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## VIOLENCE AND THE MARKET FOR FOOD. EVIDENCE FROM KENYA

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## ABSTRACT

We study the impact of post-election violence in Kenya on the food market in Mombasa and find empirical evidence against predictions of high volatility of prices following violence. Using a data set of a flour producing firm, we identify the degree of persistence in prices and quantities by means of techniques based on the concept of long memory or long range dependence. Prices are found to be highly persistent in both wheat and maize flour, with orders of integration which are around 1 or even above 1, implying permanent effects of the shocks. On the contrary, quantities, though also persistent, appear to be fractionally integrated, with orders of integration in the interval (0, 0.5) pointing towards stationarity, long memory and mean reverting behavior. Violence is associated with an insignificant increase in prices of both products and a significant decrease in quantities.

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## 1. Introduction

Violent conflict has been associated with higher malnutrition in Zimbabwe, Iraq, Liberia and Somalia (FAO, 1996; Alderman et al., 2006). This increase in malnutrition may have been a result of higher food prices. Although this is of great concern for policy makers, there is almost no evidence on how food prices change during conflict despite a growing research program that explores the microeconomic effects of violence (Blattman and Miguel, 2010). Also, applied econometrics has been employed to find persistence and memory in economic processes (Barros, Gil-Alana and Payne, 2011). However, there appears to be no line of research combining these two strands in the context of effects on food prices during violence.

In 2008, following the post-election violence in Kenya, Okello (2009) raised alarm bells by predicting that traders will raise prices by hoarding stocks, which may have a positive effect on agriculture in the medium-term but will increase poverty in the short-term. It also expressed disbelief that prices would stabilize quickly. In this paper, we study the impact of post-election violence in Kenya on the food market in Mombasa and find empirical evidence that dispels such disquieting predictions. Using a data set of a flour producing firm, we identify the degree of persistence in prices and quantities by means of techniques based on the concept of long memory or long range dependence. Prices are found to be highly persistent in both wheat and maize flour, with orders of integration which are around 1 or even above 1, implying permanent effects of the shocks. On the contrary, quantities, though also persistent, appear to be fractionally integrated, with orders of integration in the interval (0, 0.5) pointing towards stationarity, long memory and mean reverting behavior. Violence is associated with an insignificant increase in prices of both products and a significant decrease in quantities.

These results are robust to including different periods, seasonality and specifications for the error term.

This paper is linked to two distinct strands of research. First, from a macro viewpoint, it is in the same spirit as many other papers that examine the degree of persistence of economic series in order to determine the nature of shocks. Nelson and Plosser (1982) were the pioneers in introducing unit roots or I(1) models in macroeconomics. They analyzed fourteen US macroeconomic series, and, using tests of Fuller (1976) and Dickey and Fuller (1979), found evidence of unit roots in all except one of the series. In the context of unit roots, any shock to the economic system has a permanent effect, so a policy action will be required to bring the variable back to its original long term projection. On the other hand, in stationary I(0) models, fluctuations are transitory and therefore there exists less need for policy action since the series will in any case return to its trend sometime in the future. Since the seminal paper of Nelson and Plosser (1982), many articles have been written examining this issue empirically for many series and using other more elaborated unit roots testing methods. However, I(0) and I(1) models are merely two particular cases of a more general specification where the order of integration may be a real value, and thus potentially fractional. In this context, the process is said to be I(d) and the parameter d becomes crucial to determine the degree of persistence in the series: the higher the value of d is, the higher the level of association is between observations distant in time. (See Robinson, 2003, and Gil-Alana and Hualde, 2009, for updated reviews of fractional integration in economic series). By allowing d to be a non-integer value we permit a much richer degree of flexibility in the dynamic specifications of the series, not achieved when using integer degrees of differentiation. Standard methods, based on integer orders of integration, and using seasonal and non-seasonal unit roots have been employed in agricultural price series in

Palaskas and Crowe (1999), Sorensen (2002) and Jumah and Kunst (2008). Others have examined the existence of stochastic trends with no breaks (Cuddington 1992), with one structural break (Leon and Soto 1997) or even with two structural breaks (Kellard and Wohar 2006). These papers generally support the view that agricultural prices are stationary around deterministic trends, implying then transitory effects of the shocks. Our results reject this hypothesis since we obtain strong evidence against the trend-stationary representation for maize and wheat prices. In the context of fractional integration, the evidence on memory in agricultural price series is mixed and context-specific. Some have found no long memory (Wang and Tomek, 2007; Crato and Ray, 2000) and thus evidence of I(0) stationarity, whereas others have shown persistence (Jin and Frechette, 2004; Barkoulas et al., 1997; Cunado et al., 2012) with mean reverting behavior.

Second, it is in line with the recent trend towards using micro-level data to identify consequences of conflict on human capital investment (Akresh and Walque, 2011; Shemyakina, 2011) and physical investment (Singh, 2012). Research in this area also points to post-civil war torn societies showing quick recoveries. Studying the impact of the Kenyan violence, Ksoll et al. (2009) find that it reduced Kenyan flower exports by 24% overall. The conflict reduced exports by 38% for firms located in conflict areas, mainly through displacing workers but there was catch-up of exports within six months.

Although this paper is an exercise to identify the impact of violence on the specific market for food and the duration of its impact, it has policy implications that can affect lives of the poor as food prices appear to be strongly correlated with increases in overall poverty in low-income countries (Ivanic and Martin, 2008). Finally, the data for prices and sales is available before, during and after conflict which is a rare occurrence.

