The threat of oil market turmoils to food security in Sub-Sahara Africa

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Abstract

While the causal relationship between different types of oil shocks and food prices in the US and other developed countries has been extensively studied, the inter-dynamics between global oil market turmoils and food prices in Sub-Saharan Africa (SSA) remain unclear. This gap in the literature is particularly striking as populations in developing countries are much more vulnerable to food crises than those in developed countries. In this paper we use structural vector autoregressive (SVAR) models to investigate the impacts of global oil market shocks on local corn prices in several SSA countries. We estimate the structural shocks through independent component analysis, which allows for a more agnostic identification compared with conventional methods. Our key findings are that unlike US or global corn markets, African corn markets are much less sensitive to the impacts of oil-specific demand shocks, instead, disruptions in global oil supply can lead to an increase in food prices in several markets. Countries suffering from oil-supply shocks have neither strategic or natural oil reserves to buffer import shortages, nor efficient oil distribution systems that translate into food prices through higher transport costs. We show that a large share of corn price surges in 2011 and 2012 can be attributed to oil-supply shortages caused by the Libyan revolution and the oil embargo against Iran. Conversely, the shale oil boom in the US and oil production expansion in the Middle East exerted downward pressures on corn prices in three African countries in 2014/15. Forecast scenarios reveal the potential threat to corn prices in Africa from the political tensions between the US and Iran, as well as the recent oil-price war between Saudi Arabia and Russia.

Keywords: Oil shocks, agricultural markets, SVAR, Sub-Sahara Africa, food security

1 Introduction

Since the early 2000s, biofuel production has transformed agricultural commodities into energy carriers by allowing their use as feedstocks for ethanol and biodiesel. This has enabled the substitution of fuel with food, adding a new level of complexity to the traditional use of crude oil derivatives as inputs for the farming, transporting and processing of agricultural products. Since then, fuel has not only been an input but also an output of agricultural production and a novel transmission channel through which crude oil prices move with food prices in industrialized countries (Abbott et al., 2011; Serra and Zilberman, 2013). However, for developing countries where technological progress is lagging behind and biofuels are not yet available, the link between crude oil and food is not well understood (Nazlioglu and Soytas, 2011). More specifically, it remains unclear whether and how local food prices are related to global oil market dynamics, or if any existing co-movement of oil and food prices is merely determined by underlying economic demand. Consequently, policies based on an understanding of global oil and food dynamics are perhaps misguided and may not be helpful in mitigating abrupt food price movements and food price crises.

At the same time, food price swings have probably the most pervasive and far-reaching impacts on livelihoods in low-income countries. At present, some 820 million people are undernourished (FAO et al., 2019) and 736 million people live in extreme poverty, the vast majority of them in non-industrialized countries (The World Bank, 2020). SSA is a particularly vulnerable region, where 43% of the population still lives on less than 1.90 USD/day (The World Bank, 2020). In many regions of SSA, the undernourishment rate is higher than 25% and has even been rising since 2015 (FAO et al., 2019). Unlike in higher-income countries, where the food industry is able to cushion price peaks in agricultural commodities and food expenditures account for only a small proportion of living expenses, people in SSA are extremely vulnerable to price jumps in agricultural markets as they often spend large fractions of their income on food. Consequently, understanding the sources of price swings as well as the pertinent transmission channels in agricultural markets is essential to successful food and nutritional policies.

In this paper, we investigate the effects of global oil market shocks on local corn prices in a sample of SSA countries. We use SVAR models, building upon the oil market model of Kilian (2009) to identify three independent sources of oil market turmoils: oil-supply shocks, aggregated-demand shocks and oil-specific demand shocks. The model specification allows us to classify the African corn markets into three groups, (i) markets that are particularly threatened by global crude oil shocks, (ii) markets that are not linked at all to the global oil price dynamics, and (iii) markets where the co-movement of oil and food prices is determined by economic demand. Conditional on the respective link between global oil shocks and the domestic corn market, we propose policy strategies to stabilize local SSA food prices. Furthermore, we show for the first time that disruptions in global oil supply can lead to substantial surges in corn prices in Africa (e.g. during the Libyan production shortfall in 2011 and sanctions against Iran in 2012), and provide novel insights into the impending risks of food price crises in SSA resulting from future oil market shocks.

We contribute to the existing literature in several directions. Most analyses of food markets rely on reduced form vector autoregressive (VAR) or vector error correction model (VECM) specifications. Notably, few authors have overcome the lack of theoretical interpretability of reduced form VARs by means of SVAR specifications. The results of such studies show that crude oil (demand) shocks are an important source of price swings in US or global corn markets, in both the short and long term (McPhail et al., 2012; Hausman et al., 2012; Wang and McPhail, 2014). However, developing countries are characterized by different market transmissions due to imperfect competition between producers and retailers, as well as imperfect substitution between imported and domestic products (Chakravorty et al., 2019; Dillon and Barrett, 2015). Thus, the responsiveness of food markets to oil markets is likely to depend on the development status of the economy (Nazlioglu and Soytas, 2011). Furthermore, SSA is divided into net energy importers and exporters, which could add to the heterogeneity of oil shock impacts on food markets (Wang et al., 2013). Overall, the contribution of oil-supply, aggregated-demand and oil-specific demand shocks to domestic corn markets in SSA countries remains unclear and has not yet been addressed empirically. Finally, a critical discourse has recently flared up about techniques to identify oil shocks, since conventional identification approaches (e.g. recursive causation schemes (Sims, 1980) and sign and elasticity constraints (Kilian and Murphy, 2012)) crucially underestimate supply-side effects by construction (Baumeister and Hamilton, 2019a,b; Kilian, 2019; Kilian and Zhou, 2019). We provide a structural analysis based on a new and much less restrictive data-driven approach, namely independent component analysis (ICA) (Moneta et al., 2013; Lanne et al., 2017)[1], which has already proven useful in disentangling oil market dynamics (Herwartz and Plödt, 2016).

Our main results are threefold. First, SSA corn markets react differently to oil shocks compared with world markets. Unlike previous studies, we find that oil-supply shocks explain food prices more than oil-specific demand shocks. Second, SSA food markets are highly heterogeneous in their price responses to global oil shocks. We can clearly differentiate between food markets, that are affected by oil market turmoils and countries where food prices appear to be relatively independent from crude oil. Third, transport costs are the main channel for global oil-supply disruptions to transmit to local corn prices. Hence, regardless of the direction, neither net food producers nor net food buyers benefit from oil-supply shock induced price changes since they merely reflect changes in transport costs. Promising policies should build up strategic oil inventories to buffer fluctuations in oil supply, or promote efficient import and distribution systems, which are major bottlenecks in the fuel supply chains.

In section 2, we provide an overview of how food security relates to food markets in developing countries, jointly with a condensed review of the literature concerning the crude oil-food price nexus.

[1]Under a non-Gaussian distribution, independent components can be uniquely identified (Comon, 1994). The assumption of non-Gaussianity might be reasonable for economic data (e.g. price series) in general, allowing for instance leptokurtic distributions (see e.g., Chib and Ramamurthy, 2014; Cúrdia et al., 2014).

Section 3 illustrates our identification strategy and data. Subsequently, we present our findings from the baseline estimation as well as case study analysis and forecasts on recent events as well as hypothetical scenarios. We place the results in a theoretical context, derive policy implications and relate the findings to the existing literature in section 4, before we summarize and conclude in section 5. Appendix A comprises further information on the oil-food price nexus. Appendix B provides a detailed description of the identification strategy by means of ICA and Appendices C and D contain additional empirical results.

2 Food insecurity in Sub-Saharan Africa and the global oil market

The adverse effects of oil shocks on food security in SSA are not yet well understood. In this section, we briefly revisit the double-edged relationship between food security and food prices. Moreover, we provide an inventory of possible transmission channels between the oil price and food markets and assess their potential applicability to SSA markets. Finally, we review key empirical findings of the oil-food nexus literature.

2.1 Food insecurity in Sub-Saharan Africa

Globally, food security has substantially improved over the past decade.[2] One widely used measure of food insecurity is the prevalence of undernourishment (PoU) indicator, which has fallen from 14.5% in 2005 to 10.8% in 2018. Despite this long-term progress, FAO et al. (2019) conclude that food insecurity has been increasing since 2015 and much of the global increase in hunger is due to rising food insecurity in SSA. At present, 22 out of the 30 most food insecure countries are located in SSA (FAO, 2020), while 56% of people living in extreme poverty are also living in SSA (The World Bank, 2020). On the one hand, extreme poverty and hunger are often immediate results of conflicts, droughts or other shocks, which primarily affect the *availability* of food. On the other hand, much of the long-term food insecurity is due to the lack of *access* to food, mostly related to the functioning of markets and the food distribution system. Needless to say, price swings may lead to sudden disruptions in *access* to food, including in the short term. Moreover, the *stability* of food consumption is crucial for ensuring the long-term supply of adequate amounts of food to individuals

[2] The Food and Agricultural Organization of the United Nations (FAO) defines food security as *"a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life"*. Food insecurity is the lack thereof. The definition implies four dimensions of food security: (i) *availability* (ii), *access*, (iii) *utilization* and (iv) *stability* of food consumption (FAO et al., 2019).

and it is also reliant on food markets. As food security is usually an issue in poor households who dedicate large shares of disposable income to food purchases, higher food prices are often associated with deteriorating food security. However, since the majority of the world's poor also earn their incomes from agriculture - as either smallholder farmers or farm workers - higher food prices could lead to improved rural incomes and wages (Swinnen and Squicciarini, 2012). Therefore, the net impact of food price surges on food security - such as the food price crisis of 2007/08 - depends on how many of the world's poor are net food consumers and how many are net producers.

In line with the previous considerations, empirical work on the benefits of shifting levels of food prices in SSA has found mixed results. For instance, Ivanic and Martin (2008), De Hoyos and Medvedev (2009) and Arndt et al. (2008) find that higher food prices induced dramatic increases in global and SSA undernourishment during the 2007/08 food crisis. By contrast, Headey et al. (2011) and Verpoorten et al. (2013) find that higher food prices have led to substantial improvements of food security among the global poor. Such starkly contradicting results could be due to the fact that the direction and extent of the impact of food price shocks on food security is strongly dependent on the individual context. Thus, understanding asymmetric dynamics of food price developments and their underlying determinants holds paramount importance. This implies that a joint analysis of the determinants of increases and decreases in food prices can help to explain the basis of price formation in food markets and thus reduce the associated risks.

2.2 Global oil shocks and local food prices

One of the sources of both sustained surges and declines of food prices as well as increased uncertainty and instability of food security is movements in crude oil prices, particularly after the emergence of biofuel production in the mid-2000s (Tyner and Taheripour, 2007; Baffes and Haniotis, 2010; Serra et al., 2011; Abbott et al., 2011; Busse et al., 2012; Baumeister and Kilian, 2014a; Wang et al., 2014; Du et al., 2011; Nazlioglu et al., 2013; Abdelradi and Serra, 2015; Herwartz and Saucedo, 2020). Biofuels enable the production of fuel from coarse grains and vegetable oils. Thereby crude oil and some agricultural crops become substitutes for fuel production and henceforth the co-movement of these two prices has intensified. Most importantly, the US Energy Policy Act of 2005 induced a considerable expansion of US biofuel production in 2006.[3] The share of US corn harvest used for ethanol production rose from 14% to 40% and persistently changed the long-term relationship between oil and agricultural markets (Carter et al., 2016). Since then, a large body of empirical and

[3]The Energy Policy Act made ethanol produced from corn the only gasoline additive available to US gasoline producers after May 2006.

theoretical literature has examined the price relationships over time and strives to disentangle the direction and magnitude as well as the short- and long-term nature of causal effects.

Figure 1 illustrates the crude oil-food prices nexus from a theoretical perspective. The left-hand side is a stylized representation of the global crude oil market, decomposed into its three underlying source signals or shock series. Although Kilian et al. (2009) show that distinct oil shocks have fundamentally different effects on the dynamics in the oil market, most studies concerned with crude oil-food price relationships neglect the existence of different types of oil shocks. A notable exception is Wang et al. (2014), who examine the effects of underlying oil shock mechanisms on food markets using a structural model. The authors extend the model by Kilian et al. (2009) to include food prices and find that after 2006 food prices are mainly driven by oil-specific demand shocks. More specifically, if higher oil-specific demand increases the oil price, this also affects food prices. By contrast, the pass-through effect of oil-supply shocks to food prices is found to be negligible. For the period prior to 2006, the authors note that the co-movement of oil and food prices has been driven by a prolonged increase in aggregated demand, which generally raises commodity prices.

