A Causal Exploration of Conflict Events and Commodity Prices of Sudan

Junyi Chen, Shahriar Kibriya, David A. Bessler and Edwin Price[1]

Abstract

Though recent literature uncovers linkages between commodity prices and conflict, the causal direction of the relationship remains ambiguous. We attempt to contribute in this strand of research by studying the dynamic relationship of commodity prices and the onsets of conflict events in Sudan. Using monthly data ranging from January 2001 through December 2012, we identify a structural breakpoint in the multivariate time series model of prices of the three staple foods (sorghum, millet, and wheat) and conflict measure (number of conflict events) in September of 2011. Applying Structure Vector Autoregression (SVAR) and Linear Non-Gaussian Acyclic Model (LiNGAM), we find that wheat price is a cause of conflict events in Sudan. We find no feedback from conflict to commodity prices.

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1. Introduction

Higher food prices have detrimental consequences on the socio-political events in developing countries (FAO–SIFSIA, 2012) and have been shown to be related to civilian unrest as well (Bellemare, 2011; Besley and Persson, 2008; Goldstone, 1982; Lagi et al., 2011; Smith, 2014). World food prices surged to a record high in February 2011, which served as a catalyst for a series of protests in North Africa and the Middle East, including the 2011 "Arab Spring" (Bellemare, 2011; Brinkman and Hendrix, 2011). Although recent literature establishes causal linkages between food prices and conflict, the direction of the causality is still unclear. Provided that food prices continue to stay high, its causal direction and shock responses of conflict remain a germane investigation. Our study contributes to this strand of studies by investigating the causal relationships of staple commodity prices and conflict events in Sudan. Using Structural Vector Autoregression (SVAR) techniques and modern innovations of computer science search algorithms, we discover that commodity prices, especially imported ones, drive conflict events in Sudan.

Consistent with the general experience in the developing world, the prices of staple foods in Sudan increased alarmingly in 2008 (FAO–SIFSIA, 2012). The region has been beleaguered by intense armed conflict in recent years. Particularly, Sudan's second civil war (1983 – 2005) is characterized as one of longest enduring, catastrophic wars during the late 20th century (Say et al., 2012). On July 9, after the referendum in January 2011, South Sudan seceded from Sudan and became an independent country, indicating the end of Comprehensive Peace Agreement (CPA) which was signed in 2005 (FAO/WFP, 2014). Despite the independence and enduring efforts at stabilization, Sudan remains volatile due to the frequency of low-medium level conflict onsets (Raleigh et al., 2010). Recent literature shows numerous factors driving conflict: growing population (Collier and Hoeffler, 2004), natural resource endowments (Collier and Hoeffler, 1998), economic conditions such as income levels and economic growth (Berazneva and Lee, 2013; Blattman and Miguel, 2010; Miguel et al., 2004), fragile institutions and geographical attributes (Blattman and Miguel, 2010), quick and significant demographic changes such as migration (Goldstone, 2002). However, a time variant examination of the topic is yet to be conducted. With the existing inequality and unrest across regions, the soaring food prices could exacerbate the weak purchasing power of its citizens (IFAD, 2009). Given the conflict onsets, rising food prices and low political stability in the region, Sudan is an ideal country to investigate the dynamic relationships between cereal prices and conflict.

Sorghum, millet, and wheat are the main cereals consumed in Sudan (Hamid, 2003). Sorghum is the highest consumed commodity followed by wheat and millet. Sudan is self-sustainable in sorghum and millet production (Abdelrahman, 1998), while it produces at most 20% of its net wheat demand (FAO/WFP, 2011). Consumption of these cereals differs by regions and socio-economic status of the citizens. Sorghum serves as the main staple for the most impoverished in central and eastern Sudan, while millet is the staple for most people in Darfur and some regions in the western Sudan (FEWS NET, 2014a). In current times, wheat is usually treated as a substitute for sorghum and millet in northern Sudan, especially in the urban areas (Mustafa et al., 2013; FEWS NET, 2014a). Mustafa et al. (2013) report that the average consumption of wheat has increased to 1770.8 thousand tons in the 2000s from 743.5 thousand tons in the 1980s. Consequently, imports of wheat have increased substantially since 1999, and the imports amount accounted for about 75 percent of the wheat consumption from 2000 to 2010 (Mustafa et al., 2013). Increased imports caused higher price volatility and government intervention. Furthermore, the high volume of wheat imports absorbs almost all of the foreign exchange generated from total agricultural exports (Auad et al., 2007).

In a recent report, Famine Warning Systems Network (FEWS NET, 2014b) reports that 3.3 million people would face stressed and crisis levels of food insecurity, mainly caused by increasing food prices and conflict. Mahran (1996) approaches this topic from demand and supply perspective. Misselhorn (2005), using meta-analysis based on 49 household economy local-level studies, reveals the causes of food insecurity in southern Africa including conflict, poverty, and environmental factors. Hadley et al. (2012) conduct twenty semi-structured interviews in Africa and conclude that the rise in food prices could decrease food security, including non-nutritional results. Given previous studies and reports, it is plausible to draw the conjecture that rising cereal prices, violent activities, and the food shortage in Sudan are not unrelated. However, contemporary research does not draw direct time variant inference between food prices and conflict, especially in the Sudanese context. We address this gap in the literature by studying a time series dataset on commodity prices and conflict events in Sudan. In this article, we attempt to use Inductive Causation (IC) methods (Spirtes et al., 2000) to inform us on contemporaneous structure. Our treatment of the non-Gaussian commodity treatment is different from the contemporary social science literature, as we employ Linear Non-Gaussian Acyclic Model. We use a Bernanke-like Structure Vector Autoregression (SVAR) model to summarize the dynamic causal relationships between commodity prices and conflict. The rest of the paper is organized as follows: Section 2 provides a literature review on the relationship of food prices and conflict; Section 3 introduces the major methodology applied; Section 4 describes the dataset; Section 5 presents the results of estimation and Section 6 summarizes the conclusion and provides some policy implications.

2. Background and Literature Review

Current literature offers ample evidence of linkages between increasing food prices and conflict. While rising food prices may not be the direct drivers for conflict, they may well be latent drivers of conflict. High food prices increase food insecurity and can lead to social and political instability and conflict. A reverse causal flow can be argued as well. The outbreak of conflict may increase food prices because of radical ramifications such as increasing disease, death and displacement, soaring military expense, and capital damages (Brinkman and Hendrix, 2011). The following offers further theoretical and empirical evidence of both directions.