The core results of the paper are the large degree of persistence in prices and the (insignificant) increase observed in the values during the period of violence, and the intermediate-low degree of persistence in quantities and its significant decrease during violence. Nevertheless, given the low level of persistence in quantities, the recuperation in the post-violence period is expected to be fast. This result is subject to several caveats: first, it is specific to a short burst of violence. Second, it only looks at a local market where there is a duopoly. Third, there could be other underlying factors that could be causing both the violence and the drop in sales. Fourth, there may potentially be substitution towards the products of the other firm: the rival firm's data is unavailable. Fifth, the channels of the decrease in sales are not explored in this paper due to a lack of other data. There can be several mechanisms if for instance we observe a reduction in sales: first, there may be a fall in demand by the consumers. This may happen because there is a fall or expected fall in the incomes due to the violence. There may be closing of shops and damage to them. This would reduce the capacity or the number of flour-selling shops in the city leading to a drop in sales for the producing firm. Also, there may be a greater risk in opening shops or transporting the flour. In our interpretation section, we delineate the important channels that are consistent for the results and argue that a reduced demand by shopkeepers post-conflict may be responsible for the reduction in quantity. However, there is no impact on the price because the supply curve is shown to be relatively flat for the Mombasa miller.

This paper is organized as follows: in Section 2, we describe the background of the post-election violence as well as the flour market in Kenya. In Section 3, we describe the data and delineate our methodology. Section 4 reports our main results. Section 5 deals with a series of robustness checks and Section 6 concludes.

## 2. Background

From late December 2007 to March 2008, post-election violence raged throughout Kenya. This violence followed the controversial Presidential election in which the incumbent, Mwai Kibaki was declared the winner in December 2007. The Orange Democratic Movement (ODM) candidate Raila Odinga had a lead of over one million votes but suddenly, a small margin of victory was announced for the incumbent candidate Mwai Kibaki.

A United Nations Report (2008) found that violence was particularly intensive in Eldoret, the Kibera slum area of Nairobi, Mombasa and Kisumu, resulting in the deaths of over 1,200 Kenyans, the displacement of over 300,000 people, and the destruction of over 42,000 houses and businesses. Figure 1 shows the chronology of events post-elections with a focus on Mombasa.

**[Insert Figure 1 about here]**

In the violent aftermath of the contested presidential elections in December 2007, wholesale maize prices seemed to rise drastically as grain production and trade in the Rift Valley was disrupted, which is where close to 55% of the maize is produced in Kenya (Okello, 2009). This may have been both due to disruption in input or output markets. Okello (2009) suggests that political violence disrupted the transportation of fertilizer from Mombasa to the growing areas in the Rift Valley province and this led to an increase in the international price of fertilizers. A newspaper article in the People's Daily reported in May 2008 that sales of the crops dropped significantly following the eruption of the violence in Kenya. The article argued that farmers in Kenya normally prepare more than 30 percent of their land for tilling by January, but only 10 percent was ready after the violence due to unavailability of farming inputs and equipment. Agricultural experts did not know when maize prices would increase and for how long they would remain high. This feeds directly into the question of how maize stocks should be managed. The recommendation was for the government to step in to fight increasing and volatile food prices as a result of violence. However, this recommendation is not based on any systematic empirical evidence. We try to dispel this alarmist view that fails to take into account that market forces that would automatically kick in to stabilize prices.

This paper is a first step towards understanding the dynamics of food prices and quantities in response to a violence shock.

## 3. Data and Empirical Methodology

### 3.1 Data

Firm-level data is difficult to find during violence. Not only does firm-level data address part of the reverse causality bias which is present with aggregate data, it is also able to test the market reaction in the absence of government intervention as we are not aware of any subsidies being provided to the firm by the government during the period of study. The data consists of daily wheat and maize prices and quantities sold from a major miller in Mombasa to flour-selling shops in the city. These consist of supermarkets, corner shops, kiosks, wholesalers and other stores. Usually, price indices use consumer prices. This unique data set looks at producer prices and quantities, but we later compare it to the consumer prices in Mombasa and Nairobi. It includes a record of 3 years (2006 to 2008) of day-to-day level consisting of sales and prices of three product ranges within maize flour and wheat flour. However, due to missing data during several days in the sample, our work is based on weekly data, (based on weekly averages for prices and weekly total for quantities) although our results are robust to daily analysis. The series that we study is labeled 24x1, which gives the price and quantities of 24 (bales) x 1 kg. specification of flour. Our results are very robust to studying the other two series (12x2 and 24x1/2). The violence began on 27th December, 2007 and continued sporadically until the end of February / beginning of March in 2008 when the power-sharing agreement was signed. It is important to note that maize and wheat form the primary market for food in Kenya. For instance, Mukumbu and Jayne (1994) calculate that the average amount of maize meal consumed per adult in Kenya is 1.68 kg. a week and more than 12% of household income was spent on maize[1].

### 3.2 Methodology

The methodology employed is based on the concept of long memory or long range dependence. We can provide two definitions of long memory, one in the time domain and the other in the frequency domain.

Given a zero-mean covariance stationary process $\{x_t, \quad t = 0, \pm 1, \ldots\}$ with autocovariance function $\gamma_u = E(x_t, x_{t+u})$, the time domain definition of long memory implies that:

$$\sum_{u=-\infty}^{\infty} |\gamma_u| = \infty .$$

Now, assuming that $x_t$ has an absolutely continuous spectral distribution function, with a spectral density function given by:

$$f(\lambda) = \frac{1}{2\pi}\left(\gamma_0 + 2\sum_{u=1}^{\infty} \gamma_u \cos(\lambda u)\right),$$

[1] The urban poor spend 29 per cent of their budget on food, while their richer counterparts spend 21 per cent (Mutegi, 2010).

