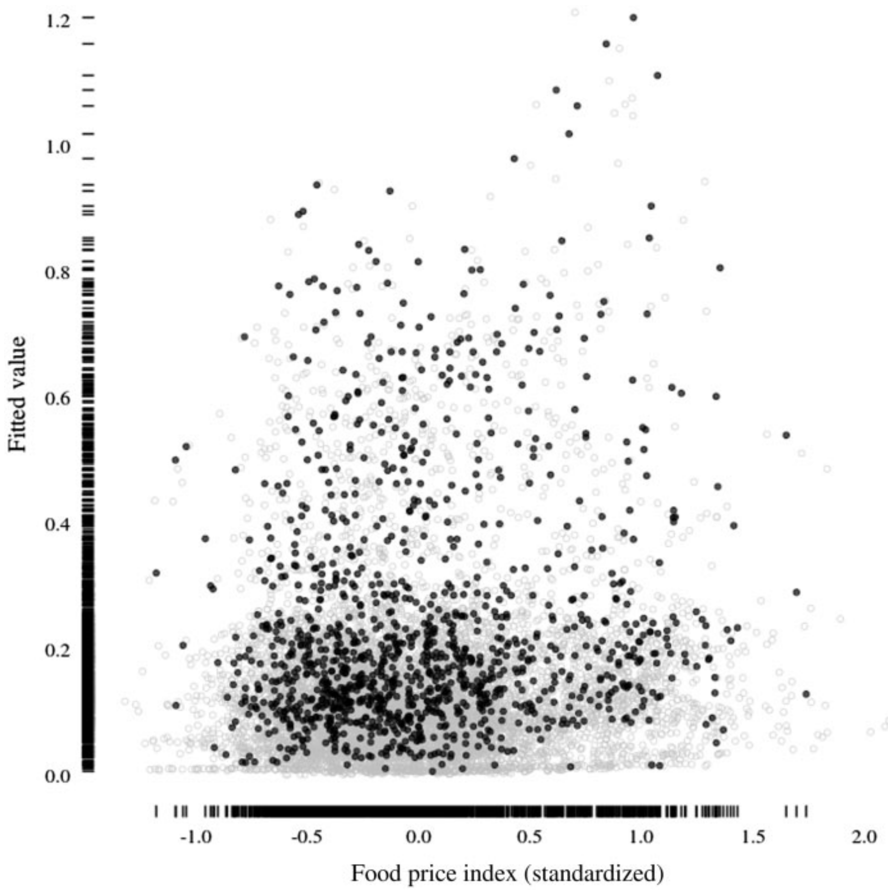

Fig. 8. Fitted values plotted against standardized values of anomalies in the food price index. The darker dots mark observations of violence, also indicated by tick marks on the axis.

violent events between 1990 and 2011.[41] In Senegal, the risk of violence is predicted to be low.[42] This seems to imply that the effect of food prices is larger in countries like South Africa, which has a negative FPI, compared with a country like Senegal, which is arguably more exposed to higher food prices due to its large food imports.[43]

There is an important caveat, however, concerning this observation, as illustrated by Fig. 8. This figure plots the fitted values against the standardized FPI, as used in the estimation of the main model. The darker shaded dots indicate observations with actual violence; these are also indicated by the tick marks on the axis. There does not seem to be a very strong correlation between larger shocks in the FPI and higher fitted values or high levels of observed violence. As the figure illustrates, most observations with violence have FPI values

41 Two hundred and fifty-two after the end of the Apartheid regime in 1994.

42 Senegal registered 89 violent events between 1990 and 2011.

43 Shocks to food prices in South Africa are larger on average to those in Senegal: 0.10 compared with −0.08.

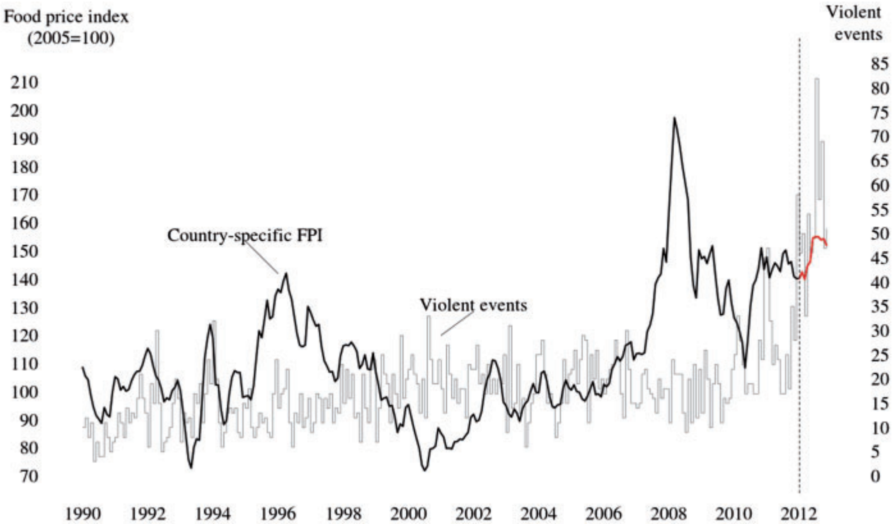

Fig. 9. Food prices over time plotted against the violence incidence level in each month between 1990 and 2012.
Sources: FAO Food Price Index, GEM Commodities, and SCAD 3.0.

between 0 and −0.5 and fitted values between 0 and 0.3, indicating low risk. There are a few exceptions to this.