Food Prices (Market) Affecting Conflict

The impoverished suffer the most from high food prices. For instance, in Africa, the under privileged spend almost half of their income on food (Smith, 2013). Goldstone (1982) suggests that food protests often erupt with high unemployment and increases in food prices. Walton and Seddon (2008) find that food riots surged in the 1970s, due to the integrated world economy where local food prices were more influenced by global political economy (Bellemare, 2011). Besley and Persson (2008) study civil war and conclude that higher world market export and import prices increase the probability of civil unrest. Similarly, Lagi et al. (2011) suggest that global food price peaks, beyond a certain threshold, could trigger social unrest with other possible contributing factors. Taking into account other determinants including government interventions, other pertinent research suggest that higher commodity prices are correlated with conflict in developing countries (Brinkman and Hendrix, 2011). Recently, Smith (2014) utilizes an instrumental variable approach and concludes that in urban Africa a sudden surge of domestic food prices contributes to civil unrest. Nevertheless, some scholars argue the same causal direction with different effects. Demuynck and Schollaert (2008) demonstrate that a fall of tropical agricultural commodities' prices could fuel conflict by instigating a rebellion. Similarly, Brückner and Ciccone (2010) show that a drop in commodity prices increases the probability of civil war.

Conflict Affecting Food Prices

Conflict events tend to impede food production, input supplies, and output storage (Hitzhusen and Jeanty, 2006). Consequently, slight changes in supply could greatly affect prices since the demand for food is essentially inelastic. Therefore, conflict and its associated political and social instability could drive food prices (Brinkman and Hendrix, 2011). Sufficient evidence indicates that socio-political events and wars, especially armed conflict and terrorism, usually have significant effects on markets

(Kollias et al., 2011). Guidolin and La (2010) study a large sample of internal and inter-state conflict events and conclude that national stock markets tend to perform positively when there is an onset of conflict rather than responding negatively.

To summarize, not only can high food prices lead to conflict, but also conflict could contribute to high food prices. For instance, riots swept through the Middle East and North Africa, partly resulting from high food prices. In turn, the insecurity afterwards disrupted the commodity markets (Brinkman and Hendrix, 2011). The vicious cycle can cause even higher food prices and more intense conflict events.

3. Methodology

As our data on commodity prices and the number of conflict events are observed in time sequence. Recent explorations of such time variant data on commodity prices include time series analysis of food and energy prices in India by Bhatt and Kishor (2015) and US food prices by Lambert and Miljkovic (2010). We augment their approach by considering a structural representation and employing a non-Gaussian graphical network based algorithm to identify contemporaneous causation. We study the co-movement of commodity prices and conflict events through time with the vector autoregression (VAR) model. We follow Hsiao (1979) and construct a subset vector autoregression model to capture the relationship between the current position of commodity prices and conflict events combined with their lagged values, allowing for asymmetric lag length structure. In addition, new information in each period (innovations) is then modeled using methods from machine learning as first suggested in Swanson and Granger (1997), giving us a structural representation of commodity prices and conflict events in contemporaneous time (a structural VAR).

3.1 Vector Autoregression Model

Empirical Strategy

The unrestricted Vector Autoregression (VAR) (Sims, 1980) allows every variable to affect every other variable in a system of equations with lags of the same length, whereas the subset VAR permits a differential lag structure among variables of the system. For example, variable $\boldsymbol{y_{1t}}$ may affect variable $\boldsymbol{y_{2t}}$ with one lag, whereas it may affect variable $\boldsymbol{y_{3t}}$ with three lags. Justification for permitting such differences relates to both estimation efficiency and forecasting accuracy (Briiggemann and Liitkepohl, 2001). Sims (1980) labels the unrestricted VAR as a profligately parameterized model. The subset VAR can be treated as the traditional VAR, subject to zero restrictions (determined from data) on certain coefficients of lagged variables

$(\boldsymbol{y}_{t-1}, \boldsymbol{y}_{t-2}, \dots, \boldsymbol{y}_{t-p})$. Hsiao (1979) offers a procedure for placement of these zero restrictions (reviewed below).

Following Moneta et al. (2013), the basic structural VAR in matrix form is given as:

$$\boldsymbol{y}_t = \boldsymbol{B}_0 \boldsymbol{y}_t + \boldsymbol{B}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{B}_p \boldsymbol{y}_{t-p} + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{\varepsilon}_t \qquad (1)$$

Where $\boldsymbol{y}_t$ $(k \times 1)$ is a vector of k endogenous variables observed at time *t*. In this paper, $\boldsymbol{y}_t$ represents wheat price, sorghum price, millet price and number of conflict events ($k = 4$). The variable $\boldsymbol{x}_t$ $(d \times 1)$ is a vector of exogenous variables at time *t*. We use a set of eleven monthly binary variables to capture seasonal effects. The matrices $\boldsymbol{B}_i$ $(i = 1, \dots, p)$ are coefficients to be estimated, each associated with a particular lag of the left hand side endogenous variable $\boldsymbol{y}_t$. The index p refers to the maximum number of lags generating our system (as we are considering the subset VAR, p lags may not be the same for all elements of the vector $\boldsymbol{y}_t$). The matrix $\boldsymbol{B}_0$ represents contemporaneous coefficient matrix, with a zero for each element of the main diagonal. The vector $\boldsymbol{\varepsilon}_t$ is a $(k \times 1)$ series of white noise innovations, where $E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_s') = \boldsymbol{\Sigma}$, if $t = s$, and 0 otherwise. As in Moneta et al. (2013), we further assume that the innovations $(\boldsymbol{\varepsilon}_1, \dots, \boldsymbol{\varepsilon}_k)$ in equation (1) are independent sources of new information (independent of each other, so an information shock in series 1, say wheat price, is independent of an information shock from series 2, say sorghum price).

Equation (1) is termed a structural VAR, as elements of the matrix $\boldsymbol{B}_0$ are not necessarily all zero. It is of particular interest in this study to know which off diagonal elements are non-zero (structural information). The main reason for this is that we have monthly period of observation (monthly data), and potentially a considerable amount of inter-series interaction, can take place within the month. For instance, wheat price may well affect millet or sorghum prices and these in turn affect conflict events within the month (actually days, but such data are not available).