The definition of long memory in the frequency domain states that the spectral density function is unbounded at some frequency λ in the interval [0, π), i.e.,

$$f(\lambda) \rightarrow \infty, \quad \text{as } \lambda \rightarrow \lambda^*, \qquad \lambda^* \in [0, \pi].$$

In the past two decades, much of the relevant empirical literature in econometrics has focused on the case where the singularity or pole in the spectrum occurs at the 0 frequency,

$$f(\lambda) \rightarrow \infty, \quad \text{as } \lambda \rightarrow 0^+.$$

This is the standard case of I(d, d > 0) models of the form:

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \ldots, \tag{1}$$

where L is the lag-operator ($Lx_t = x_{t-1}$) and $u_t$ is I(0).[2] However, fractional integration may also occur at other frequencies away from 0, as in the case of seasonal/cyclical models.

Note that the polynomial $(1–L)^d$ in equation (1) can be expressed in terms of its Binomial expansion, such that, for all real d,

$$(1 - L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d(d-1)}{2} L^2 - \ldots,$$

and thus

$$(1 - L)^d x_t = x_t - d\,x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \ldots .$$

In this context, d plays a crucial role since it will be an indicator of the degree of dependence of the time series. Thus, the higher the value of d is, the higher the level of association will be between the observations. Processes with d > 0 in (1) display the property of "*long memory*", characterized because the autocorrelations decay

[2]An I(0) process is defined as a covariance stationary process where the infinite sum of the autocovariances is finite. Alternatively, in the frequency domain, a process is I(0) if its spectral density function is positive and finite at all frequencies.

hyperbolically slowly and the spectral density function is unbounded at the origin. The origin of these processes is in the 1960s, when Granger (1966) and Adelman (1965) pointed out that most aggregate economic time series have a typical shape where the spectral density increases dramatically as the frequency approaches zero. However, differencing the data frequently leads to over-differencing at the zero frequency. Seminal papers by Robinson (1978) and Granger (1980) showed that aggregation could be a source of fractional integration. Since then, fractional processes have been widely employed to describe the dynamics of many economic time series (see, for e.g., Diebold and Rudebusch, 1989; Sowell, 1992a; Baillie, 1996; Gil-Alana and Robinson, 1997).

If d = 0 in (1), $x_t = u_t$, and the series is stationary I(0) with shocks disappearing relatively fast. If d belongs to the interval (0, 0.5) the series is still covariance stationary but the autocorrelations take longer time to disappear than in the I(0) case. If d is in the interval [0.5, 1) the series is no longer stationary, however, it is still mean-reverting in the sense that shocks affecting the series disappear in the long run. Finally, if $d \geq 1$ the series is nonstationary and non-mean-reverting.

Across the paper we consider the following regression model,

$$y_t = \beta^T z_t + x_t, \qquad t = 1, 2, ..., \tag{2}$$

where $y_t$ is the observed time series, β is a (kx1) vector of unknown coefficients and $z_t$ is a set of weakly exogenous variables that might include deterministic terms such as an intercept (i.e., $z_t = 1$), an intercept with a linear time trend ($z_t = (1, t)^T$), or any other type of deterministic processes. We will also assume that the regression errors, $x_t$ in (2) are I(d) and follow equation (1). Thus, the model becomes:

$$y_t = \beta^T z_t + x_t, \quad (1 - L)^d x_t = u_t, \qquad t = 1, 2, ..., \tag{3}$$

where d can be any real value, and $u_t$ is supposed to be I(0).

The methodology employed in the paper to estimate the fractional differencing parameter d is based on the Whittle function in the frequency domain (Dahlhaus, 1989).[3] We also employ a procedure developed by Robinson (1994) allowing for testing any real value of d in I(d) models. This method is based on the Lagrange Multiplier (LM) principle and it is supposed to be the most efficient method in the context of fractional integration against local alternatives. It tests the null hypothesis $H_o$: $d = d_o$ for any real value $d_o$ in the model given by equation (3), using different types of I(0) disturbances. Given the fact that the test statistic follows a standard (normal) limit distribution it is possible to construct confidence bands for the non-rejection values of d.[4] Other parametric methods like Sowell's (1992b) maximum likelihood estimation in the time domain, and Beran's (1995) least squares approach produced essentially the same results. We also implemented a semiparametric method developed initially by Robinson (1995) and extended later by Abadir et al. (2007), where no functional form is imposed for $u_t$ in (1). This method is essentially a local 'Whittle estimator' in the frequency domain, using a band of frequencies that degenerates to zero. The estimator is implicitly defined by:

$$\hat{d} = \arg\min_d \left( \log \overline{C(d)} - 2\, d\, \frac{1}{m} \sum_{s=1}^{m} \log \lambda_s \right), \qquad (4)$$

$$\overline{C(d)} = \frac{1}{m} \sum_{s=1}^{m} I(\lambda_s)\, \lambda_s^{2d}, \qquad \lambda_s = \frac{2\pi s}{T}, \qquad \frac{1}{m} + \frac{m}{T} \to 0,$$

where m is a bandwidth number, and $I(\lambda_s)$ is the periodogram of the raw time series, $x_t$, given by:

$$I(\lambda_s) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t\, e^{i \lambda_s t} \right|^2,$$

[3] The Whittle function is an approximation to the likelihood function (Whittle, 1956).
[4] The functional form of this method can be found in any of the numerous empirical applications using this approach (Gil-Alana and Robinson, 1997; Gil-Alana, 2000; Gil-Alana and Henry, 2003; etc.)

and d $\in$ (-0.5, 0.5). Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\,(\hat{d} - d_o) \to_{dtb} N(0, 1/4) \quad as\ T \to \infty,$$

where " $\to_{dtb}$ " stands for convergence in distribution, and $d_o$ is the true value of d. This estimator is robust to a certain degree of conditional heteroskedasticity (Robinson and Henry, 1999) and is more efficient than other semi-parametric competitors. Abadir et al. (2007) extended this approach by using an extended Fourier transform in the computation of the periodogram, implying then that no prior differentiation is required when estimating the parameter d in nonstationary contexts.