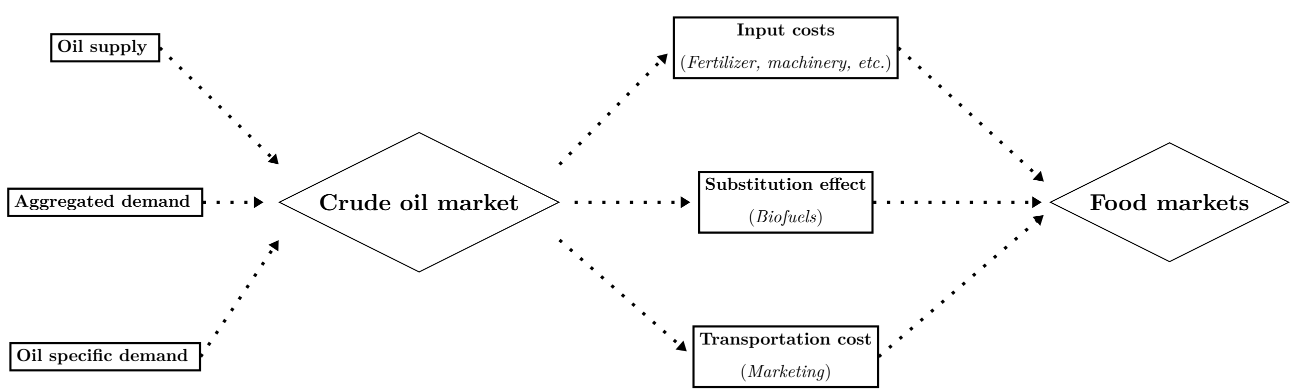

Figure 1: Transmission flow from oil shocks to food prices

The right-hand side of Figure 1 details how oil shocks in turn transmit to local food prices. Based on a careful review of the relevant literature, we encounter a set of three different transmission channels between crude oil and food prices. First, both inorganic fertilizers used on the fields and fuel consumption for machinery as inputs to agricultural production are an integral part of farmers' production costs and thus influence food supply and prices (Dillon and Barrett, 2015; Serra and Zilberman, 2013; Wang et al., 2014). Although input costs constitute a traditional link between energy and food prices, they are generally considered to contribute only marginally to the extent of the co-movement between oil and food prices (Tyner and Taheripour, 2007; Serra and Zilberman, 2013; Kristoufek et al., 2012). Second, the substitution effect associated with the production of biofuel - spurred by blending mandates - leads to oil price changes directly affecting plant-based ethanol and biodiesel prices. The majority of authors argue that the substitution effect channels the lion's share of the co-movement between the prices (Tyner and Taheripour, 2007; Serra and Zilberman, 2013; Kristoufek et al., 2012; Abbott et al., 2011). Third, transportation costs for both farm inputs and marketable output are driven by fuel prices, which in turn are derivatives of crude oil. Transport costs have been shown to be a particularly relevant transmission channel in SSA countries, where production and marketing are largely decentralized and transport absorbs a relatively large share of production and marketing costs compared with in other parts of the world (Dillon and Barrett, 2015).[4]

Serra and Zilberman (2013) evaluate a large body of literature that empirically examines the relationship between crude oil and food prices. The authors conclude that there is a broad consensus in the literature that disturbances in the energy markets are passed to food markets, and increasingly so after the emergence of biofuels. One notable exception is Qiu et al. (2012), who confirm the neutrality of food prices to energy prices in the US based on results from a structural analysis. It is striking that the majority of studies that find evidence of the non-neutrality of food prices are based on world market data or observations from industrialized countries. Evidence from emerging or developing economies is scarce and (if available) tends to find neutrality of food prices to oil markets (e.g. Nazlioglu and Soytas, 2011; Fowowe, 2016). Nazlioglu and Soytas (2011) hypothesize that direct and indirect effects of oil markets on food markets might crucially depend on the stage of development of the country, which is not sufficiently addressed in the relevant literature. Consequently, any understanding of the link between food markets in developing countries and oil markets, based on global dynamics might be fundamentally flawed and lead to misguided policy recommendations.

3 Empirical framework

The analysis in this paper highlights the response of local corn prices in SSA to global oil shocks. Due to the heterogeneity of developing countries, we estimate four-dimensional VARs for each country separately. In the following, we illustrate the empirical model and identification strategy and briefly

[4]Besides these three main transmission channels proposed by most authors, some advocate alternative channels, which we discuss briefly in Appendix A.

present the data.

3.1 Identifying oil shocks via independent components

The econometric model in our analysis is a $(K = 4)$-dimensional VAR of order p of the form

$$\begin{aligned} y_t &= \nu_t + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \\ &= \nu_t + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \mathsf{B}\varepsilon_t, \\ \Leftrightarrow \quad A(L) y_t &= \nu_t + \mathsf{B}\varepsilon_t, \qquad t = 1, ..., T, \end{aligned} \tag{1}$$

where the vector $y_t = (\Delta q_t, x_t, p_t, c_t)$ contains the change in global crude oil production (Δq_t), a measure of real global economic activity (x_t), the real global price of oil (p_t) and country-specific real corn prices (c_t). We adopt the variable selection of Wang et al. (2014), who examine the response of US corn prices to oil shocks. Furthermore, the A_i are $(K \times K)$ coefficient matrices and the u_t are K-dimensional, serially uncorrelated residuals (Lütkepohl, 2005). The model innovations are usually characterized from two perspectives: while zero mean reduced-form residuals u_t, $E(u_t) = 0$, are subject to cross-equation correlation with covariance matrix $\Sigma_u = \mathsf{B}\mathsf{B}'$, structural shocks $\varepsilon_t = \mathsf{B}^{-1} u_t$ are uncorrelated across equations with $E(\varepsilon_t) = 0$ and $\Sigma_\varepsilon = I_K$. Estimating equation (1) by least squares (LS) or maximum likelihood (ML) approaches delivers reduced form errors u_t straightforwardly. By contrast, it is more challenging to identify the structural shocks since the decomposition of the covariance matrix $\Sigma_u = \mathsf{B}\mathsf{B}'$ is not unique.

In recent decades, a large number of strategies have become available to solve the identification problem.[5] In the context of the crude oil-food price nexus, oil shocks have been traditionally identified via short-run restrictions (B is restricted to a lower triangular matrix (Baumeister and Kilian, 2014a; Wang et al., 2013, 2014)). Since exclusion constraints often do not match real-world dynamics, Kilian and Murphy (2012) suggest a more agnostic approach to model crude oil market dynamics and rely on a combination of sign restrictions and elasticity constraints. However, both strategies imply an (almost) zero short-run price elasticity of oil-supply and have therefore been strongly criticized. More specifically, Baumeister and Hamilton (2019a) show that the oil-supply elasticity is actually much stronger than previously assumed and oil-supply shocks have a much stronger contribution to the oil price in general. Both the modeling of oil-supply elasticity and the question of whether the approach of using recursive structures and/or elasticity constraints is still a legitimate identification strategy remain controversial (see e.g. Baumeister and Hamilton, 2019b;

[5] Kilian and Lütkepohl (2017) provide a thorough overview of recent identification techniques.

Kilian, 2019; Kilian and Zhou, 2019). Therefore, we use a novel and more agnostic data-driven approach based on ICA, which requires only a minimum of assumptions for identification.

Identification via independent components builds on distributional assumptions of the structural error terms (i.e. non-Gaussianity), which can be considered as external statistical information. If no more than one independent component of ε_t is Gaussian distributed, the structural matrix B can be uniquely recovered from reduced-form residuals u_t (Comon, 1994).[6] Using a simulation study, Herwartz et al. (2019) demonstrate that identification via independent components is robust to a large variety of distributional and heteroskedastic frameworks. Herwartz and Plödt (2016) show that ICA is a useful method to identify different types of oil shocks, which are in line with the corresponding literature. For details on the exact minimization procedure, we refer to Appendix B and Matteson and Tsay (2017). On the implementation side, we use the `R` packages `steadyICA` (Risk et al., 2015) and `svars` (Lange et al., ming) to determine $\widehat{\mathsf{B}}$ and $\hat{\varepsilon}_t$ and calculate all relevant SVAR statistics, respectively.

3.2 Data

The four-dimensional VAR models comprise the following variables:

Δq_t - log change in average global crude oil production $\times$ 100

x_t - global economic activity index

p_t - log of the real price of crude oil in US Dollars $\times$ 100

c_t - linearly detrended log of the real price of corn in domestic currency $\times$ 100

First, for crude oil production we use the series from the US Energy Information Administration (EIA, 2020), which is defined as the average number of crude oil barrels produced per month. Second, we calculate the real price of oil by deflating the global market price of crude oil Brent in US Dollars from the IMF with the US consumer price index.[7] Third, we use the global economic activity index - available on Kilian's website[8] - which reflects dry cargo shipping rates and is particularly constructed to capture dynamics in industrial commodity markets (Kilian and Zhou, 2018). Fourth, we retrieve the real white corn price series in local currencies from the GIEWS database of the FAO.[9]

[6]In the case of multiple independent Gaussian components, the system lacks full identification, although partial identification of the non-Gaussian components is possible (Maxand, 2019).

[7]https://data.imf.org/.

[8]https://sites.google.com/site/lkilian2019

[9]http://www.fao.org/giews

We choose corn price series to be suitable representatives for food markets in SSA within our oil-food markets model given their importance as both food and cash crops and the potential to produce ethanol from corn. Corn is the most important crop in Africa in terms of both production and consumption. Since 2015, annual production ranged between 75 and 85 million tons, which was more than twice the production of wheat, for instance. We consider corn prices for Chad, Ethiopia, Ghana, Kenya, Mozambique, Nigeria, Tanzania and Zambia, where the price series are available from January 2006 until June 2019, which determine the horizon for our oil-food market model, resulting in $T = 162$ observations. We use retail prices unless only wholesale prices are available. All price series are collected at those food markets that are most important in the respective countries and considered to be representative for their respective domestic market situation. Some of the series contain missing values, which we linearly interpolate.[10] As the world reference price for corn, we use spot prices for yellow corn No. 2 from the Chicago Board of Trade (CBOT).[11] On the implementation side, we estimate the reduced-form VAR models with $p = 3$ lags as suggested by the Akaike information criterion (AIC).

4 Empirical findings

Since the decomposition of the reduced-form covariance matrix $\Sigma_u = \mathsf{B}\mathsf{B}'$ is not unique under normality, at least three out of four structural shock series need to be non-Gaussian to ensure identification. We perform component-wise kurtosis and skewness tests as implemented in the `R` package `normtest` (Gavrilov and Pusev, 2014) on the four estimated shock series for each country. The results displayed in Table 4 in Appendix C indicate excess skewness and kurtosis at least in three out of four shock series for all countries, which is consistent with the findings of Lütkepohl and Netşunajev (2014) and Herwartz and Plödt (2016), who detect that oil shocks tend to be non-Gaussian. Since there is clear evidence of non-Gaussian source signals in the data, the structural shocks are uniquely determined from a statistical perspective.

Nevertheless, a crucial modeling step in statistical identification is the labeling of shocks, since the estimated matrix $\widehat{\mathsf{B}}$ is only unique up to column sign and column permutation. In addition, it is not guaranteed that model-implied effects of independent shocks have an economically

[10]Series for Chad, Kenya and Mozambique each contain one missing observation.

[11]Notably, global markets are dominated by yellow corn, whereas in SSA white corn constitutes the bulk of consumption. However, the two goods are fairly comparable as they constitute important staple foods within their respective food markets. As a robustness check, we also used the corn FOB gulf of Mexico price from the World Bank commodity price database. The results are qualitatively not different.

meaningful interpretation. A common approach to link the independent components with an economic interpretation is to label the columns of $\widehat{\mathsf{B}}$ according to a theory-based sign pattern. The entries in $\widehat{\mathsf{B}}$ correspond to the impact effects of the shocks on the variables in the system. Kilian and Murphy (2012) powerfully argue for a clear pattern of impact directions in the oil market: A negative oil-supply shock ($\varepsilon_s < 0$, i.e., an unexpected shortage of crude oil on global markets) lowers oil production and economic activity and raises the price of oil. A positive aggregated-demand shock ($\varepsilon_{ad} > 0$, i.e., an unexpected increase in global economic activity, which raises the demand for all industrial commodities) has positive effects on all variables on impact. A positive oil specific demand shock ($\varepsilon_{osd} > 0$, i.e. an unexpected higher demand specifically for crude oil) increases oil production and the price of oil and dampens economic activity.[12] Table 1 displays a summary of the expected

Table 1: Theoretical impact directions of global oil shocks on the variables in the empirical model as suggested by Kilian and Murphy (2012). The signs are normalized such that all shocks have a positive impact on the oil price p_t.