The model offered in equation (1) can be reformed as a standard VAR. This is, perhaps, most easily seen via two steps. First move the contemporaneous value of $\boldsymbol{y}_t$ in equation (1) to the left hand side of the equation to get equation (2):

$$(\boldsymbol{I} - \boldsymbol{B}_0)\boldsymbol{y}_t = \boldsymbol{B}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{B}_p \boldsymbol{y}_{t-p} + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{\varepsilon}_t \qquad (2)$$

Finally merely solve equation (2) for $\boldsymbol{y_t}$. This operation gives us equation (3), the reduced form VAR (or subset VAR if the $\boldsymbol{B_i}$ $(i = 1, \dots, p)$ matrices contain nonzero elements somewhere).

$$\begin{aligned}\boldsymbol{y_t} &= (\boldsymbol{I} - \boldsymbol{B_0})^{-1}\boldsymbol{B_1}\boldsymbol{y_{t-1}} + \cdots + (\boldsymbol{I} - \boldsymbol{B_0})^{-1}\boldsymbol{B_p}\boldsymbol{y_{t-p}} + (\boldsymbol{I} - \boldsymbol{B_0})^{-1}\boldsymbol{B}\boldsymbol{x_t} \\ &\qquad + (\boldsymbol{I} - \boldsymbol{B_0})^{-1}\boldsymbol{\varepsilon_t} \\ &= \boldsymbol{A_1}\boldsymbol{y_{t-1}} + \cdots + \boldsymbol{A_p}\boldsymbol{y_{t-p}} + \boldsymbol{A}\boldsymbol{x_t} + \boldsymbol{u_t} \qquad (3)\end{aligned}$$

Here $\boldsymbol{u_t}$ is a vector of white noise innovation process in which its covariance matrix $E(\boldsymbol{u_t}\boldsymbol{u_t'}) = \boldsymbol{\Sigma_u}$ is not necessarily diagonal. Notice the innovation vector $\boldsymbol{u_t}$ is now a combination of the original independent shocks $\boldsymbol{\varepsilon_t}$: $\boldsymbol{u_t} = (\boldsymbol{I} - \boldsymbol{B_0})^{-1}\boldsymbol{\varepsilon_t} = \boldsymbol{A_0^{-1}}\boldsymbol{\varepsilon_t}$.

Our goal is to estimate the reduced form VAR in equation (3) and then offer evidence on the particular contemporaneous structural ordering behind the matrix $\boldsymbol{A_0^{-1}}$. This problem was first described and its solution was hinted at in the paper by Swanson and Granger (1997). Bessler and Akleman (1998) offer the first data-based solution to this task, which followed the suggestions provided in Swanson and Granger (1997).

When specifying the SVAR in this paper, the method of search proposed by Hsiao (1979) using the Hannan-Quinn (Hannan and Quinn, 1979) loss criterion will be employed to determine the optimal lag length of each variable in each equation (3). [2] Hsiao's method is an iterative procedure to specify the optimal lag length of each variable in each equation separately for more efficient estimations. However, this technique is sensitive to the rank of the importance of the independent variables considered, which rests on prior theory (Kling and Bessler, 1985).

The Identification of SVAR

Since the lag structures suggested by the SVAR (equation (3)) are usually complex and difficult to interpret, we consider the corresponding vector Moving Average (MA) representation. We follow the presentation in Moneta et al. (2013):

[2] Hannan-Quinn criterion (HQ) is computed according as follows:

$$HQ = \ln|\Sigma| + 2k\ln(\ln T)/T,$$

Where Σ is the estimated non-orthogonal innovations correlation matrix from a first estimated VAR (equation (3)), k is the number of parameters fit and T is the number of observations. Other information criteria (Schwarz loss) were also studied and gave similar results.

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \sum_{j=0}^{\infty} \boldsymbol{\varphi_j} \boldsymbol{u_{t-j}} = \boldsymbol{\mu} + \sum_{j=0}^{\infty} \boldsymbol{\varphi_j} \boldsymbol{A_0} \boldsymbol{A_0^{-1}} \boldsymbol{u_{t-j}} = \boldsymbol{\mu} + \sum_{j=0}^{\infty} \boldsymbol{\Psi_j} \boldsymbol{\varepsilon_{t-j}} \quad \text{[3]} \qquad (4)$$

where the matrix $\boldsymbol{\varphi_j}$ and $\boldsymbol{\Psi_j}(= \boldsymbol{\varphi_j A_0})$ represent the moving average parameters and the impulse response from $\boldsymbol{y_t}$ to the shocks $\boldsymbol{\varepsilon_{t-j}}$ respectively; $\boldsymbol{\mu}$ is the mean of $\boldsymbol{y_t}$. One advantage of SVAR is to render sufficient information for policy analysis, such as $\boldsymbol{\Psi_j}$. Thus, it is vital to obtain the matrix $\boldsymbol{A_0}$, which completes the transformation from $\boldsymbol{u_t}$ (not orthogonal information shocks) to $\boldsymbol{\varepsilon_t}$ (orthogonal information shocks). Usually, the constraint that the contemporaneous causal structures among variables of interest $(y_{1t}, y_{2t}, \dots, y_{kt})$ should be acyclic is imposed. This implies that $\boldsymbol{A_0}$ is lower triangular (Moneta et al., 2013). In the following section, we will summarize a data-based method to detect the causal structure among the variables in the vector $\boldsymbol{y_t}$, instead of treating such a structure as *a priori* determined. Besides this assumption, the non-normality of the innovation terms is also needed in order to make full use of higher-order statistics of the variables.

The Innovation Accounting Techniques

Innovation accounting techniques serve as useful tools to depict the dynamic interaction among variables. One such approach is the impulse response function (IRF), which describes how every series in the system responds to a one-time-only shock in each series. However, considering the case studied in the present paper, a better summary of the moving average representation (equation (4)) is the Forecast Error Variance Decompositions (FEVD). FEVD assesses the relative importance of each series (wheat, sorghum, and millet prices and conflict events) on each other at different horizons (distances into the future).The premise of implementing the innovation accounting methods above is orthogonal error covariance. Swanson and Granger (1997) point out that FEVD can only be easily understood regarding to the orthogonalized innovations. To obtain orthogonal innovations, early studies apply a Cholesky factorization to the contemporaneous innovation covariance matrix. Unfortunately, different orderings lead to different conclusions on the innovation accounting analysis (Bessler, 1984). An alternative, Bernanke Decomposition approach (Bernanke, 1986) is employed in this study, which relaxes the just-identified structure assumption for the VAR residuals. To discover the causal structure among the four variables in contemporaneous time, directed acyclic graphs (DAGs), with the linear non-Gaussian acyclic model (LiNGAM) search algorithm are used.