## 4. Core results

### 4.1 Statistical analysis

Figure 2 provides a graphical illustration of the changes in prices and sales of wheat and maize during the sample period. The price series appears more stable than the quantity series and there also appears to be an upward trend in prices.

**[Insert Figure 2 about here]**

The results below show high persistence in prices and medium-low persistence and mean reversion in quantities (Tables 1 and 2), and Table 3 displays the effects of violence on prices and quantities of maize and wheat flour.

Table 1 reports results for the estimated values of d and their corresponding 95% confidence bands of the non-rejection values of d using Robinson's (1994) parametric approach, in the model given by (3) with $z_t = (1, t)^T$, $t \geq 1$, $(0, 0)^T$ otherwise, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, ..., \tag{5}$$

under the assumption that the error term $u_t$ is first a white noise process, then an AR(1) structure, and finally employing the exponential spectral model of Bloomfield (1973), which is a non-parametric approach of modeling the error term $u_t$ that produces autocorrelations decaying exponentially as in the AR(MA) case.[5] Following the standard approach in the literature we consider the three cases of: a) no regressors (i.e., $\beta_0 = \beta_1 = 0$ a priori in (5)), an intercept ($\beta_0$ unknown and $\beta_1 = 0$ a priori), and an intercept with a linear time trend ($\beta_0$ and $\beta_1$ unknown). This also helps us test for the Prebisch-Singer hypothesis, which states that primary commodity prices will experience a secular deterioration in terms of manufactured goods in the long run. This has policy implications for developing countries whose biggest exports are generally primary commodities. However, Cuddington (1992) and Kellard and Wohar (2006) show little support for the Prebisch-Singer hypothesis and our results with time trends are also in line with theirs.

We see in this table that the results differ substantially for prices and quantities. Thus, for prices, most of the estimates of d are around 1 or above 1, while the estimated values of d in case of the quantities are all of them strictly smaller than 1. We observe that the time trends are not required in any single case, the intercept being sufficient to describe the deterministic part of the series.

**[Insert Table 1 about here]**

Starting with the prices, we notice that if the error term is white noise the order of integration is above 1 for the two products, maize and wheat and the unit root is rejected in favor of higher orders of integration. However, in the more realistic case of autocorrelated errors (with AR(1) or Bloomfield) the unit root null cannot be rejected, the order of integration being slightly below 1 in case of maize and slightly above 1 in case of wheat prices.

[5] The model of Bloomfield (1973) accommodates very well in the context of fractional integration, especially with the tests of Robinson (1994). See Gil-Alana (2004).

If we focus now on the quantities we observe that the estimated values of d are in the interval (0, 0.5) implying then long memory (d > 0), stationarity (d < 0.5) and mean reverting behavior (d < 1).

**[Insert Table 2 about here]**

In Table 2, we derive estimates of d based on Robinson's (1995) semiparametric Whittle function for a selected group of bandwidth numbers, and find consistent evidence of unit roots for prices and stationary long memory for quantities.

Next we focus on the effect of violence and consider now a regression model with an intercept, but including also a dummy variable, adopting the value 1 in the period corresponding to violence [last week of December, 2007 until first week of March, 2008], 0 otherwise. In other words, the regression model is now:

$$y_t = \alpha + \alpha^* I(t \in V) + x_t; \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots . \qquad (6)$$

Here, I(▪) is the indicator function and V refers to the referred period of violence. We obtained the estimated values for the intercept (α), the increase/decrease during the period of violence (α*), the fractional differencing parameter (d) and the coefficient for the AR/Bloomfield autocorrelated part, noting that we perform the analysis for the cases of white noise, AR(1) and Bloomfield disturbances.

**[Insert Table 3 about here]**

Several features are observed in Table 3. First, the estimates of the fractional differencing parameter are not affected by violence, being very similar to those reported in Tables 1 and 2. Thus, d ranges from 0.843 to 1.278 in case of maize prices and from 1.058 to 1.190 for wheat prices, implying in all cases no evidence of mean reverting behavior. On the contrary, the estimates of d for quantities range between 0.229 and 0.379 for maize and are between 0.158 and 0.369 for wheat. This shows strong evidence for mean reversion for both wheat and maize. Also, it is noticeable the fact that the $\alpha^*$-

coefficients are positive though insignificant in the two prices series and negative and statistically significant in case of the quantities (sales).

### 4.2 Economic Interpretation

How can these coefficients be interpreted in the light of the background in Kenya, where the Kenyan government was being chastised for not stepping in to reduce the hike in prices of maize that the authors argued had gone up *because* of conflict? First, it seems that prices did not rise during the period of conflict even though quantities sold went down by the sampled miller in Mombasa. Second, to unearth the reason behind this shift in quantity but not in the price, one needs to rule out two out of three microeconomic mechanisms. The three mechanisms would be the following:

a) an upward shift of the positively sloping supply curve, with the demand curve being horizontal. This would give us a decrease in equilibrium quantity but no change in the price.

b) an upward shift of the positively sloping supply curve and a leftward shift of the negatively sloping demand curve.

c) a leftward shift of the negatively sloping demand curve with a horizontal supply curve.