	Shocks		
Variable	$\varepsilon_s \rightarrow$	$\varepsilon_{ad} \rightarrow$	$\varepsilon_{osd} \rightarrow$
Δq_t	$-$	$+$	$+$
x_t	$-$	$+$	$-$
p_t	$+$	$+$	$+$
c_t	?	?	?

impact directions of the structural shocks on the variables. Even though it is unclear how shocks from the global crude oil market affect domestic corn prices in SSA, shock labeling is possible due to the unique response of the oil market series. The average impact relation matrix of the eight SSA countries reads as

$$\bar{\widehat{\mathsf{B}}} = \begin{bmatrix} \underset{(22.36)}{-0.56} & \underset{(4.86)}{-0.15} & \underset{(2.97)}{0.19} & \underset{(0.67)}{0.03} \\ \underset{(3.93)}{-5.96} & \underset{(33.54)}{19.57} & \underset{(1.05)}{-1.54} & \underset{(1.53)}{-1.97} \\ \underset{(4.07)}{2.18} & \underset{(3.63)}{2.81} & \underset{(24.45)}{7.03} & \underset{(0.06)}{0.03} \\ \underset{(1.39)}{0.70} & \underset{(1.40)}{0.95} & \underset{(0.60)}{-0.28} & \underset{(12.04)}{8.57} \end{bmatrix}, \tag{2}$$

where the values in parentheses denote the t-ratios.[13] With exception of element $\bar{\widehat{\mathsf{B}}}_{12}$ (i.e the response

[12] The fourth independent component contains other agriculture-specific shocks that are innovations in the corn price series, which cannot be explained by the three oil market shocks. We do not further characterize this shock, and label it as residual shock.

[13] The t-ratios are obtained as the ratio of the group means of the eight different countries and the corresponding

of oil production to an aggregated-demand shock), the sign pattern of the upper left 3×3 matrix is in line with the theoretical impact directions in Table 1. Moreover, the fourth column of $\hat{\bar{\mathsf{B}}}$ shows no significant impact effect on any of the first three variables, leading to the conclusion that the residual shock series has no explanatory content for the oil market variables on average.

In view of the results of the normality tests and the signs of the impact relation matrices, we detect three shock series that are consistent with previous oil market studies, namely oil-supply shock, aggregated-demand shock and oil-specific demand shock. This finding allows us to assess the impacts of the three independent sources of oil market turmoils on local corn markets in SSA to determine policy strategies that stabilize food prices.

4.1 Sub-Sahara African corn markets differ compared with world markets

When discussing the relationship between oil and corn prices in SSA, a natural starting point is to clarify whether African corn markets are driven by the same dynamics as world prices. Figure 1 displays the cumulative per cent growth of SSA corn prices compared with global corn prices since 2006. Shortly after the US biofuel expansion, the global corn price increased by about 75%. Baumeister and Kilian (2014a) and Wang et al. (2014) mainly attribute this price surge to the higher demand for corn due to a substitution effect from fossil-fuel to biofuel. However, at the same time, corn prices in SSA decreased by about 28% on average, which indicates that US policy interventions have not been transmitted to SSA markets. Another point in case is the international food price crisis of 2007/08, during which global corn prices increased by approximately 90%, while SSA corn markets responded more ambivalently and prices only increased by about 50% on average. For instance, the corn price in Nigeria more than doubled between August 2007 and July 2008, whereas the corn price in Zambia only increased by about 20%. Overall, it appears that some SSA countries remain relatively unaffected by global events, which may be due to poor market integration, but it also reflects that domestic food prices in SSA are particularly subject to local shocks, such as extreme weather or civil unrest.

For example, even though the corn price in Mozambique also roughly doubled from August 2007 to June 2008, it had already peaked in May 2006 following an unexpected shortfall in corn production (Figure 11 in Appendix C). During this particular rally, the Mozambican corn price doubled in just three months as opposed to the seven-month surge of the 2007/08 episode. From December 2015 to January 2016, corn prices in Mozambique again increased abruptly by about

standard errors. The vectors in the matrix $\widehat{\mathsf{B}}$ for each country are ordered according to the sign pattern in Table 1.

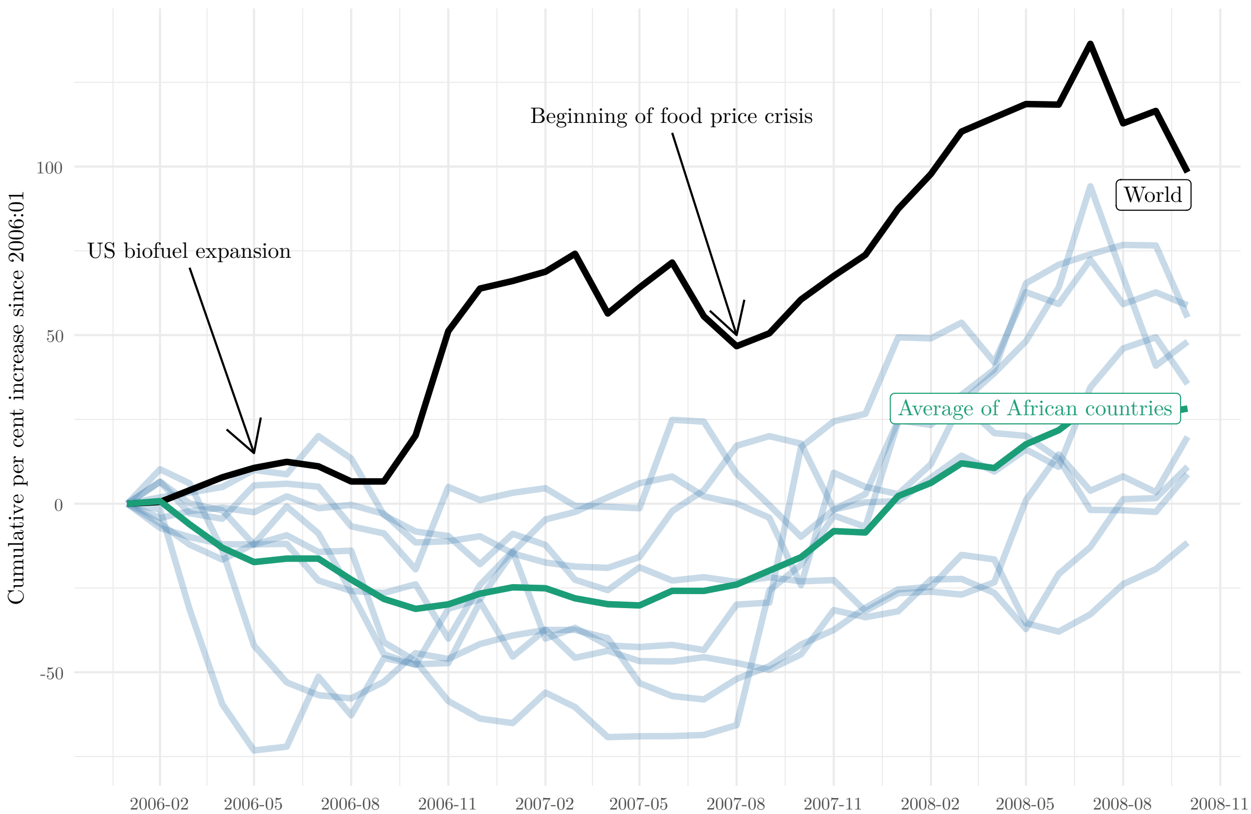

Figure 2: Comparison of cumulative percentage growth in real global corn prices and real African corn prices after the US biofuel mandate in May 2006 and during the international food price crisis in 2007/08. Light blue lines represent the single African countries, and the green line shows the average of SSA countries.

270% after drought periods. Similar patterns can also be observed in Tanzania in 2015 and 2016, when real food prices more than doubled and then rose again by more than 50% after a year of severe droughts. Over the entire period, the international food price crisis appears to be a relatively minor episode in SSA corn prices, which tend to be much more dependent on local events.

We further examine the different movements of African corn market prices compared with world market prices by replacing the corn price in the baseline model in equation 1 with a ratio of local prices and global prices, i.e.

$$y_t = \begin{pmatrix} \Delta q_t \\ x_t \\ p_t \\ c_t^{\text{local/global}} \end{pmatrix},$$

and calculate impulse response functions (IRFs). We construct $c_t^{\text{local/global}}$ as the ratio of price indices by standardizing all real corn price series to a unit value in January 2006.[14]

Table 2: Significant response directions to oil market shocks of African corn prices relative to global corn prices. An increase of local corn prices relative to global corn prices at the 5% (10%) significance level is indicated by '++' ('+'). A decrease of local corn prices relative to global corn prices at the 5% (10%) significance level is indicated by '– –' ('–'). Significance is obtained from bootstrapped IRFs.

	Oil-supply shock	**Aggregated-demand shock**	**Oil-specific demand shock**
Chad	0	0	0
Ethiopia	++	0	0
Ghana	0	–	– –
Kenya	++	0	– –
Mozambique	0	–	0
Nigeria	0	++	–
Tanzania	0	0	–
Zambia	0	–	–

Table 2 provides an overview of statistically significant responses of the ratio $c_t^{\text{local/global}}$ for at least one time point over 30 periods. The signs in the last column of Table 2 suggest that world prices show a stronger positive response to an unexpected higher demand for crude oil than most SSA corn prices, i.e. most SSA corn markets are less sensitive to oil-specific demand shocks. The second column confirms the findings from Figure 2 that African corn markets move rather ambiguously during periods of high economic demand. The first column shows that some SSA corn markets are more sensitive to global oil-supply disruptions than others such that oil-supply shocks could have fundamentally different impacts on SSA food prices compared with global prices. In sum, we note that SSA corn markets are different not only compared with world markets, but also compared with

[14]We do not discuss the issue of shock labeling again, because three out of four series remain the same and the sign pattern in Table 1 still applies for the model with relative prices.

each other, i.e. we find considerable heterogeneity of SSA corn markets regarding their response to global oil shocks. Moreover, we observe that SSA corn markets are relatively less affected by global structural changes than world corn prices.

4.2 The role of oil-supply shocks in Sub-Saharan African corn markets

One way of disentangling the many potential country-specific effects and transmission channels is to take a more disaggregated perspective and investigate the response of corn prices to each oil shock separately. This section examines the link between the global oil-supply and corn markets in SSA using IRFs and forecast error variance decompositions (FEVDs) in conjunction with three case studies. All results are obtained from the baseline model specification in equation (1).

4.2.1 Do unexpected oil production shortfalls cause corn prices in Africa to surge?

Figure 3 depicts the estimated IRFs of the three local corn prices, which show a significant response to an unexpected oil-supply shortage. A comparison with the point estimates of the remaining countries is provided in Figure 12 in Appendix C.

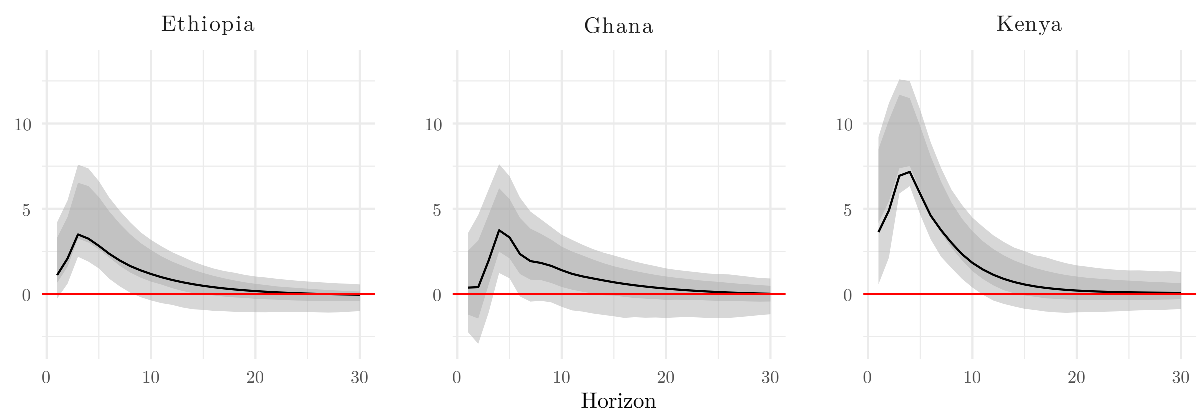

Figure 3: Responses of corn prices in Ethiopia, Ghana and Kenya to an oil-supply shortage joint with 68% and 90% confidence bands obtained from 2000 bootstrap iterations (Hall, 1992).