Cross-validation is used as an additional check, letting the model generate forecasts for out-of-sample data from 2012. Figure 9 extends Fig. 3 to include data on the FPI and violence for 2012. It can be seen that there is some pro-cyclical movement in the time series. This corresponds to the earlier results that showed the estimated effect of food prices on violence has increased since 2007. Given the results in the literature so far and concerns about future food price levels, it would be interesting to see if food prices can be used to accurately forecast whether some countries are more at risk of violence compared with others. Although I mentioned earlier that the majority of studies ignore predictions, one possible exception to this is the paper by Lagi *et al.* (2011), who argued that, based on extrapolation of the trend in food prices between January 2004 and May 2011, by mid-2012 there would likely be a point of instability.

I therefore use the main model to generate predicted values for 2012, the results for which are shown in Fig. 10. The figure shows the predicted values against the FPI where the darker dots indicate either the incidence (a) or outbreak of violence (b).[44] Figure 10(a) shows that both the observed levels of violence and the predicted values are skewed towards higher values of the FPI, between 0 and 0.5. This lends some support for the hypothesis that higher food prices lead to violence. However, we should add the nuance that the model does not accurately capture the outbreak of violence, as shown in Fig. 10(b). On average, the predicted number of events is 0.3 for cases where there was an outbreak of violence compared with 0.5 for violence incidence.

44 The outcome variable in the main model captures the outbreak of violence, as it accounts for violence levels in $t-1$.

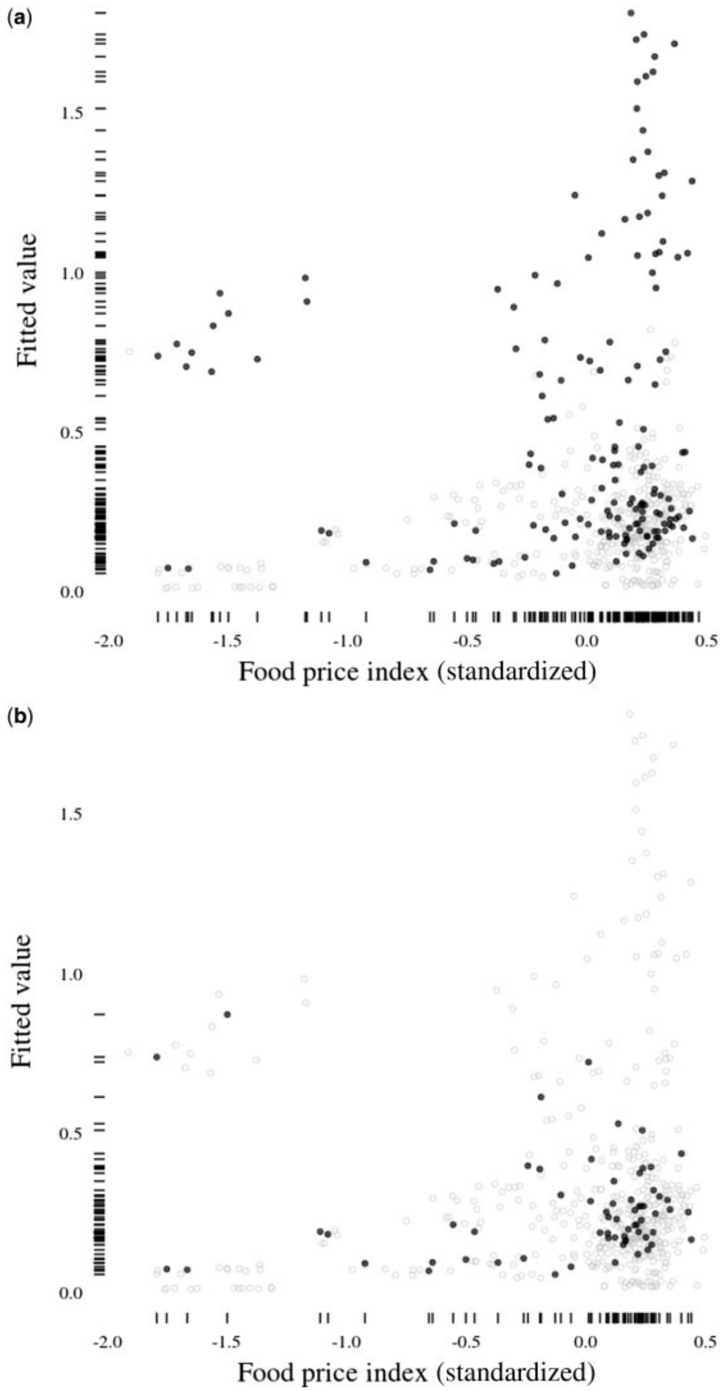

Fig. 10. Fitted values plotted against standardized values of anomalies in food price index for the 2012 out-of-sample data. The darker dots mark observations of violence in panel (a) and outbreak of violence in panel (b), also indicated by tick marks on the axis.