The channel (a) can be ruled out as the demand for flour has been shown to be inelastic, implying a steep and negatively sloping demand curve. We can also infer that a flat demand curve is improbable for the Mombasa shopkeepers.

To distinguish (b) from (c), we collected monthly consumer prices over the sampled period from Mombasa and Nairobi for maize (they were unavailable for wheat) from the Ministry of Agriculture, Kenya. If the producer prices of maize and wheat were driven by local factors for the miller (for example, transportation costs, local weather, etc.), we should expect low correlation between the monthly variation in our 24x1 series and the government-collected data. This would imply a positively sloping supply curve in the local markets. If however, there is high correlation, prices would be determined at the national level, suggesting a flat supply curve.

We observe a correlation of 0.94 for both Mombasa as well as Nairobi government price data and our series for maize over the 3 year period. This means that the only explanation for the decrease in quantities but no change in prices is (c). We know from our analysis of fractional integration that this decrease is likely to be temporary, but there may be welfare implications associated with the shift in the demand curve along a flat supply curve. The decrease in demand here should be interpreted more generally as the reduced-form demand of shopkeepers who are purchasing from the miller. There is evidence against hoarding by shopkeepers and also against liquidity constraints of households across the different maize and wheat series. For instance, expected substitution by households from 24x1 to 12x2 may be evidence in favor of at least (expected) liquidity constraints and the reverse may imply hoarding. However, this does not seem to happen. One explanation may be that the shopkeepers were worried about theft from their shops during conflict and were reducing the quantity purchased from the miller. This is in line with anecdotal evidence and news reports of looting of shops in Mombasa during the post-election violence. For example, a Unitarian Universalist Service Committee article (2008) reports in January following the violence in Mombasa:

> *"Street vendors are not optimistic about the resumption of normal business activities. The security has deteriorated drastically, and people are struggling to protect themselves and their property ... street vendors' incomes have declined substantially because they have to open late and close early due to the insecurity.*

*Access to merchandise is difficult because wholesalers are staying open for a very short time."*

## 5. Robustness checks

Firstly, the estimates of d seem to be robust across the different types of I(0) disturbances, including the case of seasonal AR processes for $u_t$ as reported in Appendix Table 1. We also note that the effects of conflict are consistent for both wheat and maize and robust to including seasonality effects. Moreover, the persistence parameters remain similar after removing the conflict period from our analysis.

We also computed for each of the four series (wheat and maize, prices and quantities) the estimates of d first from a sub-sample ending before the violence started, and then re-estimated d adding successively one observation each time. Then, we plotted the estimates (along with the 95% bands) to see if the parameter has remained stable across the sample (including the violence period).

To calculate the recursive estimates of d, we began with a sample of 100 observations, i.e. with data ending at the week [26.11.2007 – 2.12.2007], and then, we added one observation each time till the end of the sample period (31 December 2008).

**[Insert Figure 3 about here]**

Figure 3 displays the estimated values of d (along with the 95% confidence intervals) for the prices of maize and wheat; followed by maize and wheat quantities respectively. In all cases, the model considered is the one with an intercept and AR(1) disturbances, since it seems the most plausible specification in all cases.

The estimate of d for maize prices remains relatively stable across the sample period with a sudden slight increase in the value of d around the point 106 (2$^{nd}$ week in January 2008) though quickly returning to its previous value in the following cases.

Note, however, that the fact that the estimated value of d returns to its previous value has nothing to do with the effect of the shocks. In the case of wheat prices, there is a sudden decrease at 114 ($1^{st}$ week in March 2008) though once more recovering fast; for quantities, the results are also quite stable, observing only a sudden increase in wheat at the initial period of violence (point 105). In general, the same conclusions as those reported in Section 4 hold: the estimates of d for maize and wheat prices are close to the unit root case, while those for quantities move about 0.3 for maize and about 0.4 for wheat, implying long memory and mean reverting behavior.

## 6. Conclusion

This paper contributes to the econometric literature of food prices in the context of a developing country, Kenya. First, we test for the persistence and presence of unit roots in producer prices and quantities of wheat and maize in Mombasa. We find high persistence in price and relatively lower persistence in quantity. However, we believe the main contributions of this paper are two-fold: first, it gives us an estimate of the impact of post-election violence in Kenya on food prices, which is hugely important for understanding food security during conflict. In particular, we find evidence against the alarmist view that prices of essential commodities increase during conflict. This is because even the demand by shopkeepers for flour decreases post-conflict. There is also evidence against hoarding by shopkeepers and liquidity constraints of households across the different maize and wheat series. Second, it is able to recover a reduced-form shift in the demand for wheat and maize flour by shopkeepers following the conflict. This is because we observe a reduction in quantity sold to shopkeepers during violence but no effect on price. These results are robust to alternative econometric specifications. We also infer after collecting monthly data from the Kenyan Agricultural Department that producer price variation in the market for maize in Mombasa is highly correlated with consumer prices in Nairobi and Mombasa. This implies a flat supply curve. However, these results may not be easily generalized to predict the persistence of prices and quantities of other flour firms within Kenya or firms in other industries with similar market structures at the local level. Nevertheless, this paper shows that we can link micro-analysis with the recent developments in applied econometrics and provide policy implications in the context of an arguably exogenous event. We feel that this is the first step in understanding the effect of violence on food security. Moving forward, further analysis is necessary to impute the relative importance of the underlying mechanisms as well as the interaction of different market structures with responses to violence. This can only be solved through rigorous data collection at the firm-level in fragile countries.