In Ethiopia, Ghana and Kenya, corn prices sharply rise and reach their maximum after about two months as a reaction to a global oil-supply shortage. The effect is rather persistent and only slowly fades out after about two years (with 68% confidence). Even with 90% confidence, we find a significant response of the corn price to an oil-supply shock in all three countries. In addition, FEVDs displayed in Table 3 reveal that the explanatory content of oil-supply shocks in the variation of corn prices remarkably differs between the countries. We can clearly separate corn markets affected by oil-supply disruptions (Ethiopia, Ghana, Kenya) from corn markets that are largely unaffected by oil-supply shocks (Chad, Nigeria, Tanzania, Zambia). In the first group, in particular, we find that the relative importance of oil-supply shocks increases in the long term and explains a large part of variation in the corn price. In comparison with most African corn markets, global corn markets show an opposite response with a diminishing explanatory content of oil-supply shocks.

Table 3: Contribution of oil-supply shocks to h-step ahead FEVD of local corn prices in SSA markets and world markets.

	$h = 1$	$h = 10$	$h = 30$	$h = \infty$
Chad	1	3.1	4.6	4.6
Ethiopia	1.6	12.9	13	13.1
Ghana	0.2	8.8	8.8	8.8
Kenya	20.9	52.3	47.7	46.5
Mozambique	0.1	3	3.2	3.2
Nigeria	1.1	1	1.5	1.7
Tanzania	0.5	1.6	1.7	1.7
Zambia	3.2	2.3	2.5	2.5
World	8.7	6.2	4.9	4.9

4.2.2 Two case studies of oil-supply disruptions: The Libyan revolution and Iranian nuclear sanctions

Oil-supply disruptions are often regarded to have only minor impacts on oil prices and other commodity prices. The hypothesis is grounded on the assumption that, due to a large number of oil-producing countries, bottlenecks of oil production in one region lead to an increase of oil production in other regions, and a decline of oil production caused by geopolitical events - for example, in the Middle East - accounts for only a small fraction of global oil production (e.g. Hamilton, 2009; Kilian, 2009; Kilian and Murphy, 2012). Regarding food prices, Wang et al. (2014) find that oil-supply shocks have negligible impacts on agricultural commodity prices. As this discrepancy between the recent literature and our results emerges, the impact of oil-supply shocks in SSA warrants a more nuanced level of analysis.

Baumeister and Kilian (2014a) argue that if there is a link between oil-supply shortages and corn price increases there should be some reaction of corn prices during certain historical events. For instance, the authors look at the sharp spike in the oil price in July 1990 when Saddam Hussein invaded Kuwait and find no remarkable increase of agricultural commodity prices in the US. Since the SSA price series do not cover this historical event, we consider two more recent events as case studies to investigate whether the explanatory content of oil-supply shocks in Ethiopia, Ghana and Kenya persists during these time periods. In particular, we examine the effects of the Libyan oil production shortfall in 2011 and the oil embargo against Iran in 2012. Both events are frequently considered as examples of oil price surges with a strong contribution of negative oil-supply shocks (Baumeister and Kilian, 2014b; Kilian and Lee, 2014).[15]

The fall of the eighths largest oil producer in the world

As a consequence of the ongoing civil unrest in Libya and its neighboring countries following the Arab spring, the Libyan revolution began in February 2011. In the following months, the oil production in Libya dropped from 1.48 million barrels per day (mdb) in January 2011 to 0.08 mdb in May 2011. Worldwide, the oil production decreased by about 3.6% during this time period, and it took until December 2011 for global oil production to return to pre-crisis levels. The rather long delay in the recovery of oil supply was mainly caused by internal disputes in the organization of the petroleum exporting countries (OPEC) about the need for an oil production expansion, and hence, it took until June 2011 for Saudi Arabia to increase its oil production from 8.86 mbd to 10 mbd.[16] In addition, the fact that the heavy and sour oil from Saudi Arabia is generally considered to be of lower quality than the light and sweet oil from Libya made it difficult to find buyer countries, which caused further delays in global oil-supply.[17]

Figure 4 shows that immediately after the onset of the Libyan revolution, the corn price in

[15] The authors describe oil price increases during these two time periods as mixtures of oil-supply shocks and oil-specific demand shocks. Nevertheless, both studies base on the oil-supply elasticity constraint by Kilian and Murphy (2012), which leads to an insufficiently small effect of oil-supply shocks by construction (Baumeister and Hamilton, 2019a). This circumstance points to the assumption that the actual share of oil-supply shocks on these price surges is indeed much higher.

[16] Data on the country-specific oil production comes from the US Energy Information Administration.

[17] Light and sweet crude oils have a lower density and lower content of sulfur, which is desirable because they can be processed into gasoline fuels with much less sophisticated mechanisms. Even though, crude oils from different geographic origins are largely interchangeable, they are not perfect substitutes and oil production slumps cannot immediately be absorbed by other producers. More information on crude oil in general can be found - for instance - in World Energy Council (2016).

Kenya almost doubled and reached the maximum during the entire sample in July 2011. In Ethiopia, the corn price increased by about 70% and the corn price in Ghana responded with some delay but increased by about 40% until August 2011. By contrast, corn prices in the remaining African countries increased moderately by about 25% in the same time span, which is comparable with the development of the world market price during this period.

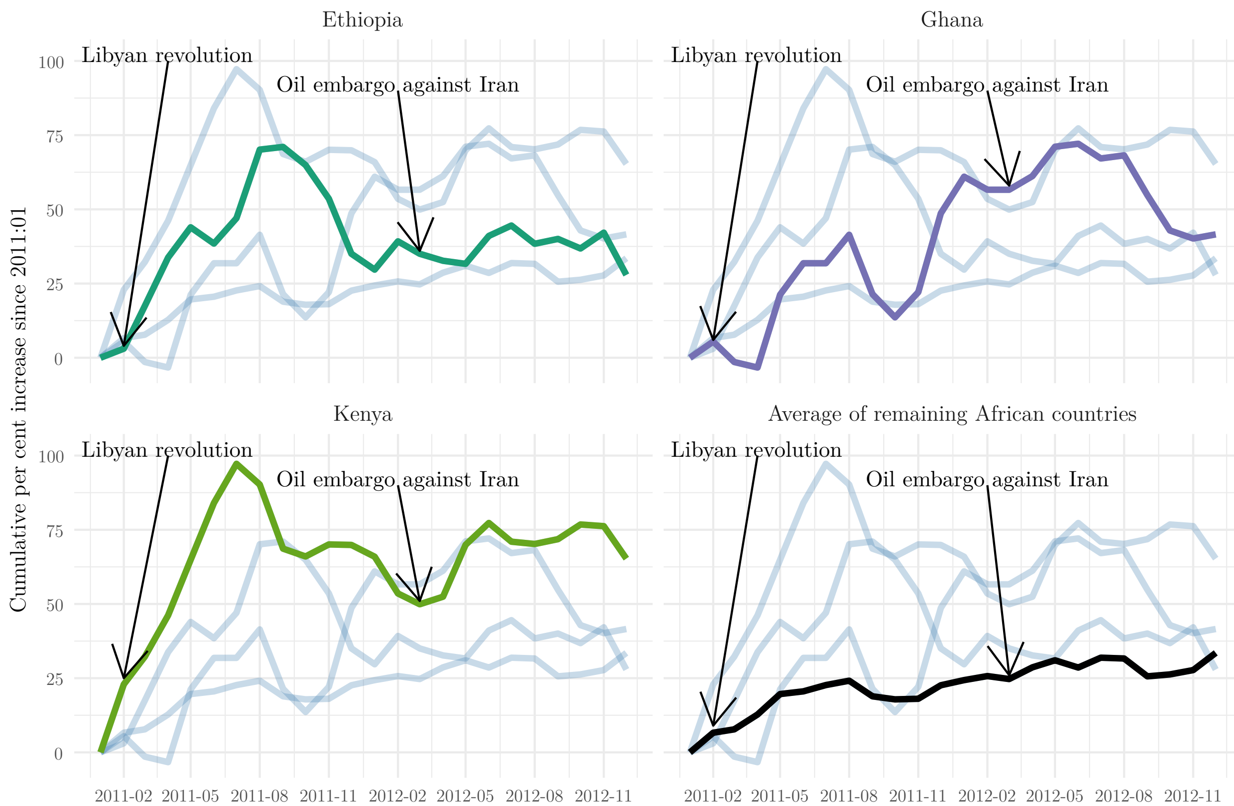

Figure 4: Comparison of cumulative percentage growth of real corn prices in Ethiopia, Ghana and Kenya with remaining SSA countries after the Libyan oil production shortfall in 2011 and the oil embargo against Iran in 2012.

The oil embargo against Iran

Due to its nuclear weapon program, the ongoing political tensions with Iran entered a new phase in early 2012 when the US and the EU introduced a new series of oil import sanctions. Because most OECD countries refrained from buying Iranian oil, the production output in Iran dropped from around 4 mbd in January/February 2012 to 3.1 mbd in October 2012. However, global oil production recovered quickly such that the worldwide production only diminished by about 0.8% from March to June 2012, and it already exceeded the pre-embargo level by July 2012. The main reason appears to be that the other OPEC members (in particular Saudi Arabia) showed no interest in supporting the Iranian government by freezing their production ceilings. By contrast, the government in Saudi Arabia immediately signaled its willingness to close the supply gap caused by the loss of Iran's heavier type crude oil.

Figure 4 shows that the increase in corn prices in Ethiopia, Ghana and Kenya was much lower after the nuclear sanctions against Iran, compared with the increase after the Libyan revolution, which is in line with the circumstance that the global oil supply shortage was quickly compensated. Nevertheless, the corn price in Kenya increased by about 25% in three months and about 10% (15%) in Ethiopia (Ghana).

Particularly for Kenya and Ghana, we find two clear peaks of the corn prices between early 2011 and late 2012 before they started to return to the average of the other African countries. In combination with the results from the IRFs shown in Figure 3 and the FEVDs documented in Table 3, oil-supply shocks appear to have major impacts on corn price movements in three countries. However, even if the sharp increase in the corn prices shortly after two oil-supply disruptions hints towards oil-supply shocks as the main trigger, the precise role of oil supply during these events is still not convincingly clear. To further investigate the price surges displayed in Figure 3, we return to the structural analysis and disentangle the contribution of each shock (oil-supply shock, aggregated-demand shock and oil-specific demand shock) to the corn price surges in Ethiopia, Ghana and Kenya during the Libyan revolution and the oil embargo against Iran by means of historical decomposition.

Disentangling the price surges in 2011 and 2012

Historical decompositions have become a popular tool in the SVAR literature to disentangle alternative sources of oil price surges (e.g. Kilian and Murphy, 2012; Kilian and Lee, 2014; Herwartz and Plödt, 2016). In particular, Kilian and Lee (2014) propose measuring the change in a series y_{it} explained by a structural shock ε_j by comparing the difference between the contribution of ε_j to y_{it} at time point y_{iT_1} and time point y_{iT_2} with the total change in the series between the respective dates. We apply this method to analyze the effects of oil shocks on corn price increases in Ethiopia, Ghana and Kenya during the Libyan revolution and Iranian nuclear sanctions.