[3] Note that the exogenous variables (seasonal dummy variables) are excluded from this equation (4), suggested by Hsiao-search method when we specify the SVAR model.

3.2. Linear Non-Gaussian Acyclic Model (LiNGAM)

A contemporaneous causal structure reveals the joint distribution of the variables observed as well as measures and forecasts the consequence of drivers (Shimizu et al., 2006). Several search algorithms have been used by contemporary researchers: PC algorithm (Spirtes et al., 2000), Greedy Equivalence Search (GES) algorithm (Chickering, 2003), Linear Non-Gaussian Acyclic Model (LiNGAM) algorithm (Shimizu et al., 2006), etc. PC algorithm has been widely used and it assumes Gaussian data in tests of conditional independence. Consequently, it may not be able to identify a unique matrix $\boldsymbol{A_0}$. GES algorithm relies on variance-covariance to attempt a structural identification of $\boldsymbol{A_0}$, leading again to a plethora of observationally equivalent structures (alternative $\boldsymbol{A_0}$ matrices which cannot be distinguished from one another based on the data). Moreover, the assumption of the Gaussian distributed innovations is usually not the case in most empirical studies (Moneta et al., 2013).

In this paper, we utilize Independent Component Analysis (ICA)-based LiNGAM to discover the causal structure under the assumption behind model in equation (4) – no hidden confounders and reduced form innovation terms with non-Gaussian distributions (Shimizu et al., 2006).[4] The model is presented as follows (following Shimizu et al., 2006):

$$u_i = \sum_{k(j)<k(i)} b_{ij} u_j + e_i + c_i \;, \tag{5}$$

where $u_i, i \in \{1,2, \dots, p\}$ denotes the observed innovations from an estimated form of equation (4), which can be organized in a causal order $k(i)$. That is, only the earlier variable could affect the later variable, not vice versa. Coefficient b_{ij} summarizes the causal effect from variable u_j to u_i , e_i represents the non-Gaussian, mutually independent innovations and c_i is constant. The relationship in equation (5) can be graphically reflected by a directed acyclic graph (DAG) with vertices u_i and edges – non-zero b_{ij}.

Removing the mean of each variable u_i, then the equation (5) can be transformed into the matrix representation:

$$\boldsymbol{u} = \boldsymbol{B}\boldsymbol{u} + \boldsymbol{e} \tag{6}$$

Where $\boldsymbol{B}$ represents the coefficient matrix, which could be permutated to strict lower triangular form according to the causal ordering $k(i)$. Denote $\boldsymbol{A} = (\boldsymbol{I} - \boldsymbol{B})^{-1}$, then

[4] In fact, LiNGAM is mainly for the continuous-valued data (Shimizu et al., 2006). Even though the values in the series of conflict events range as integers from 0 to 154, they cover many different values. Thus, still we can manipulate LiNGAM.

$$\boldsymbol{u} = \boldsymbol{A}\boldsymbol{e} \tag{7}$$

Where $\boldsymbol{A}$ could also be permutated to lower triangular form.[5]

Independent component analysis (ICA) (Hyvärinen et al., 2004), a technique of uncovering non-Gaussian hidden factors, plays a crucial role in LiNGAM. Following Shimizu (2014), ICA can be expressed as:

$$\boldsymbol{u} = \boldsymbol{A}\boldsymbol{s} \tag{8}$$

Where $\boldsymbol{u}$ and $\boldsymbol{s}$ stand for the observed variables ($\boldsymbol{u}$) and the independent components (information shocks $\boldsymbol{s}$). The elements s_j in $\boldsymbol{s}$ are mutually independent latent variables, with non-Gaussian distributions (the independent components).

As a result, the equation (7) symbolizes the linear independent component analysis (ICA) model (8). ICA makes use of non-Gaussianity to estimate the mixing matrix $\boldsymbol{A}$ given the linear and ample observed data $\boldsymbol{u}$. Moreover, the fix-point algorithms proposed by Hyvärinen (1999) can be applied to estimate $\boldsymbol{A}$ efficiently, such as 'FastICA' algorithm (Moneta et al., 2013). After obtaining the estimated matrix $\boldsymbol{A}$, we can calculate the coefficient matrix $\boldsymbol{B}$. Nonetheless, the order and scaling of the independent components are left to be determined. The detailed operations can be referred to Shimizu, et al. (2006) and Shimizu (2014). Finally, knowing the vertex and causal order, we can draw a complete DAG. LiNGAM is an attractive algorithm for the present study since it accommodates non-Gaussian innovations, allowing us to identify complete causal structure without prior knowledge. As will be demonstrated below, our data are highly non-Gaussian.

4. Data

For this research we use data on commodity prices and conflict events of Sudan from January 2001 to December 2012. The information on wheat, sorghum and millet prices is collected from Global Information and Early Warning System (GIEWS) Food Price Data and Analysis Tool, Food and Agricultural Organization (FAO) of the United Nations. The GIEWS database reports monthly prices of these commodities from the Khartoum port.

The data for the number of conflict events are obtained from Armed Conflict Location & Event Dataset (ACLED) (Raleigh et al., 2010) over the same period. The ACLED database provides disaggregated conflict analysis and crisis in African countries. It collects comprehensive real-time data on political violence in Africa, including the

[5] Different from "strict lower triangular matrix", some diagonal elements could be zero in low triangular matrix.

exact dates and locations of conflict events, the types of event, the groups involved, fatalities, and changes in territorial control. The data statistics description is given in Table 1. To present a more direct visual understanding, plots of the time series data are displayed in Figure 1. A common characteristic the price of wheat, sorghum, and millet share is an upward trend, which may indicate that they are not stable. The number of conflict events in Sudan seems stable, except for a peak between 2011 and 2012.

Table 1. Summary Statistics on Wheat Price, Sorghum Price, Millet Price and Conflict Events in Sudan; 2001.1 – 2012.12 Monthly Data.