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**Figure 1: Timeline - Chronology of Post-Election violence in Kenya**

| Date (Dec.07-Mar.08) | Events |
|---|---|
| Dec-27 | The 2007 presidential election is held. At the time, the Orange Democratic Movement (ODM) candidate Raila Odinga had a lead of over one million votes but suddenly, a small margin of victory was announced for the incumbent candidate Mwai Kibaki. |
| Dec-30 | Violent clashes erupt throughout the country and are especially violent in Nairobi's Kibera slums, in ODM-dominated Kisumu and Naivasha in the Rift Valley and in Mombasa. |
| Jan-01 | The Government of Kenya issues a statement titled, "Violence in Kenya Does Not Mean the Country is Burning" and states that "the population directly affected by the violence is less than 3% of the Kenyan population. The police are containing the affected areas where there is violence". |
| Jan-02 | Five more deaths reported in Mombasa. |
| Jan-07 | Reports suggest that local media sources were pressured by the government to not report deaths or violent events. |
| Jan-09 | More violent attacks occur in Kibera slums and Kisumu, Kakamega, Eldoret, and Naivasha in the Rift Valley. Several Kenyans in Nairobi rally together to start Ushahidi, a campaign to raise awareness of the violence in Kenya. |
| Jan-19 | At least one killed, two shot in the hand, another shot in the thigh, including a 2.5 year old boy. |
| Jan-24 | Transportation in Mombasa is still blocked. |
| Jan-25 | Second wave of retaliation violence begins and lasts for 6 days. |
| Feb-28 | Power-sharing agreement signed and peace achieved. The violence following the election leaves over 1,200 dead and 300,000 displaced. |
| Sources: | The East African Standard, Goldstein and Roditch (2008), Halperin (2008). |

**Figure 2: Time series plots: Prices and Quantities, maize and wheat flour**

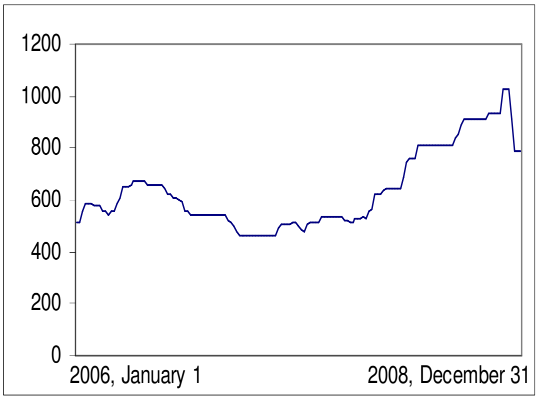
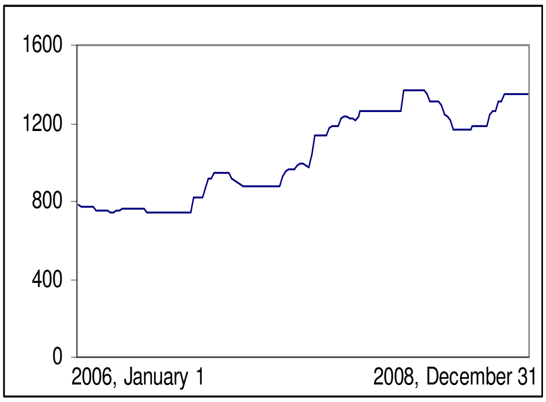
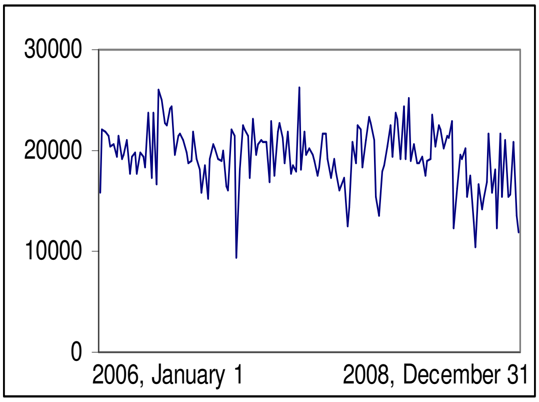
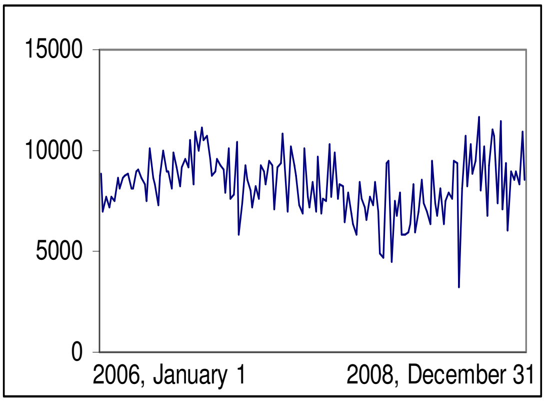
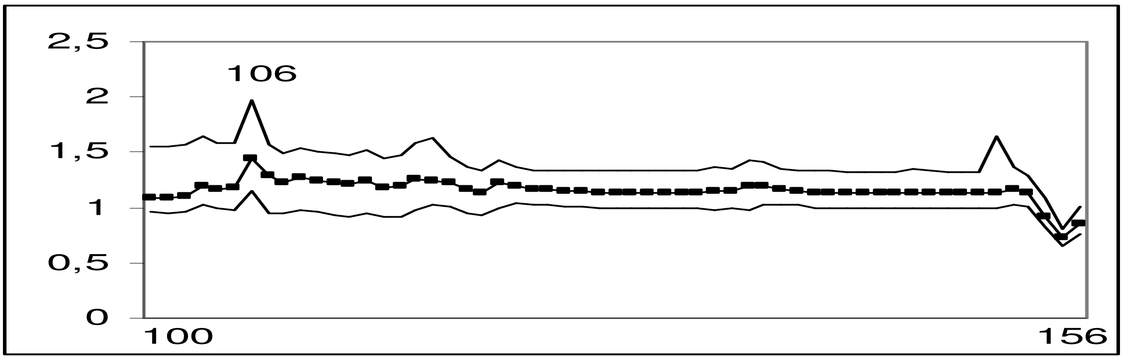
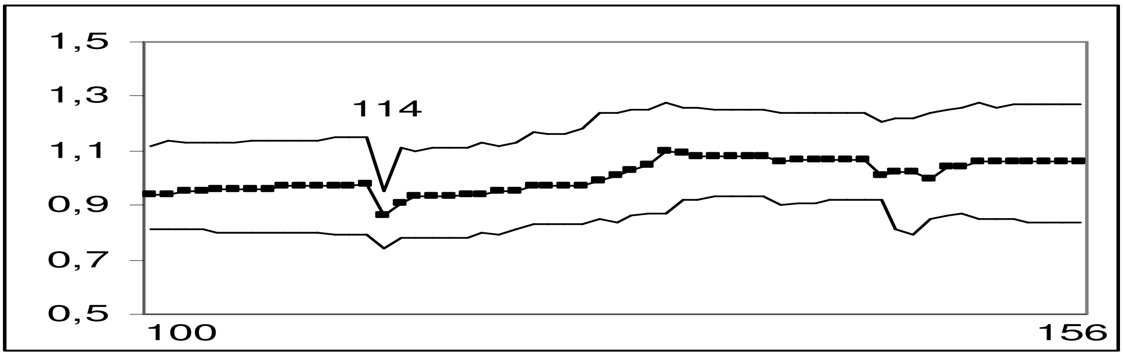
| PRICE MAIZE 24X1 | PRICE WHEAT 24X1 |
| --- | --- |
|  |  |
| **QUANTITY MAIZE 24X1** | **QUANTITY WHEAT 24X1** |
|  |  |