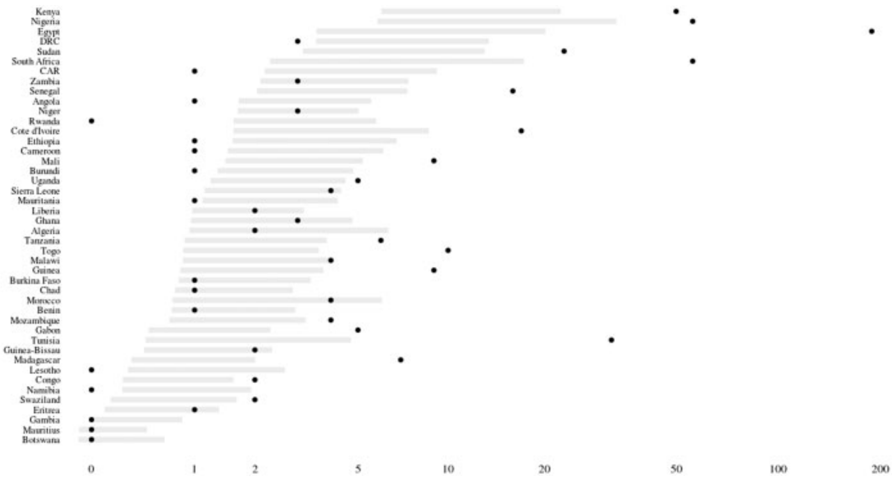

Fig. 11. The 95% prediction intervals for aggregated forecast of violence levels for 2012 out-of-sample data along with the observed total level of violence.

The relatively poor performance of the model is also illustrated by Fig. 11, which summarizes the forecast number of events per country along with the observed number of events. For each individual country, a 95% interval is calculated for each observation, which are then aggregated to give the lower and upper bounds on the expected number of violent events in 2012. As already discussed in previous sections, the model under-estimates the intensity of individual events. Using alternative estimation methods, such as Poisson or logit models with truncated outcome variable, gives similar results to those shown here. These results are also robust to using nominal, rather than detrended prices, which might better capture the trend. Using different model specifications, such as removing the year indicators, or estimating a simple model as shown in column 1 of Table B4 (in the Supplementary Appendix) does not improve the accuracy. More worrying is that the results are also similar when excluding the FPI variable from the model. This low loss in predictive power was also something established for the in-sample data in Fig. 6. These results illustrate that, at least for 2012, food prices are of limited use in trying to predict civil unrest.

5. Conclusion

Despite the social relevance of the subject, there is still relatively little known about the impact of higher food prices on the poor in general and on civil unrest in particular. Anecdotal evidence on food riots provides some support for the claim that higher food prices are linked to civil unrest, as higher food prices create a greater sense of relative deprivation, leading to grievances among the population that could culminate in violence. Recently, there has been a surge in quantitative research on the subject with, for conflict studies, a remarkable convergence in results linking higher food prices to civil unrest ranging from riots to civil conflicts. The current literature is fairly agnostic, however, about trends in food prices as well as food consumption patterns. To address this gap, I therefore estimate the effect of food prices on civil unrest, detrending international food prices and constructing a country-specific FPI based on a country's food import pattern. This approach better models the effect of differences in international food prices on the occurrence of civil unrest. The regression analysis shows that higher food prices correspond to higher violence levels, reflecting results in the literature. This effect is robust to different model specifications as well as estimation methods, and the results also show that the relation between food prices and unrest seems to be mainly driven by the price of the basic staples, i.e. the cereals and specifically wheat. However, the magnitude of the estimated effect is fairly minor, with a two standard deviation increase in the FPI corresponding to an additional event in a country-month.

To get a better understanding of the link between food prices and unrest, I move beyond the orthodox approach of using *p*-values to determine the strength of a model and focus on the predictive power of the model. For the in-sample data, I find that the model explains the aggregate risk of unrest in each country reasonably well. However, the predictive power of the FPI variable is not as strong as the level of statistical significance would suggest, based on examining the fitted values and their corresponding observed shocks in food prices. Focusing on out-of-sample forecasts and predictions, using data for 2012, I find that the inclusion of the FPI variable does very little to improve the predictive performance of the model. These results cast some doubts on the claim of a strong link between food prices and civil unrest.

Supplementary material

Supplementary material (the Appendix) is available online at the OUP website.

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