Series	Units	Mean	Standard Deviation	Coefficient of Variation
Wheat Price	Sudanese Pound/90kg	98.466	38.109	0.387
Sorghum Price	Sudanese Pound/90kg	74.377	40.418	0.543
Millet Price	Sudanese Pound/90kg	108.250	62.375	0.576
Conflict Events	Number of Conflicts/Month	22.868	21.084	0.922

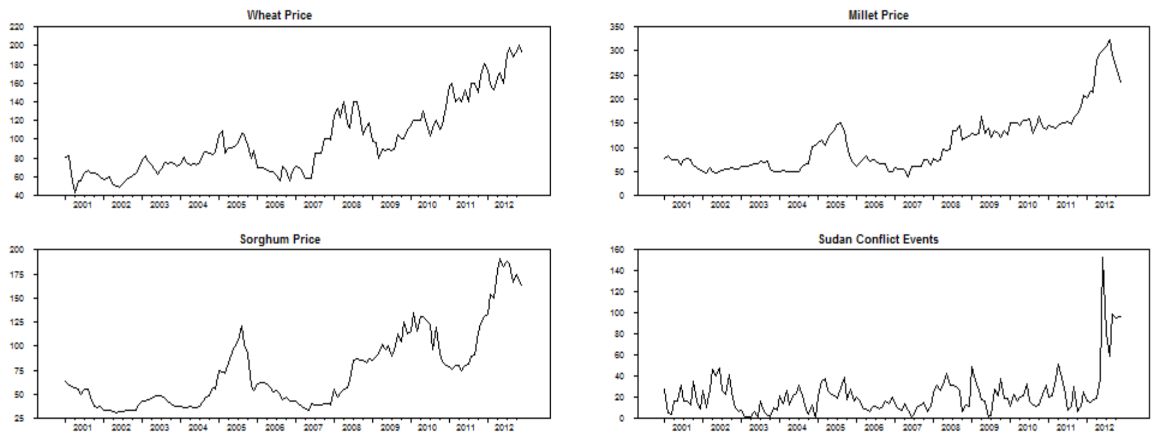

Figure 1. Plots of Wheat Price, Sorghum Price, Millet Price and Conflict Events in Sudan; 2001 - 2012, Monthly Data.

5. Results

5.1. Stationarity

VAR model is applied to describe the dynamic interrelationship among stationary variables. That is, any particular variable measured over time should be tied to its mean. Otherwise, it will lead spurious regression if we fail to balance the series' order on the both sides of the equation (Bessler and Kling, 1984). Therefore, the first and necessary step in time-series analysis should be to examine if the levels of each series are stationary. One standard unit-root test procedure — Augmented Dickey-Fuller (ADF) test is applied to check whether the four series (wheat price, sorghum price, millet price, and conflict events in Sudan) are stationary or not. The null hypothesis is that there exists a unit root (nonstationary). ADF test statistics suggest that three commodity price series are I(1) at the 5% significance level, while the conflict events in Sudan is I(0). They are consistent with the visual judgment suggested by Figure 1.

5.2. Model Specification & Structure Test

The optimal lag length in each equation is chosen by the standard: the Hannan and Quinn measure with the Hsiao-Search method. Regression Analysis of Time Series (RATS) software is implemented for the estimation of SVAR model. However, according to the plots of the innovations from the estimation of SVAR, we find some jumps in the conflict events series between 2011 and 2012 (which indicates potential heterogeneity). Therefore, a structural breakpoint during this period (January 2001 – December 2012) is possible, which may be due to the regime changes occurring in Sudan (July 2011).In order to test this hypothesis, the Bai and Perron (1998, 2003) procedures are applied. As a result, the "conflict events" series suggest a structural break in September, 2011, where we also observe a peak in the corresponding innovation series. Additionally, the other three series do not indicate the necessity of any breakpoints. Interestingly, the 95% confidence interval provided by the Bai-Perron test ranges from July 2011 to October 2011, which is consistent with regime changes in Sudan[6].

5.3. Estimation Results of SVAR

With the same techniques (Hsiao search algorithm with H&Q criteria), the optimal lags for each equation are selected; the results are presented in Table 2 to Table 5. Then, we regress the SVAR model again from January 2001 to September 2011, with robust variance-covariance matrix considering the possible heteroskedasticity.[7] The estimation results of the SVAR model specified above are listed in Table 6. According to Table 6, each variable's own one period lag could exert statistically significant and positive effect on itself at the 1% level. Wheat price shows up significantly (5% level) in the millet price equation, whereas it is not the case for the other commodity prices in some other price series. In terms of the relationship between commodity prices and conflict events, only one period lagged wheat price has a significantly positive effect on the number of conflict events in Sudan. These results seem to suggest that wheat price is the most significant in this particular system. We will take advantage of the innovation techniques shown below to depict the dynamic relationship among the variables of interest. The plots of the innovations derived from the SVAR above are presented in Figure 2. Additionally, applying ADF test on these innovations suggests that all the residual series are stationary.

Table 2: Hsiao Search on Specification of Wheat Price

[6] South Sudan seceded from Sudan on July 9, 2011, which is likely to influence the structural of the conflict events time series.

[7] We also estimate the same model from 2001.1 to 2011.7, and from 2001.1 to 2011.10, which were the confidence limits of the 95% level (i.e., the lower and upper boundaries of the confidence interval) suggested by the Bai-Perron test. The results are not reported here but available upon request.

HQ	Constant	Seasonal Dummies	Lags of Wheat Price				Lags of Sorghum Price				Lags of Millet Price				Lags of Conflict Events			
			-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
6.701	X																	
6.974	X	X																
4.600*	X		X															
4.623	X		X	X														
4.610	X		X	X	X													
4.635	X		X	X	X	X												
4.626	X		X				X											
4.653	X		X				X	X										
4.672	X		X				X	X	X									
4.698	X		X				X	X	X	X								
4.622	X		X								X							
4.646	X		X								X	X						
4.668	X		X								X	X	X					
4.655	X		X								X	X	X	X				
4.618	X		X												X			
4.644	X		X												X	X		
4.660	X		X												X	X	X	
4.673	X		X												X	X	X	X

Each row represents an alternative specification of the dynamic representation of wheat price (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet price or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

Table 3: Hsiao Search on Specification of Sorghum Price

HQ	Constant	Seasonal Dummies	Lags of Sorghum Price				Lags of Millet Price				Lags of Wheat Price				Lags of Conflict Events			
			-1	-2	-4	-5	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
6.756	X																	
7.037	X	X																
4.313	X		X															
4.313	X		X	X														
4.290	X		X	X	X													
4.290[8]*	X		X	X	X	X												
4.297	X		X	X	X	X	X											
4.322	X		X	X	X	X	X	X										
4.342	X		X	X	X	X	X	X	X									
4.354	X		X	X	X	X	X	X	X	X								
4.298	X		X	X	X	X					X							
4.325	X		X	X	X	X					X	X						
4.317	X		X	X	X	X					X	X	X					
4.310	X		X	X	X	X					X	X	X	X				
4.314	X		X	X	X	X									X			
4.341	X		X	X	X	X									X	X		
4.337	X		X	X	X	X									X	X	X	
4.364	X		X	X	X	X									X	X	X	X

Each row represents an alternative specification of the dynamic representation of sorghum price (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet prices or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

[8] It is 4.2895 if four digits are kept. Thus, it is the minimum.