**Figure 3: Evolution of the estimation of d across the sample using recursive estimates**

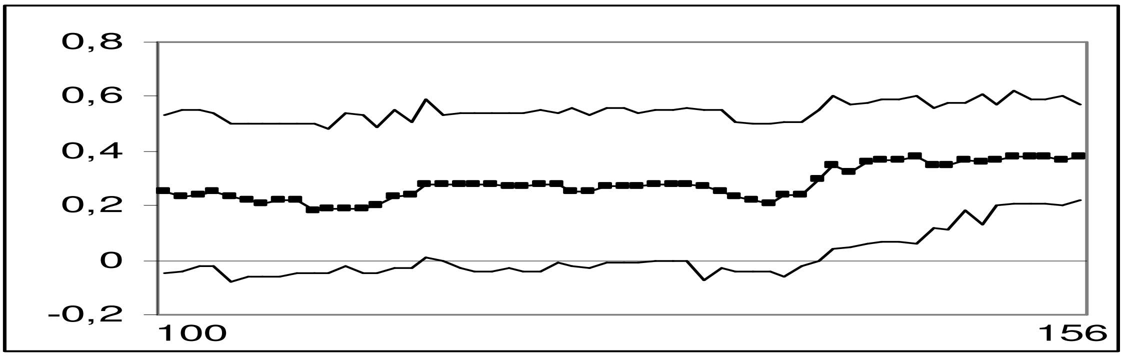
**i) Prices: MAIZE24X1**



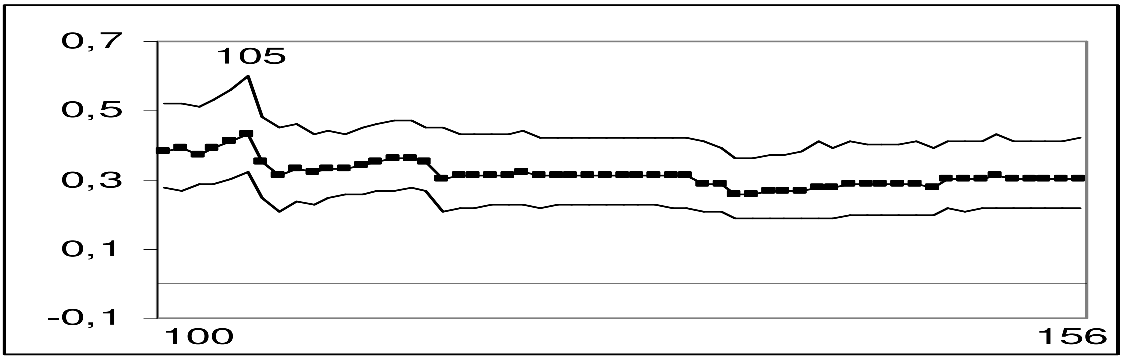

**ii) Prices: WHEAT24X1**




**iii) Quantities: MAIZE24X1**




**iv) Quantities: WHEAT24X1**




The thin lines refer to the 95% confidence bands for the values of d.