Figure 5 shows that oil-supply shocks are almost exclusively responsible for the corn price increases in 2012 in all three countries, i.e., at least 70% of the corn price increase can be attributed

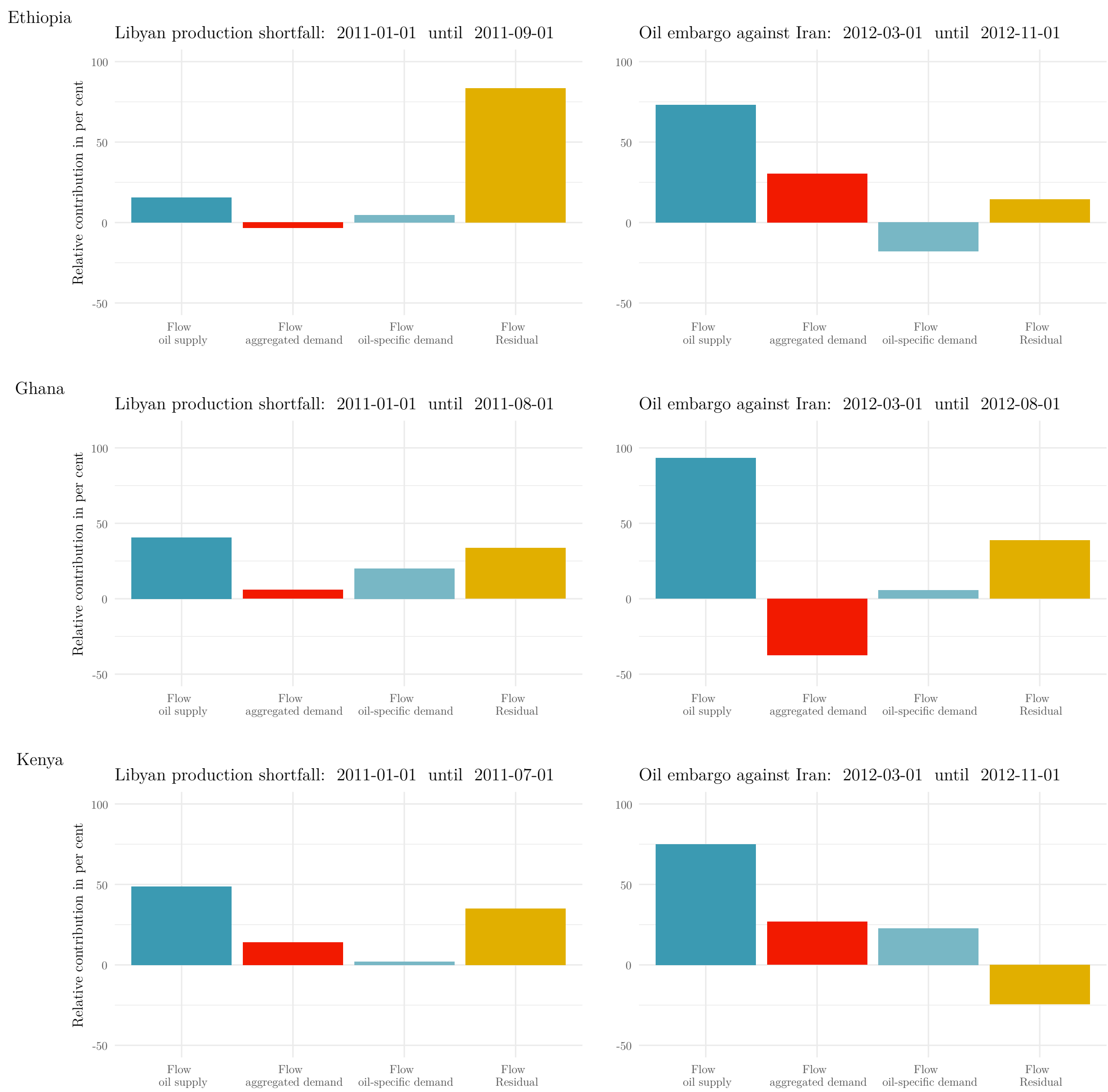

Figure 5: Relative contribution to cumulative change in domestic corn prices in Ethiopia, Ghana and Kenya during the Libyan production shortfall and the oil embargo against Iran by structural shocks. The contributions of the four shocks add up to 100%, which represents the total corn price increase.

to oil-supply shocks. Moreover, at least one other shock series exerts downward pressure on the corn price in each country, leading to the conclusion that corn prices could have been even higher in fall 2012 due to oil-supply shocks. The circumstances are slightly different during the Libyan revolution in 2011. Particularly in Ethiopia, the lion's share of the corn price surge in 2011 can be attributed to non-oil related shocks. However, in Ghana and Kenya we still find a rather high explanatory content of oil-supply shocks, i.e. half of the strongest corn price surge in Kenya is most likely due to the downfall of the Libyan oil production. Although the situation is somewhat less dramatic for Ethiopia and Ghana, the hypothesis that oil-supply shocks were important determinants of the corn price increases in 2011 and 2012 in Ethiopia, Ghana and Kenya can be confirmed.

4.2.3 A case study of an oil-supply boom: The expansion of oil production in the US and Middle East

Thus far, we have investigated how negative oil-supply shocks have triggered corn price surges, although recently oil production has tended to increase in several regions, and therefore it also holds interest to examine whether positive oil-supply shocks have exerted downward pressure on corn prices.

About a decade ago, it was well established that global oil production would no longer keep pace with growing economic oil demand, due to the decline of traditional oil fields and the declining discovery of new fields (e.g. Hamilton, 2013; Benes et al., 2015). However, the invention of hydraulic fracturing (so-called 'fracking') in conjunction with horizontal drilling has made it possible to extract crude oil from rock formations characterized by low permeability, which is commonly referred to as tight oil or shale oil. The new technique is primarily used in the US and sparked the ongoing US shale oil boom in 2009 (Kilian, 2017). Even though 2009 marks the reversal of the long-standing decline in US oil production since the late 1970s, it took about three more years for US oil production to start substantially expanding. By April 2015, the total US oil supply had increased from 6 mbd in December 2011 to 9.6 mdb. As a result, the government first abolished the export ban on crude oil in 2014 and eventually lifted all remaining export restrictions by December 2015, which paved the way for a remarkable expansion of US crude oil exports.[18]

In addition to the US shale oil boom, several countries in the Middle East further expanded their production capacities. Predominantly, Saudi Arabia and Iraq were responsible for a sizable share of the production surge in the region. Iraq increased its oil production from 3 mbd to 4.5 mbd from January 2014 to January 2016. Despite the threat of terrorist activities from the Islamic State, the Iraqi government was able to upgrade the midstream infrastructure (e.g. pipelines and pumping stations) in the southern oil fields - where 90% of the country's oil is produced - and to

[18]The US crude oil export ban was part of the Energy Policy and Conservation Act, which was established in 1975 in response to the 1973 oil crisis.

start marketing Basra Heavy grade crude oil.[19]

Kilian (2017) shows that in conjunction with the US shale oil boom, the oil production expansion in the Middle East led to a 10$ reduction in the price of crude oil in 2014/15. We investigate how the real price of corn in Ethiopia, Ghana and Kenya would have evolved from 2014 to 2016 if one had replaced all oil-supply shocks with zero, as if neither the shale oil boom nor the oil production expansion in the Middle East had occurred. Kilian and Lee (2014) and Kilian (2017) propose counterfactuals for the construction of such scenarios by subtracting the cumulative contribution of oil-supply shocks from the evolution of the real corn price.

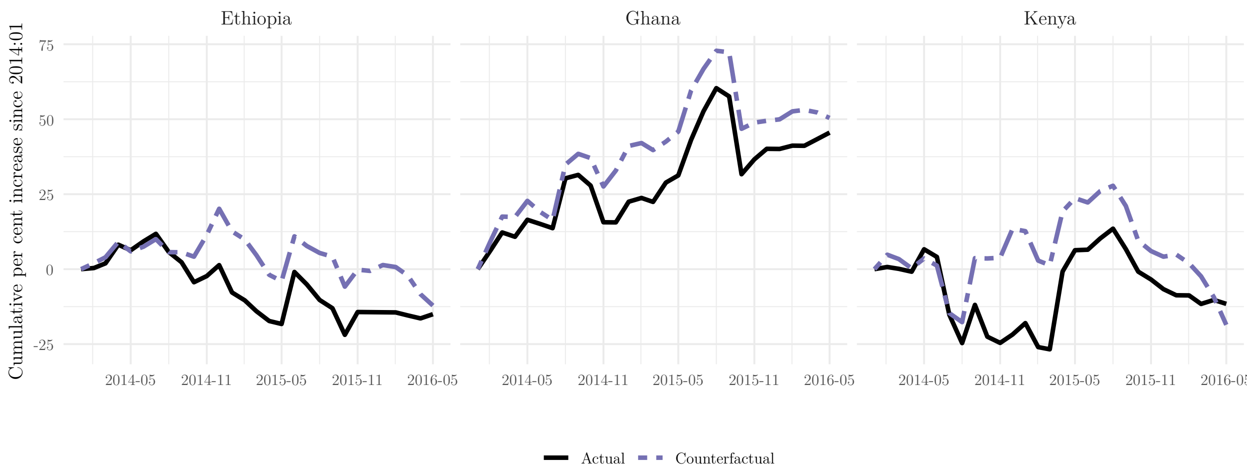

Figure 6: Comparison of cumulative percentage growth of real corn prices in Ethiopia, Ghana and Kenya since January 2014 with and without effects from shale oil boom and expansion of production capacity in the Middle East.

Figure 6 shows that on average the real price of corn in all three countries would have been about 10% higher between early 2014 and mid-2016 without oil supply shocks. Corn prices in Ethiopia and Ghana would have been 20% higher and in Kenya even 35% higher without the downward pressure from increasing oil-supply in late 2014. The US shale oil boom reached its temporary peak in 2015 and US oil production declined in late 2015/early 2016 along with global oil production, whereby the negative effects from oil-supply shocks on corn prices in Africa abated in mid 2016.

[19] A more detailed description of the oil production expansion in Iraq can be found in Asghedom (2016)

4.2.4 Why are some Sub-Saharan African corn markets responsive to oil-supply shocks and others not?

In the previous sections, using country specific IRFs and FEVDs statistics and case study analysis we illustrated the heterogeneous responses of SSA corn prices to oil-supply shocks. Moreover, we highlighted several possible reasons that help to explain why oil-supply shocks are the most powerful instigators of domestic corn price fluctuations among all oil shocks in Ethiopia, Ghana and Kenya.

While upon first glance the importance of oil-supply shocks to SSA food markets is not intuitive in light of the existing evidence concerning global oil shocks and US food markets (Baumeister and Kilian, 2014a; Wang et al., 2014), it finds support in the literature on the crude oil-food price nexus in developing countries to some extent (Nazlioglu and Soytas, 2012). Furthermore, since food markets in developing countries and even more so in SSA countries are vertically poorly integrated (Pinstrup-Andersen, 2015), and systematically different in terms of stability patterns (Minot, 2014), it is unsurprising if they also depend on oil markets differently compared with global food markets. Dillon and Barrett (2015) show that in some cases local food prices in SSA are more subject to international oil price fluctuations than to global food price movements. The authors conclude that in contrast to other parts of the world, transport costs are a major determinant of local food prices in some SSA regions, particularly in Ethiopia, Kenya and Tanzania.

Our empirical results suggest that two of these countries' corn markets are most exposed to oil-supply shocks. In Ethiopia and Kenya, a large share of the arable land and farms are spread out over the countries. With markets being equally dispersed, transport comes in as an important part of the cost function of production and marketing of corn. Coupled with particularly bad road connectivity and long travel times in both countries (Dorosh et al., 2012), transport costs are likely to form a substantial share of costs along the supply chain and oil-supply disruptions are presumably transmitted to food prices through this channel (see Figure 1).

Figure 7 shows the development of the transportation costs in Kenya compared with countries that do not respond to unexpected oil-supply shortages.[20] During the Libyan revolution in 2011, half of corn price increase in Kenya of over 90% could be attributed to oil-supply shocks and at the same time transportation costs increased by about 20% (2.1% on average per month) while transportation costs in the other three countries grew with the average rate of about 0.6% per month. Conversely, during the shale oil boom in 2014 and 2015 - when oil production was expanded at global levels

[20] Data for transportation costs is defined as the consumer price index in the transportation sector and can be downloaded from the national bureaus of statistics. Due to the generally poor data availability in SSA countries, we cannot provide statistics about the transportation costs in the remaining countries.

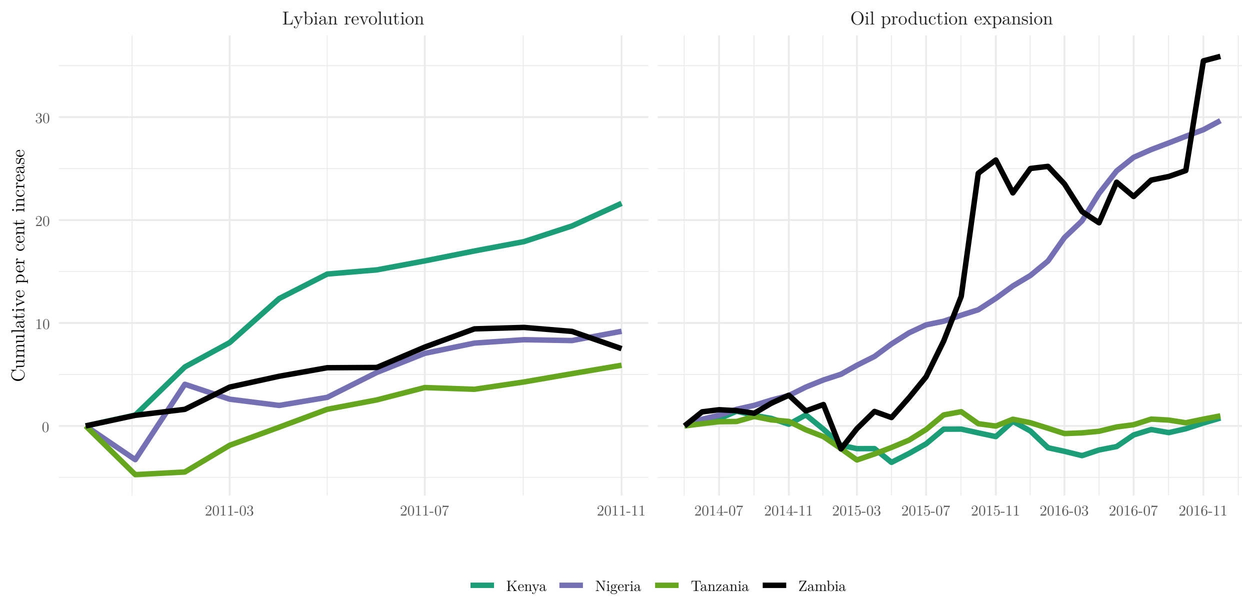

Figure 7: Comparison of cumulative percentage growth in transportation costs during the Libyan revolution and during the oil production expansion in several regions.