Table 4: Hsiao Search on Specification of Millet Price

HQ	Constant	Seasonal Dummies	Lags of Millet Price				Lags of Sorghum Price				Lags of Wheat Price				Lags of Conflict Events			
			-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
7.375	X																	
7.649	X	X																
4.999	X		X															
5.012	X		X	X														
5.036	X		X	X	X													
5.061	X		X	X	X	X												
5.014	X		X				X											
5.020	X		X				X	X										
5.038	X		X				X	X	X									
5.065	X		X				X	X	X	X								
4.979*	X		X								X							
5.005	X		X								X	X						
5.013	X		X								X	X	X					
4.990	X		X								X	X	X	X				
5.005	X		X								X				X			
5.030	X		X								X				X	X		
5.031	X		X								X				X	X	X	
5.048	X		X								X				X	X	X	X

Each row represents an alternative specification of the dynamic representation of millet price (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet price or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

Table 5: Hsiao Search on Specification of Conflict Events

HQ	Constant	Seasonal Dummies	Lags of Conflict Events				Lags of Wheat Price				Lags of Sorghum Price				Lags of Millet Price			
			-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4	-1	-2	-3	-4
4.981	X																	
5.208	X	X																
4.571	X		X															
4.597	X		X	X														
4.617	X		X	X	X													
4.641	X		X	X	X	X												
4.550*	X		X				X											
4.571	X		X				X	X										
4.597	X		X				X	X	X									
4.618	X		X				X	X	X	X								
4.574	X		X				X				X							
4.585	X		X				X				X	X						
4.611	X		X				X				X	X	X					
4.632	X		X				X				X	X	X	X				
4.573	X		X				X								X			
4.600	X		X				X								X	X		
4.625	X		X				X								X	X	X	
4.623	X		X				X								X	X	X	X

Each row represents an alternative specification of the dynamic representation of conflict events (in current time) as a function of a constant only, a constant and 11 seasonal dummy variables, a constant and lags of wheat price, sorghum price, millet price or conflict events. HQ represents Hannan and Quinn criteria. We select that model specification that minimizes HQ. We report only four lags of each variable here, in actuality we search over twelve lags of each. All HQ measures on the unreported lags are higher than metrics shown in the table. An asterisk (*) indicates minimum.

Table 6: Estimate Result on SVAR, 2001.1 – 2011.9 Monthly Data.

Dependent Variable		Variable	Coeff	Std. Error	T-Stat	Signif
Wheat Price (WT)	1	Constant	4.7583	3.0158	1.5778	0.1146
	2	WT{1}	0.9573	0.0367	26.0829	0.0000
Sorghum Price (SOR)		Variable	Coeff	Std.Error	T-Stat	Signif
	1	Constant	3.2379	1.6623	1.9479	0.0514
	2	SOR{1}	0.8265	0.1312	6.2977	0.0000
	3	SOR{2}	0.3812	0.1624	2.3479	0.0189
	4	SOR{3}	-0.0855	0.1946	-0.4393	0.6604
	5	SOR{4}	-0.3291	0.1234	-2.6663	0.0077
	6	SOR{5}	0.1635	0.1080	1.5144	0.1299
Millet Price (MIL)		Variable	Coeff	Std.Error	T-Stat	Signif
	1	Constant	-1.2769	2.6651	-0.4791	0.6319
	2	WT{1}	0.1435	0.0700	2.0503	0.0403
	3	MIL{1}	0.8831	0.0583	15.1602	0.0000
Conflict Events (CE)		Variable	Coeff	Std.Error	T-Stat	Signif
	1	Constant	1.7848	3.2123	0.5556	0.5785
	2	WT{1}	0.0778	0.0387	2.0094	0.0445
	3	CE{1}	0.5444	0.0747	7.2899	0.0000

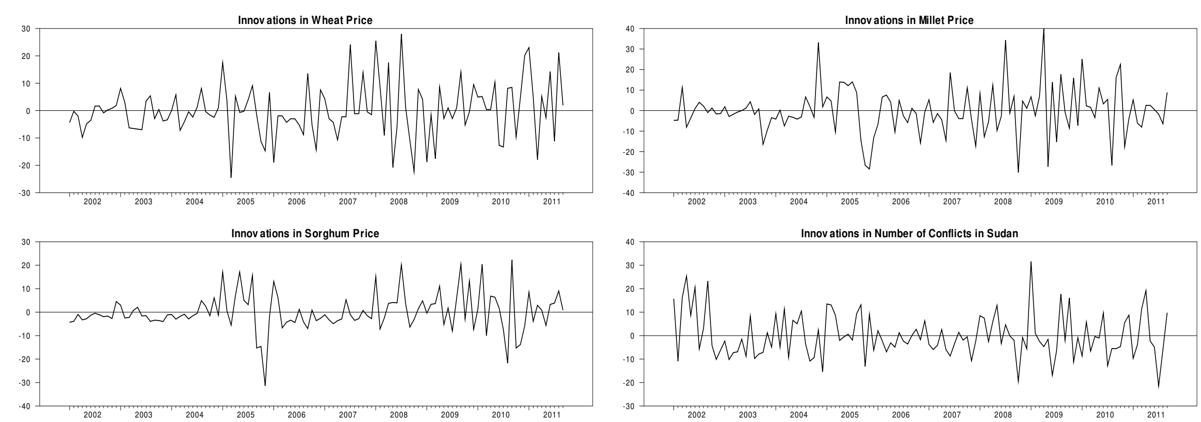

Figure 2. Plots on Innovations from a SVAR on Wheat Price, Sorghum Price, Millet Price and Conflict Events; 2001.1 – 2011.9, Monthly Data.