**Table 1: Estimates of d and 95% confidence band of non-rejection values of d**

| | | | | | | |
|---|---|---|---|---|---|---|
| **a) Prices** | | | | | | |
| | **Maize (24x1)** | | | **Wheat (24x1)** | | |
| | No regressors | **An intercept** | A linear trend | No regressors | **An intercept** | A linear trend |
| **White noise** | 0.994<br>(0.893, 1.141) | **1.265**<br>**(1.122, 1.466)** | 1,265<br>(1.123, 1.464) | 0.972<br>(0.872, 1.103) | **1.182**<br>**(1.083, 1.321)** | 1.184<br>(1.084, 1.322) |
| **AR(1)** | xxx | **0.840**<br>**(0.725, 1.021)** | 0.814<br>(0.632, 1.022) | xxx | **1.062**<br>**(0.838, 1.267)** | 1.063<br>(0.851, 1.270) |
| **Bloomfield** | 0.877<br>(0.754, 1.061) | **0.952**<br>**(0.824, 1.170)** | 0.950<br>(0.804, 1.171) | 0.921<br>(0.739, 1.152) | **1.063**<br>**(0.914, 1.269)** | 1.063<br>(0.898, 1.271) |
| **b) Quantities** | | | | | | |
| | **Maize (24x1)** | | | **Wheat (24x1)** | | |
| | No regressors | **An intercept** | A linear trend | No regressors | **An intercept** | A linear trend |
| **White noise** | 0.557<br>(0.481, 0.649) | **0.228**<br>**(0.145, 0.335)** | 0.202<br>(0.111, 0.318) | 0.487<br>(0.419, 0.568) | **0.207**<br>**(0.149, 0.283)** | 0.199<br>(0.137, 0.279) |
| **AR(1)** | 0.684<br>(0.524, 0.845) | **0.363**<br>**(0.187, 0.570)** | 0.351<br>(0.155, 0.565) | 0.692<br>(0.605, 0.797) | **0.338**<br>**(0.258, 0.442)** | 0.335<br>(0.248, 0.442) |
| **Bloomfield** | 0.719<br>(0.581, 0.900) | **0.333**<br>**(0.153, 0.576)** | 0.299<br>(0.113, 0.569) | 0.821<br>(0.704, 0.971) | **0.417**<br>**(0.299, 0.563)** | 0.417<br>(0.292, 0.569) |

In parenthesis, the 95% confidence interval of the non-rejection values of d using Robinson (1994). xxx means that convergence is not achieved. In bold, the significant models for the deterministic terms.

**Table 2: Estimates of d based on Robinson's (1995) semiparametric Whittle function**

| **PRICES** | m = 5 | 10 | 12 | 13 | 15 | 20 |
|---|---|---|---|---|---|---|
| MAIZE 24X1 | 1.128* | 1.317 | 1.023* | 1.015* | 0.937* | 0.958* |
| WHEAT 24X1 | 0.669* | 1.253* | 1.317 | 1.413 | 1.201* | 1.295 |
| **QUANTITIES** | m = 5 | 10 | 12 | 13 | 15 | 20 |
| MAIZE 24X1 | 0.168+ | 0.219+ | 0.213+ | 0.239 | 0.261 | 0.369 |
| WHEAT 24X1 | 0.233+ | 0.279 | 0.190+ | 0.444 | 0.501 | 0.388 |
| 95% I(0) Conf. | (-.367, 0.367) | (-.260, 0.260) | (-.237, 0.237) | (-.228, 0.228) | (-.212, 0.212) | (-.183, 0.183) |
| 95% I(1) Conf. | (0.632, 1.367) | (0.739, 1.260) | (0.762, 1.237) | (0.771, 1.228) | (0.787, 1.212) | (0.816, 1.183) |

*: Evidence of unit roots (d = 1) at the 5% level. +: Evidence of stationarity I(0) (d = 0). m is the bandwidth number

**Table 3. Estimates of d and $\beta_1$ in the context of a dummy variable for the violence period**

| | | | | | | |
|---|---|---|---|---|---|---|
| **i) Prices** | | | | | | |
| | White noise | | AR(1) | | Bloomfield-type | |
| | d (Conf. band) | $\beta_1$ (t-val.) | d (Conf. band) | $\beta_1$ (t-val) | d (Conf. band) | $\beta_1$ (t-val.) |
| MAIZE – 24X1 | 1.260 (1.115, 1.455) | 4.223 (0.312) | 0.847 (0.753, 1.012) | 0.0003 (0.0002) | 0.922 (0.803, 1.150) | 1.423 (0.104) |
| WHEAT -24X1 | 1.185 (1.081, 1.333) | 6.675 (0.513) | 1.061 (0.831, 1.265) | 2.198 (0.162) | 1.060 (0.909, 1.262) | 2.161 (0.164) |
| **ii) Quantities** | | | | | | |
| | White noise | | AR(1) | | Bloomfield-type | |
| | d (Conf. band) | $\beta_1$ (t-val.) | d (Conf. band) | $\beta_1$ (t-val) | d (Conf. band) | $\beta_1$ (t-val.) |
| MAIZE – 24X1 | 0.208 (0.127, 0.314) | -317.524 (0.260) | 0.384 (0.206, 0.585) | **-195.094 (-1.726)** | 0.381 (0.173, 0.649) | **-187.098 (-1.725)** |
| WHEAT -24X1 | 0.133 (0.064, 0.223) | **-1662.84 (-3.122)** | 0.250 (0.146, 0.379) | **-1542.08 (-2.422)** | 0.288 (0.155, 0.467) | **-1515.71 (-2.322)** |

In bold, significant coefficients at the 5% level.

**APPENDIX**
**TABLES**

**Appendix Table 1**

**Estimates of d (and 95% confidence bands)**

| PRICES | MAIZE24X1 | WHEAT24X1 |
|---|---|---|
| Seasonal AR(1) | 1.308 (1.209, 1.428) | 1.158 (1.096, 1.230) |

**Estimates of d (and 95% confidence bands)**

| QUANTITIES | MAIZE24X1 | WHEAT24X1 |
|---|---|---|
| Seasonal AR(1) | 0.223 (0.173, 0.281) | 0.154 (0.110, 0.201) |