- transport costs dwindled in Kenya and Tanzania, while increasing faster than usual in Zambia and Nigeria (about 1% on average per month). The movements of the respective series support the hypothesis that transportation costs are a major transmission channel of oil-supply shocks in SSA.

One possible reason for the extraordinary vulnerability of local transport costs to global oil-supply disruptions is the notoriously low strategic oil reserves in Kenya and Ethiopia. Both countries are net importers of crude oil and do not dispose of sufficient oil inventories to quickly buffer import shortages. The backlog has been recognized by the respective ministries, which in the past have called for the creation of national strategic reserves (Ministry of Water and Energy of Ethiopia, 2013; Ministry of Energy and Petroleum of Kenya, 2015). With the strong importance of transport costs for producers as well as a high import dependency of fossil fuels, these countries are counter-examples against the neutrality hypothesis of food markets to oil-supply shocks (Wang et al., 2014; Baumeister and Kilian, 2014b).[21]

The circumstances are slightly different for Ghana. Traditionally, Ghana was a major net energy importer and the Ghanaian Energy Commission (2006) warned of a possible oil and petroleum shortage due to a lack of strategic oil reserves and refinery capacities. In combination with a substantial dispersion of a large corn-producing smallholder sector and bad road quality, it is likely

[21] More recent discoveries of oil fields in both Kenya and Ethiopia could obviously change this in the near future.

that transport costs are highly supply-shock-prone, similar to Kenya and Ethiopia. The situation changed in 2011 when the exploitation of off-shore oil reserves allowed Ghana to become step-wise less dependent on energy imports. Nevertheless, with an oil production between 0.1 and 0.2 mbd, Ghana still imports a considerable amount of crude oil, which explains the significant weaker overall reaction of local corn prices to global oil-supply shocks in Ghana over the entire sample. In further support of the hypothesis that susceptible transportation costs are the main transmission channel of oil-supply shocks in SSA countries, one can consider the case of Nigeria. As the largest net exporter of crude oil in our sample and boasting strategic oil reserves, corn markets in Nigeria remain unscathed from oil-supply shocks while being rather responsive to aggregated-demand shocks.

In combination with potential bottlenecks in the fuel supply chain in Ethiopia, Ghana and Kenya, we detect further country-specific characteristics that could help to explain the strong response of local corn prices in our sample. Kenya's smallholder farming is dominated by corn production. More than 70% of national corn output are produced by smallholders (D'Alessandro et al., 2015) and 98% of smallholders produce corn (Dorosh et al., 2012), i.e., direct substitutes are scarce in case of rising corn prices. Additionally, government interventions in both fuel and food markets could be obstacles to buffer oil-supply shocks. In Kenya, a heavily criticized open tender system was in place in which the winning company was put in charge of importing the entire petroleum demand for the industry (Matthews, 2014). Moreover, in Ethiopia fuel markets are subject to public tender systems in which fuel imports are granted to a limited number of companies. Additionally, Kenya operates an agency that strongly intervenes in grain markets by purchasing and selling substantial amounts in an effort to stabilize prices. While monopolistic or oligopolistic import structures do not necessarily imply inefficient fuel supply, they can quickly turn into narrowing bottlenecks in the supply chain in cases of collusion or poor management.

By contrast, while Tanzania exhibits similar corn as well as oil market dependencies as Kenya and Ethiopia, its corn markets are not responsive to oil-supply shocks. Unlike in Kenya and Ethiopia, Tanzanian petroleum markets are much less subject to government intervention (Dillon and Barrett, 2015). However, regarding corn, national policy is more regulative. Although domestically, the government refrained from intervening in domestic corn markets and limits its role to building up stocks, Tanzania has frequently suspended international trade to protect from international food price movements at times in which at least one of its region was declared as food insecure (Minot, 2010). Altogether, it seems that Tanzania has managed to isolate domestic corn prices from international shocks and oil shocks, through trade and domestic policy that supports the self-sufficiency of farmers (Wenban-Smith et al., 2016), as well as minimizing cross-border movements of corn.

In sum, we can deduce two main findings regarding the heterogeneous responsiveness of SSA corn markets to oil-supply shocks. First, transportation costs are an important transmission channel between oil market movements in SSA. Second, policy relating to strategic oil reserves and fuel imports as well as policy governing agricultural and energy markets shape the buffering mechanisms against oil-supply shocks via fuel prices in both food and energy markets.

4.3 The role of aggregated-demand and oil-specific demand shocks in Sub-Sahara African corn prices

According to Table 2, SSA corn markets are less responsive to aggregated-demand shocks as well as oil-specific demand shocks compared with world markets. The results shown in Figure 8 confirm the findings documented in Table 2. Next, we briefly analyze the role of aggregated-demand shocks and oil-specific demand shocks on SSA corn prices, in a first step using IRFs and in a second step using a case study.

4.3.1 Does increasing commodity demand raise corn prices in Sub-Sahara Africa?

Aggregated-demand shocks only unfold their impacts in vertically well integrated markets

Aggregated-demand shocks are often considered as the driving force behind fluctuations in corn prices (e.g., Wang et al., 2014). However, the only SSA corn price that is pushed in an upward direction by higher aggregated commodity demand is the Nigerian one. All other corn prices under scrutiny show either no significant reaction or even a small negative reaction for a few periods. The underlying presumption about the impacts of aggregated-demand shocks on corn prices is that higher economic activity increases not only the demand for oil, but also the demand for agricultural commodities. For example, when international prices rallied in response to higher aggregated demand in 2007/08, SSA prices only moderately increased. A likely explanation for diverging responsiveness to global commodity demand is the lack of vertical integration of both energy and food markets.

The circumstances are slightly different in Nigeria, where two factors come into play. First, an increase in global economic activity increases commodity demand and therefore Nigerian oil exports. In turn, increased export demand raises national economic activity as crude oil production accounts for a large fraction of the Nigerian GDP.[22] Increased national economic activity could translate into rising food demand and prices. This transmission is consistent with the finding of Wang et al. (2013), who show that for net exporters of crude oil a higher global commodity demand generates

[22] Between 8 and 38% (The World Bank, 2020) in our sample period

increased income. Second, since the Nigerian economy is well connected to the global economy via strong crude oil trade ties, aggregated demand also spurs demand for non-oil commodities in Nigeria, for instance, agricultural commodities.

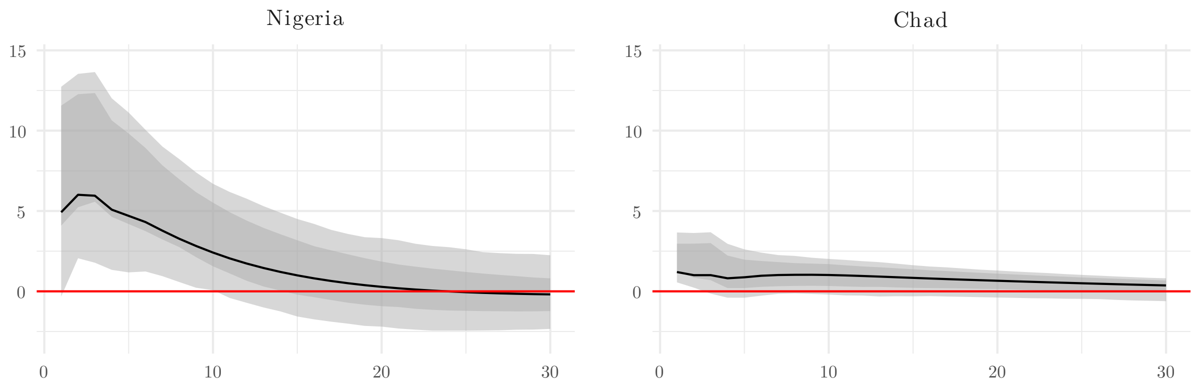

Figure 8: The left panel shows the response of the corn price in Nigeria to a positive aggregated-demand shock and right panel shows the response of the corn price in Chad to a positive oil-specific demand shock joint with 68% and 90% confidence bands obtained from 2,000 bootstrap iterations.

Oil-specific demand shocks are not determinants of corn price surges in SSA due to the lack of biofuel production

While we note that world corn prices increase in response to an oil-specific demand shock, we cannot find this response for SSA corn prices, with the only exception of Chad, where corn prices show a small positive reaction for the first two periods in response to an unexpected higher demand for crude oil.[23] Wang et al. (2014) find that after the emergence of large-scale biofuel production in 2006, food prices are much more sensitive to oil-specific demand shocks, which the authors attribute to the substitutability between corn and crude oil as inputs to fuel production. However, this relationship presumes either existing capacities to produce biofuel or free trade with negligible transaction costs to swiftly convert corn into biofuel in other locations via global markets. Both presumptions are unlikely to hold in the context of SSA. First, in relative terms, SSA continues to represent less than 1% of global biofuel production. In our sample, only Kenya and Ethiopia appear with non-zero values in the respective statistical databases, although both produce substantially less than 1 mbd per day, at least up until 2015 (EIA, 2020). Thus, the integration of biofuels into national energy

[23]The case of Chad is discussed in more detail in appendix D.

mixes remains in its very infancy in SSA. Second, while corn trade between SSA countries is common, corn exports of SSA countries to countries with ethanol-producing capacities do not occur (FAO, 2020). Consequently, local competition between food and fuel is negligible in these countries and local prices are not linked directly to local energy prices. Poor vertical food market integration additionally implies minimal relevance of the global substitution effect between biofuels and food crops as a transmission channel between energy and local food markets (Hatzenbuehler et al., 2017; Pinstrup-Andersen, 2015). Altogether, we conclude that oil-specific demand impacts only affects food prices when opportunities of biofuel substitution are available, which is strongly in line with the results of Dillon and Barrett (2015).

Similar to the oil-supply shock analysis in the previous sections, it makes again sense to consult case studies to better understand the role of both aggregated-demand shocks as well as oil-specific demand shocks in SSA food markets.

4.3.2 A case study on the role of demand shocks: The international food price crisis of 2007 and 2008

Already in 2003, the long-term decline of real food prices since the 1970s came to halt and turned around to start an upward trend. By the end of 2006, the FAO's food price index (FPI) had increased by 44% compared with its level in January 2003. Starting in 2007, international food prices began to rally and the FPI increased by 68% until it reached a peak level in June 2008. While the FPI reflects a multitude of food products, some specific commodity price spikes were even more dramatic; for instance, rice prices doubled within five months (Baffes and Haniotis, 2010). This food price explosion has not only been associated with profound changes in poverty and food insecurity (e.g. De Hoyos and Medvedev, 2009; Headey et al., 2011) but also resulted in cases of civil unrest (Bellemare, 2015).

Some international organizations and authors have warned of the threat to African food prices as well as food security from international food price surges (Wiebe et al., 2011; Wodon and Zaman, 2008, e.g.). However, as illustrated in Figure 2, the movements of the corn prices in Africa are extremely diverse in 2007/08, with some series doubling their values and some series almost moving sideways. Next, we consider only SSA corn markets where we find either at least an indication that the international dynamics in 2007/08 are transmitting to local prices, or corn markets that respond significantly to aggregated-demand or oil-specific demand shocks. Figure 9 depicts the actual and counterfactual paths of the corn prices in Chad, Ethiopia, Ghana and Nigeria during the international food crisis. Although all price series exhibit some remarkable price surges, demand shocks have only marginal effects.

Figure 9: Comparison of cumulative percentage growth of real corn prices in Ethiopia, Ghana, Nigeria and Tanzania since June 2007 with and without cumulative demand shocks.

The only exception where corn prices would have been 19% lower on average in 2007/2008 without the upward pressure of high aggregate demand is Nigeria. In May 2008, 40% of the price surge in Nigeria can be attributed to cumulative effects from aggregated-demand shocks. By contrast, there is no indication of aggregated-demand shocks as sources of the price rally in 2007/08 for any other local corn price. Overall, both demand shocks played only a minor role in all countries under consideration, both during the international food crisis and throughout the entire sample.