5.4. Directed Acyclic Graphs (DAGs) Results

DAGs are employed to discover the causal flows on the contemporary innovations from the SVAR (January 2001 – September 2011) above. DAGs are available in the software TETRAD V (Ramsey et al., 2013). We fit the models summarized in Tables

2 – 5 equation by equation using Ordinary Least Squares (OLS) and a system using Seemingly Unrelated Regressions (SUR). The innovations from each procedure are quite similar and most importantly, the graph structures from both OLS and SUR innovations are the same.

5.4.1 Normality Test Result

To decide the specific search algorithm for analyzing our estimated innovations, we investigate if the innovations (errors) follow Gaussian distributions. PC (or GES) algorithm requires that the residuals from the SVAR model are Gaussian distributed (normal distributed), whereas LiNGAM assumes that at most one residual follows Gaussian distribution. Therefore, normality tests including skewness test, kurtosis test, and Jarque-Bera test (Jarque and Bera, 1980, 1987) are executed for each innovation series derived from the SVAR. The Jarque-Bera test statistic is chi-squared distributed with two degrees of freedom under the null hypothesis that the data are normally distributed (i.e., for normal distribution, skewness is 0 and kurtosis is 3, or equivalently the excess kurtosis is 0). We present the test for normality results in Table 7.

From Table 7, we observe that skewness statistics do not exhibit strong evidence of significant asymmetric property (only the innovations of the conflict events reject the null hypothesis at the 1% significance level); the kurtosis statistics indicate peaks for only in sorghum and millet price innovation series at the 1% significance level. Finally, and most importantly, all of the Jarque-Bera test statistics, considering both skewness and kurtosis together, exceed the critical value at the 1% significance level, except the residuals from the wheat price (at the 10% significance level). The normality tests suggest that each innovation series has non-normal distribution, albeit the relatively weak evidence for the non-Gaussian distribution in wheat price innovations. Therefore we use LiNGAM search algorithm to explore the contemporaneous causal structure[9].

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[9] In fact, in the case of unique Gaussian component, the model can still be estimated with LiNGAM given that the exclusive Gaussian part cannot interact with any other components with non-Gaussian distribution (Hyvärinen et al., 2004).

Table 7. Normality Tests for the Innovations, 2001.1 – 2011.9 Monthly Data.

Variables	Skewness[10]	Kurtosis (excess)[11]	Jarque-Bera[12]
	(P-Value)	(P-Value)	(P-Value)
Wheat Price	0.297	0.873	5.431
	(0.196)	(0.061)	(0.066)
Sorghum Price	0.070	2.872	40.294
	(0.761)	(0.000)	(0.000)
Millet Price	0.341	1.927	20.380
	(0.137)	(0.000)	(0.000)
Conflict Events	0.721	0.745	12.832
	(0.002)	(0.111)	(0.002)

5.4.2 LiNGAM Algorithm Result

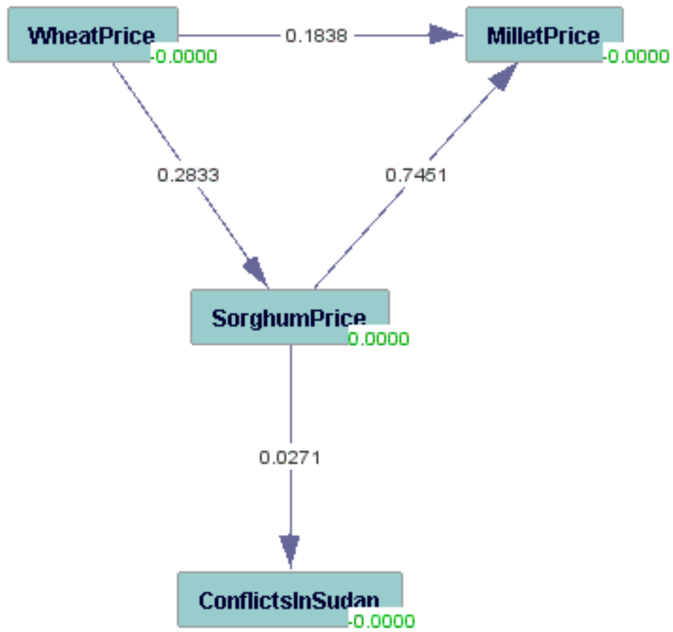
The DAG found summarizing the causal structure for the four variables is displayed in Figure 3.[13] New information stemming from commodity market has an effect on conflict situation in Sudan: the innovations of wheat price could affect innovations in conflict events through sorghum price. Figure 3 also indicates that wheat price is exogenous. Wheat price will influence the innovations in other cereal prices and conflict events in Sudan directly or indirectly, indicating that wheat market is the dominant market. In addition, among the three commodity prices, directed edges (information flows) are also observed from wheat price to millet price and from sorghum price to millet price. The positive relationship is given on each arrow, indicating that cereals are substitutes.

[10] Skewness test is a test of symmetry of the probability distribution of a random variable (the null hypothesis is skewness: 0).

[11] Krutosis test is a test of peakedness of the probability distribution of a random variable (the null hypothesis is kurtosis = 3 or excess kurtosis = 0).

[12] Jarque-Bera test is a normality test of innovations, taking into account of both skewness and kurtosis. Details can refer to Jarque and Bera (1980, 1987).

[13] The graph structure is found using LiNGAM algorithm found on the Carnegie Mellon, Department of Philosophy, TETRAD homepage: http:///www.phil.cmu.edu/projects/tetrad



LiNGAM

Figure 3. Pattern of Causal Flow among Innovations in Wheat Price, Sorghum Price, Millet Price and Conflict Events Based on LiNGAM, SVAR.

5.5. Forecast Error Variance Decompositions (FEVD)

With the contemporary causal relationships displayed above (Figure 3), we perform Bernanke factorization (see Estima's description of this software procedure embedded in RATS (Doan, 2010)). The corresponding FEVD results are shown in Table 8. The uncertainty in each series at horizons 0, 1, 2 and 12 months ahead is measured as the column labeled "Standard Error". This measure is accounted for by innovations in each series. We label each series' contribution under the columns headed by the label "Due To". The sum of entries in any row is 100 (allowing rounding errors). For example, looking ahead 12 months, all of the uncertainty in Conflict Events is accounted for by variation in Conflict (87.215%), Wheat Price (12.745%), Sorghum Price (0.040%), and Millet Price (0.000%). So wheat price shocks account for part of the uncertainty in Conflict Events at the 12-month horizon.

Table 8. Percentage of Forecast Uncertainty Accounted for by Innovations from a SVAR in Each Series at Horizons 0, 1, 2, and 12 months ahead.

Horizon (Months Ahead)	Standard Error	Due to: Wheat Price	Due to: Sorghum Price	Due to: Millet Price	Due to: Conflict Events
	(Wheat Price)				
0	9.708	100.000	0.000	0.000	0.000
1	13.439	100.000	0.000	0.000	0.000
2	16.116	100.000	0.000	0.000	0.000
12	27.656	100.000	0.000	0.000	0.000
	(Sorghum Price)				
0	7.880	12.181	87.819	0.000	0.000
1	10.223	12.181	87.819	0.000	0.000
2	13.223	12.181	87.819	0.000	0.000
12	24.599	12.181	87.819	0.000	0.000
	(Millet Price)				
0	11.581	10.958	22.575	66.467	0.000
1	15.814	15.006	21.549	63.445	0.000
2	18.803	19.336	20.451	60.213	0.000
12	33.712	54.143	11.626	34.231	0.000
	(Conflict Events)				
0	9.345	0.006	0.046	0.000	99.948
1	10.670	0.561	0.045	0.000	99.394
2	11.084	1.608	0.045	0.000	98.347
12	11.926	12.745	0.040	0.000	87.215

The uncertainty in each series at horizons 0, 1, 2 and 12 months ahead is measured as the column labeled "Standard Error". This measure is accounted for by innovations in each series. We label each series' contribution under the columns headed by the label "Due To". The sum of entries in any row is 100 (allowing rounding errors). For example, looking ahead 12 months, all of the uncertainty in Conflict Events is accounted for by variation in Conflict Events 87.215%, Wheat Price, 12.745%, Sorghum Price, 0.040% and Millet Price, 0.000%. So Wheat Price shocks account for part of the uncertainty in Conflict Events at the 12-month horizon.

Forecast error variance decomposition (FEVD) illustrates how much of the variation in one variable at horizon $t + s$ can be accounted by the innovations in each variable at horizon t. Due to the space, we only present the FEVD at horizon 0 (contemporaneous time), 1, 2, 12 months ahead (i.e., $s = 0, 1, 2, 12$). Generally, within a short period (e.g., 0, 1 or 2 months), each variable can be almost explained by the shocks from its own history, such as wheat price (100%), sorghum price (87.819%), millet price (66.467%), and conflict events (99.948%) in contemporaneous time. However, moving to a longer run (12 months), other variables play a more important role in explaining the variation in their uncertainty. For instance, wheat price explains as much as 54.143% of the price variation in millet at the 12-month horizon, which is much higher than the portion it explains in contemporaneous time (10.958%).

Specifically, wheat is exogenous throughout the12 month horizon, since 100% of price volatility can be accounted by innovations in its own market, regardless of horizons. Relatively, sorghum is less exogenous, in that around 12% of price volatility is explained by innovations in the wheat market. In terms of millet, approximately two thirds of its price volatility is attributed to information arising in wheat and sorghum markets. At the horizon of 12 months, wheat will account for majority (more than half) of the volatility in millet price. The volatility of conflict events in Sudan is primarily explained by itself and wheat price (volatility of sorghum price can explain a very small part of conflict uncertainty, around 0.045%). Moreover, wheat price will display a greater influence on the incidence of conflict events in Sudan as the horizon increases. In sum, the interaction between commodity prices and conflict centers on the interface between wheat price and conflict events in Sudan.[14]

6. Conclusion and Discussion

In this paper, we attempt to discover the interaction among three major cereal prices (wheat, sorghum, and millet) and the onset of conflict events in Sudan, with Structure Vector Autoregression (SVAR). Normality tests applied to informational innovations suggest that the Linear Non-Gaussian Acyclic Model (LiNGAM) can be executed to identify contemporaneous causal structures. The combination of these methods enables us to identify the dynamic interaction among three cereal markets and conflict events. Specifically, the Directed Acyclic Graphs (DAGs) and the innovation accounting techniques (FEVD) suggest that the only linkage between commodity prices and conflict events is the shocks from the wheat market on conflict levels, through the sorghum market. This impact persists for almost two years, even though it decreases over time. Interestingly, as well, we find no feedback from conflict to commodity prices.

The cereal consumption patterns in Sudan may provide a plausible explanation of the causal path uncovered here. Historically sorghum has been the most popular staple food of Sudan. In recent years, consumer preferences, especially in urban and peri-urban areas have shifted to wheat (Abdelrahman, 1998; Mustafa et al., 2013; Jayne et al., 2010). In the absence of proportional increase in production of wheat, imports have been the primary means of meeting this access demand of wheat. Consequently, the net price of wheat has also increased. Our empirical results of contemporaneous effects show the consequences of this phenomenon. We find that rising wheat price

[14] Results from Vector Error Correction Model (VECM) are consistent with SVAR that cereal prices do move conflict, while VECM indicates millet price is the driver of conflict instead of wheat price. Perhaps the different results based on different models are due to our modest sample size (144 observations).

causes sorghum price to increase (perhaps due to the weak substitution effects). Our graphical representation illustrates that the increase in the cereal prices causes a surge of conflict outbreaks. In addition, structural analysis of the data (January 2001 – December 2012) suggests a potential breakpoint in September 2011. This coincides with the regime change as Sudan after July 2011 was separated from its southern part.

Considering these results, we offer some policy perspectives and suggestions. As imported commodities such as wheat obtains more popularity in Africa, the concern regarding self-sufficiency is often disregarded on free market and trade grounds. However, policy makers should not ignore that often times African countries lack conditions necessary for such an environment (Letiche, 2010). Policies including subsidy and price regulation may help lower the onset of conflict events to some extent. Programs enhancing domestic production of wheat (such as introducing advanced technology) are possibly a more sustainable solution. As Mustafa et al. (2013) point out, “Wheat production has consistently been supported by government interventions either through subsidized inputs or price setting, however, it rarely exceeds 20 percent of the domestic requirement (some 1.8 million MT) and the remaining 80 percent is imported (FAO/WFP, 2011).” If high food prices act as a catalyst for conflict, lowering or keeping reasonable food prices and supply with effective policy could reduce the incidence of conflict and stabilize countries. A caveat has to be made here. Despite the multifaceted and complex links between conflict and commodity prices, we cannot conclude that one is the other’s necessary or sufficient condition, taking into consideration many other potential factors. Still, our results suggest that cereal prices play a vital role in conflict onset. Moreover, in order to promote peace-building and to mitigate conflict, controlling wheat price may have an effect in the Sudanese context.

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