4.4 What are the future threats to corn price stability from global oil market shocks?

We note that the main threats to local food security from the global oil market are oil-supply shocks. In particular, corn prices in Ethiopia, Ghana and Kenya are affected by changes in oil-supply. In this section, we construct forecast scenarios to assess the sensitivity of reduced-form VAR forecasts to (hypothetical) future global oil market related events based on the method of forecast scenarios described in Baumeister and Kilian (2014b).

These forecasts cannot be interpreted as the most likely future outcomes, but rather simulate the corn price movements in case of unlikely but extreme events. Since structural shocks have expectations equal to zero, all future demand and supply shocks are usually set to zero in a reduced-form VAR forecast. However, forecast scenarios are based on the idea of feeding into the model a non-zero future shock sequence. To account for interventions by policymakers and changes in the behavior of other agents based on the critique by Lucas (1976), constructed shock series for the forecast scenarios are not allowed to be extraordinarily large but have to be within the range of historical events.

What if the tensions with Iran escalate?

After Iran and the P5+1[24] countries agreed upon restricting the Iranian nuclear program in exchange for ending the sanctions against Iran in 2015, the oil production quickly reached its pre-embargo level, and Iran again took its place as the fourth largest oil producer in the world with about 4.5 mbd of crude oil pumped out from the ground. However, in 2018 political tensions intensified again, which motivated the US administration to withdraw from the Iran deal and reimpose the sanctions whereby by early 2019 Iranian oil production almost halved to 2.7 mbd. In January 2020, the conflict between Iran and the US culminated with the killing of the Iranian general Qassem Soleimani by US battle drones.

In the first scenario, we investigate what would happen if the conflict between the Iran and the US further escalated and Iranian oil production collapsed by 60%, which corresponds to a reduction

[24]The P5+1 refers to the UN Security Council's five permanent members plus one non permanent member

of 1.7 mbd or a global reduction of 2.1%. A drop in the global oil production of such a magnitude is comparable with the reduction during the Libyan revolution or after the US reimposed the sanctions in 2018, and hence it is well within the variation of historical data. We simulate such an oil-supply shock for one single period and afterwards set all shocks to zero again.

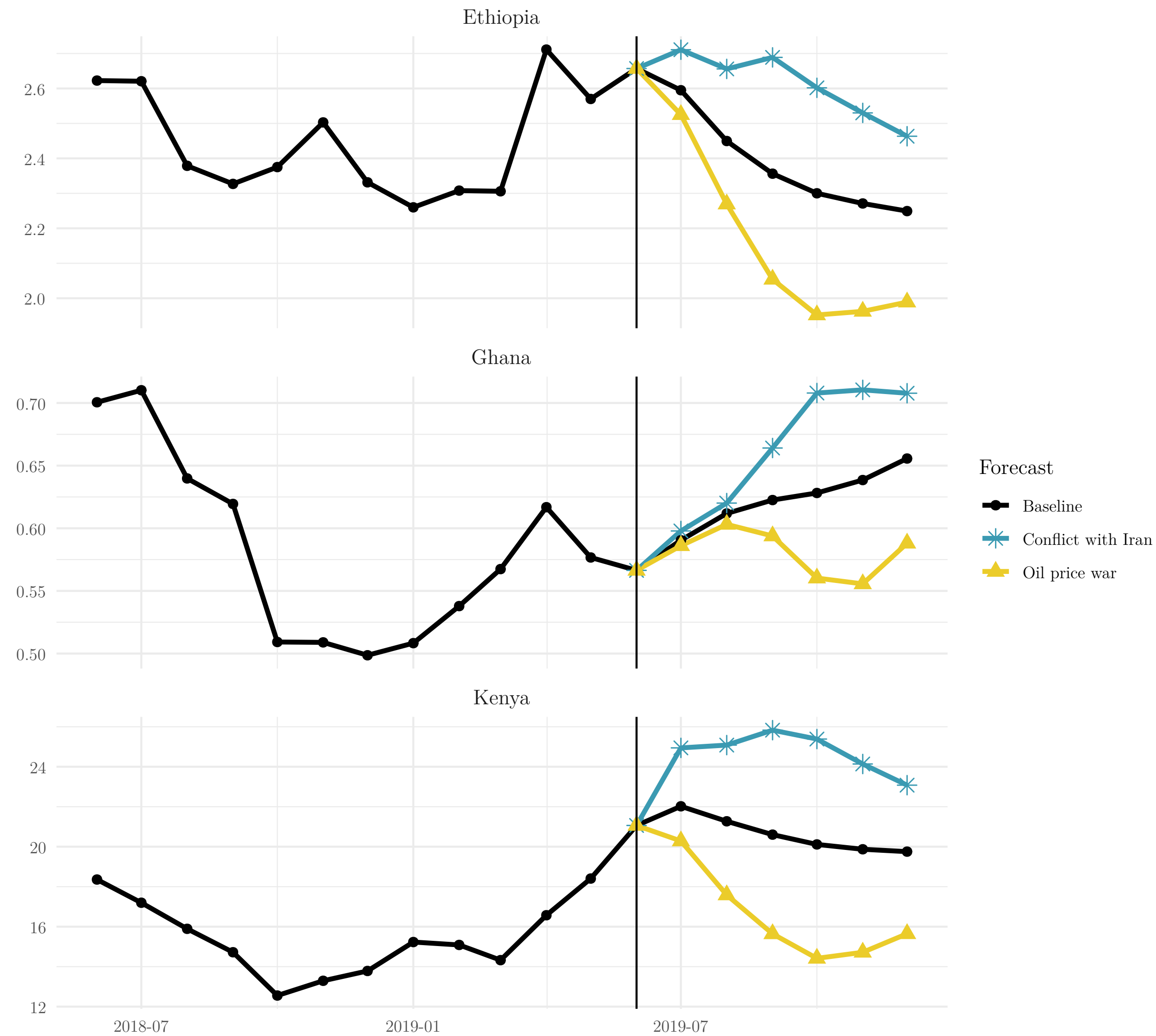

Figure 10: Alternative forecast scenarios for local real corn prices in domestic currencies. The vertical lines represent the beginning of the forecast periods.

Figure 12 shows that a potential breakdown of Iranian oil production can be expected to lead to a considerably higher corn price in Ethiopia, Ghana and Kenya. The predicted real price of corn exceeds the baseline forecast by around 15% in Ethiopia and Ghana and by about 25% in Kenya after approximately five months. As already discussed in Section 4.2.4 the corn price increase could be much lower if local governments successfully build up strategic oil reserves to buffer oil-supply shortages.

What are the consequences of an oil price war?

During the SARS-CoV-2 outbreak in early 2020 and the prospect of a global economic slowdown, the OPEC tried to stabilize oil prices by lowering its production ceilings. However, Saudi Arabia and OPEC+ member Russia were unable to agree on a cut in production, which prompted Saudi Arabia to raise its production ceilings to make oil production unprofitable for Russia.

In the second scenario, we simulate the consequences if Saudi Arabia and Russia unexpectedly increase their oil production. The production expansion was about 3 mbd, which is equivalent to a 3.6% increase in global oil production, much larger than the highest single oil-supply shock in our sample. Therefore, we generate one oil-supply shock that increases global oil production by 1.4% and a second one which increases global oil production by 1.2% one month later in an attempt to replicate the real-world scenario. Figure 12 shows that corn prices in Ethiopia would be 10% lower, in Ghana about 6% lower and in Kenya about 18% lower, on average, six months after the shocks. The downward pressure on the corn price is comparable with the effects from the shale oil boom in 2014/15, but although it is achieved within a much shorter time span. Since the actual increase in oil production is even stronger, the effect on the price of corn would be equally more pronounced after a sizable reduction in transport costs.

5 Conclusions

Oil prices are closely linked to food prices, particularly after the onset of large-scale biofuel production about one-and-a-half decades ago. As developed countries increasingly mandated the conversion of agricultural crops to fuel by policy, worries about adverse effects on food prices in more vulnerable regions of the world emerged in light of globally integrated markets. Consequently, a sizable body of literature examines the price relationships of crude oil and food prices and has gained a better understanding of the effects of oil markets on food prices. However, many of previous works on the crude oil-food price nexus suffer from three major shortcomings: (i) they only analyze the impacts of oils shocks on food markets in developed countries, (ii) they do not differentiate between the alternative sources of oil price fluctuation, and (iii) most of the structural analyses rely on zero restrictions or elasticity constraints, which are prone to underestimate the effects from oil-supply shocks. In a data-based manner, we disentangle the causal relationships between the global crude oil market and domestic food prices according to alternative sources of oil market turmoils in eight SSA countries by means of ICA.

We provide three main novel insights into the response of SSA corn markets to global oil shocks. First, we find that fundamental changes as well as general dynamics on global corn markets influence SSA food markets very differently compared to how they impact global food markets. SSA corn markets are significantly less sensitive to oil-specific demand shocks and more responsive to oil-supply shocks. Overall, we attribute the non-responsiveness to oil-specific demand shocks to the absence of biofuel substitution opportunities, and fail to diagnose increased global biofuel production (including output stimulated by policy mandates) as a determinant of corn prices in SSA.

Second, SSA corn markets are not only different compared with global corn markets, but also very heterogeneous among themselves. We detect three corn markets - namely in Ethiopia, Ghana and Kenya - that are particularly sensitive to global oil-supply shocks. Some of the largest corn price surges in Ethiopia, Ghana and Kenya can be attributed to global oil-supply disruptions. For example, half of Kenya's strongest corn price increase in early 2011 is due to the unexpected shortfall of Libyan oil production. Conversely, the shale oil boom in the US combined with the production expansion in the Middle East in 2014/15 reduced corn prices by between 10% and 20% in Ethiopia, Ghana and Kenya. Moreover, we find that the price surges in SSA corn markets during the international food price crisis in 2007/08 are not linked to the crude oil market. The corn markets in the remaining SSA countries are more or less independent of global crude oil market dynamics and much more subject to unexpected local shocks.

Third, transport costs are the main channel for oil-supply shortfalls to transmit into corn price increases in SSA, while other transmission channels hold minimal importance in SSA. We conclude that SSA countries are particularly vulnerable to oil-supply shocks due to their (temporary) lack of both strategic and natural oil reserves. Further contributing factors are poor road connectivity combined with long travel distances and inefficient oil distribution systems.

Finally, we simulate the consequences of different hypothetical events on local SSA corn prices, i.e. a shutdown of Iranian oil production and the oil price war between Saudi Arabia and Russia. A shortfall in Iranian oil production can increase corn prices in SSA countries by up to 25%, while SSA countries can benefit from a global oil price war that leads to corn prices that are up to 18% lower, on average. Such unusual responsiveness of SSA countries to oil-supply shocks has rather straightforward implications for the food security of both net food buyers and food sellers, since price increments or reductions are merely changes in transaction costs. However, ensuring a stable supply of energy and fuel supports a more stable food market and is a promising policy option to mitigate the adverse effects of global oil-supply shocks on food security.

We suspect that in general, food markets in developing countries - such as those in SSA - respond more heterogeneously to the global oil market than previously thought. In particular, the vulnerability of oil shocks depends on a variety of country-specific characteristics surrounding food production sectors and energy distribution systems. Given that both are often subject to government intervention, policy could be key in determining the magnitude of the threat of oil shocks on food security.

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Appendix

A Alternative transmission channels from crude oil to food markets

Some authors argue that exchange rates are another transmission channel for oil market turmoils transmitted to food markets. For instance Abbott et al. (2011), Nazlioglu et al. (2013) and Wang et al. (2014), consider potential wealth effects to allow the oil price and oil shocks, respectively, to lead to currency appreciation or depreciation. Others consider exchange rates more as exogenous determinants of food markets rather than as part of possible transmission channels of oil shocks to food markets (e.g. Dillon and Barrett, 2015; Tyner, 2010; Wang and McPhail, 2014; Chakravorty et al., 2019; Zhang and Qu, 2015). Besides the theoretical exogeneity of exchange rates within the oil-food nexus, reasons for omission simply stem from empirical infeasibility. While it is rather straightforward to take exchange rate effects into account by including an appropriate indicator in respective multivariate time series models, in case of small sample sizes adding further dimensions to structural models might result in a lack of degrees of freedom, since the number of parameters increases quadratically with the number of dimensions. Additionally, increased trader activity on derivative markets could also constitute a pathway for oil price movements to transmit to food prices (Du et al., 2011; Wang et al., 2014). Nonetheless, this presumption still lacks sound theoretical foundations as well as empirical evidence. Therefore, we refrain from accounting for further dynamics in our analysis.

B Identification by means of independent components

Matteson and Tsay (2017) suggest an approach based on the so-called distance covariance of Székely et al. (2007) - denoted $\mathcal{U}_T$ - for the implementation of ICA. More specifically, for a K-dimensional vector of structural shocks ε_t at time $t = 1, \ldots, T$ the distance covariance $\mathcal{V}^2$ detects dependence between two subsets of the components. Between the kth component $\varepsilon_{t,k}$, $k \in \{1, \ldots, K\}$ and all subsequent ones ε_{t,k^+} with $k^+ = k+1, \ldots, K$, dependence is measured by $\mathcal{V}^2(\varepsilon_{t,k}, \varepsilon_{t,k^+})$ which is the distance between the characteristic functions $\varphi_{\varepsilon_{t,k},\varepsilon_{t,k^+}}$ and $\varphi_{\varepsilon_{t,k}}\varphi_{\varepsilon_{t,k^+}}$, the joint characteristic function and the one under independence, respectively. To measure mutual dependence - i.e. dependence of all possible combinations between the variables $\varepsilon_{t,1}, \ldots, \varepsilon_{t,K}$ - the dependence criterion reads as

$$\mathcal{U}_T(\varepsilon_{t,1}, \ldots, \varepsilon_{t,K}) = T \cdot \sum_{k=1}^{K-1} \mathcal{V}^2(\varepsilon_{t,k}, \varepsilon_{t,k^+}). \tag{3}$$

In the sense of Hodges-Lehman (HL) estimation, the distance covariance $\mathcal{U}_T(\hat{\varepsilon}_{t,1}, \ldots, \hat{\varepsilon}_{t,K})$ is then minimized to identify $\hat{\varepsilon}_t = \mathsf{B}^{-1}\hat{u}_t$ with least dependent components, which consequently determines the estimated matrix $\widehat{\mathsf{B}}$. Conditional on a particular nuisance free test statistic, the HL estimator of a parameter of interest is the specific parameter value obtaining the largest p-value when subjected to testing. Principles of HL estimation motivate detecting least dependent structural shocks by minimizing non-parametric dependence criteria.

C Further empirical results and data

Table 4: Test results on kurtosis and skewness of the estimated structural shocks. Values in parentheses denote p-values.

		$\hat{\varepsilon}_1$	$\hat{\varepsilon}_2$	$\hat{\varepsilon}_3$	$\hat{\varepsilon}_4$
Chad	Kurtosis:	3.07 (0.85)	4.60 (0.00)	3.41 (0.26)	4.21 (0.01)
	Skewness:	0.17 (0.38)	−0.50 (0.01)	−0.47 (0.02)	0.33 (0.08)
Ethiopia	Kurtosis:	2.98 (0.96)	4.58 (0.00)	3.50 (0.15)	8.01 (0.00)
	Skewness:	0.23 (0.23)	−0.40 (0.04)	−0.46 (0.02)	−0.72 (0.00)
Ghana	Kurtosis:	2.60 (0.26)	3.68 (0.05)	3.89 (0.02)	5.23 (0.00)
	Skewness:	0.27 (0.16)	−0.30 (0.11)	−0.45 (0.02)	−0.31 (0.10)
Kenya	Kurtosis:	2.82 (0.62)	3.52 (0.13)	4.30 (0.00)	3.76 (0.04)
	Skewness:	0.21 (0.26)	−0.13 (0.49)	−0.71 (0.00)	−0.09 (0.62)
Mozambique	Kurtosis:	3.74 (0.04)	4.73 (0.00)	3.40 (0.24)	8.36 (0.00)
	Skewness:	0.19 (0.32)	−0.66 (0.00)	−0.52 (0.01)	1.10 (0.00)
Nigeria	Kurtosis:	2.98 (0.96)	4.52 (0.00	3.56 (0.12)	4.03 (0.01)
	Skewness:	0.17 (0.34)	−0.40 (0.04)	−0.41 (0.03)	−0.17 (0.38)
Tanzania	Kurtosis:	2.57 (0.22)	3.68 (0.05)	3.29 (0.43)	4.77 (0.00)
	Skewness:	0.26 (0.26)	−0.14 (0.45)	−0.47 (0.02)	0.41 (0.03)
Zambia	Kurtosis:	3.04 (0.91)	4.20 (0.01)	3.54 (0.1)	3.14 (0.70)
	Skewness:	0.21 (0.27)	−0.48 (0.01)	−0.49 (0.02)	−0.48 (0.01)

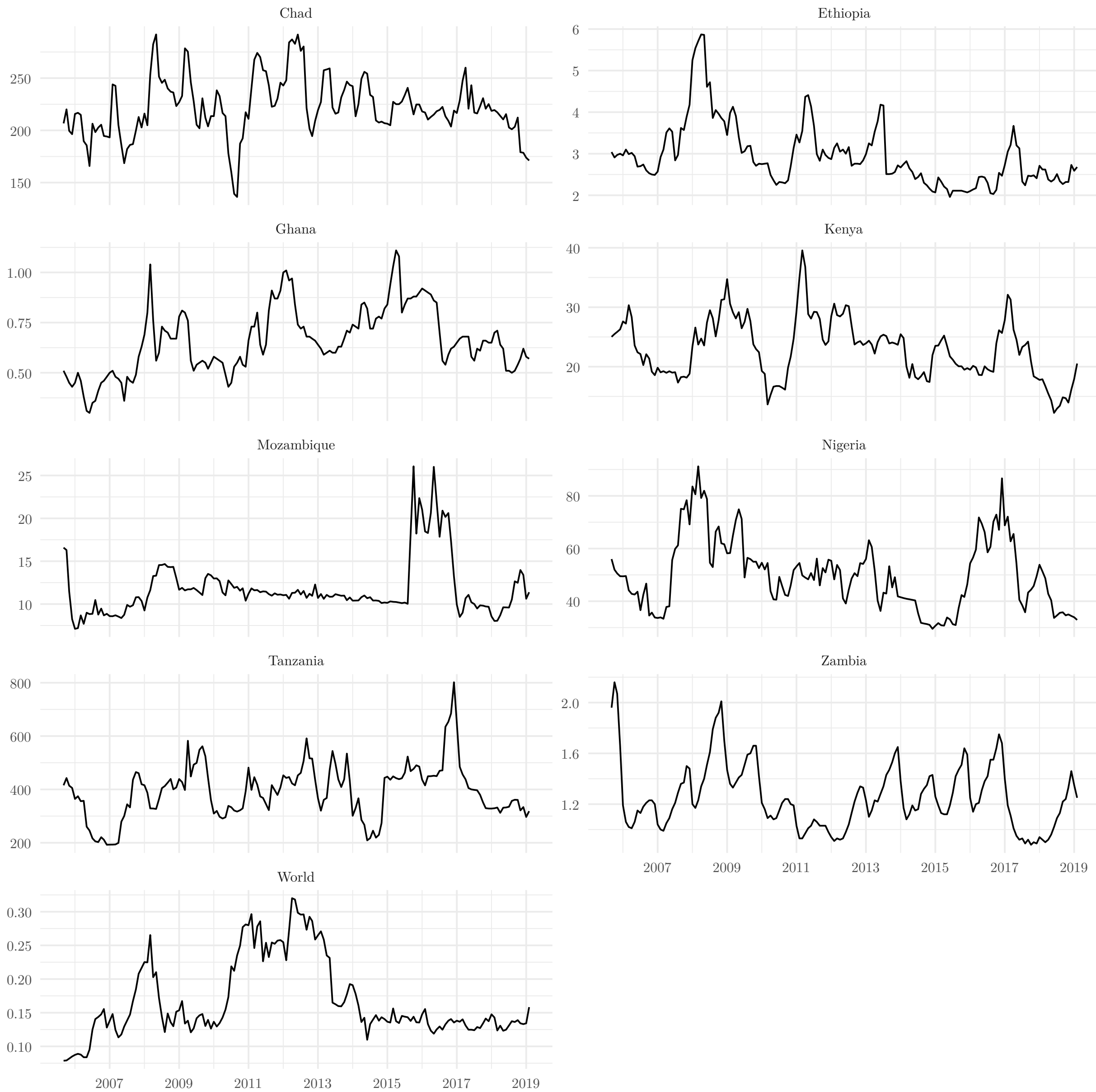

Figure 11: Real corn price series in domestic currency. World prices are given in US Dollars.

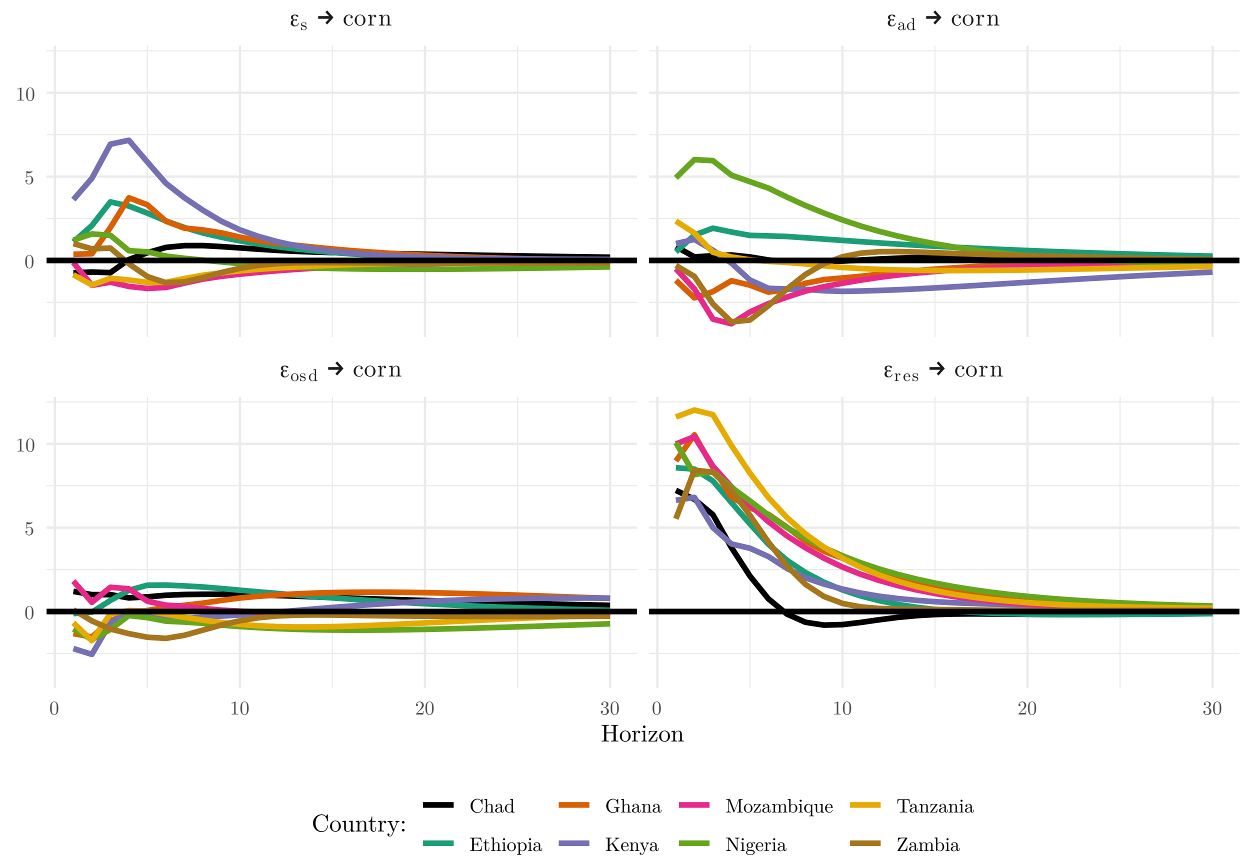

Figure 12: Point estimates of corn price reactions in Africa to different types of oil shocks and a non-oil related shock to corn price.

D Country case: Chad

Chad is the only country in our sample whose market is responsive to oil-specific demand shocks. Even though biofuel production capacities are also not available in Chad, its corn markets are surprisingly similar to global corn markets. One possible reason for this circumstance is compared with to all other countries in our sample, in Chad corn constitutes an unusually minor share of caloric intake in diets. Calorie supply per day and person stands at 130 kcal in 2017 which is less than half of that in Nigeria, one-third of that in Ethiopia, and one sixth of that in Kenya for instance (FAO, 2020). With low consumption rates, much more abundantly available substitutes such as sorghum, millet and wheat can easily compensate the country-specific impacts of oil shocks such that (in the absence of impeding policies and trade barriers) local corn price dynamics in Chad reflect those of global prices.