Food Production Shocks and Agricultural Supply Elasticities in Sub-Saharan Africa

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Abstract

This paper estimates the food supply elasticity in SSA. Building up on commodity storage theory, we empirically estimate food supply functions for SSA. Our identifications strategy relies on exogenous weather shocks as instruments. This approach further allows to quantify the exposure of SSA food markets to weather events. We use data from FAO, USDA, WFP and public climate data to model 3 commodities in 173 food markets in 34 countries in SSA. Results suggest that (i) food supply in SSA is more elastic than global food supply, and (ii) prices are much more subject to exogenous weather events than global prices are. Moreover, we find substantial heterogeneity of food market responses to weather shocks and price developments by crops. These results are in line with commodity storage theory as in absence of opportunities to build inventories, producers will not shift supplies across time periods. Promoting storage activity - also through imports - and investing in storage facility can smoothen consumption, stabilize markets and reduce long term production uncertainty in the region.

1 Introduction

In spite of the long-term decline of world hunger, in Sub-Saharan Africa (SSA) food insecurity has been rising again since 2014 (FAOSTAT, 2020). This development is partly due to frequent and sudden supply-side shocks. Many of the most severe food price shocks that threaten food security – at least in the short-term – originate from extraordinary local or regional crisis events (FAOSTAT, 2020). For instance, the infamous drought in Somalia in 2017 left more than 6 million people without sufficient access to food and spread into South-Sudan as well as Nigeria. A similar supply shock occurred in the aftermath of the tropical cyclone in Mozambique in 2019, leading to food price surges in Mozambique, Zimbabwe and Zambia (FEWS, 2020). Most recently, within the realms of COVID-19, local droughts, conflicts, and the ongoing locust infestation, food prices have risen to record levels in many regions of SSA since 2014.

In many parts of the world shocks on the food supply side are usually compensated by abundant levels of food stocks, international trade as well as market efficiency (Wright, 2011). By contrast, in SSA grain reserves are low – often even nonexistent – and many regions are not connected to international markets while market efficiency is generally low (e.g. Abdulai et al., 2006; von Cramon-Taubadel, 2017). Thus, food markets in SSA are notoriously more volatile and vulnerable to shocks. Moreover, as market prices are an important signal

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to producers to shift supply, unstable markets result in further misallocation of food production capacities of the next period – even in the absence of stocks. This interdependency over time thus can further exacerbate market instability and weaken resilience against market shocks.

Nevertheless, food markets in SSA are also very heterogeneous and the response – as much as its degree – of producers to price signals, and markets to exogenous shocks varies vastly across the continent. While for global food markets, both supply and demand analysis over time as well as market responses have been studied intensively, such insights on SSA food markets are scarce. This gap in the literature is particularly striking since the majority the global food insecure live in SSA and a number of global policy efforts target the strengthening of food markets in SSA. Thus, understanding both the extent of market vulnerability to supply shocks as well as the supply elasticity in SSA food production are key for successful market development and resilience.

This paper identifies food supply functions and determines the effect of exogenous weather shocks on prices and supply, as well as the supply elasticity in SSA. We build up on the data compiled in Porteous (2019) that includes production data and agricultural commodity prices from FAO and USDA for major food crops in SSA from 2002-2013. We extend this dataset until 2020 to construct a panel on the regional level covering 173 food markets that trade 3 commodities in 34 SSA countries. With regards to model and identification we follow, Ghanem and Smith (2020), Hendricks et al. (2015) and Roberts and Schlenker (2013) and specify a supply function for SSA and employ climate data as well as linear production shocks as instrumental variables to identify the parameters. Aside from identifying the supply elasticity of food production SSA, this dual approach additionally allows to identify both the effects of production shocks in general as well as climate related shocks on food markets. We estimate the IV model using country, market and crop specific fixed effects. Moreover, the fixed effects regime allows inference on the respective levels and thus describe specific factors that shape market functioning. Finally, based on time fixed effects allow to determine the effects of specific past market shocks, e.g. the flood in Mozambique in 2017 or the drought in Somalia in 2007 in case studies by means of historical decompositions.

Our innovations to the literature are twofold. First, with regards to the estimation strategy of food supply functions, we propose a causal dynamic empirical model using panel data as opposed to time series models. While related works have focused on global and food supply dynamics as aggregates across commodities, we investigate food supply functions in the context of SSA food markets that are crop specific. Second, with regards to the theory of comparative storage (Wright, 2011), we provide novel empirical insights on markets where stock levels are low or even zero in contrast to other studies that focus on markets where stocks are relatively more abundant.

Our preliminary results are threefold. First we find that weather related effects on food prices in SSA are 8-20 times more pronounced than on global food prices. This result helps to quantitatively explain the heterogeneity of SSA food prices and low levels of market integration. Second, the elasticity of food supply is on the upper end of that of global estimates, This means that farmers in SSA are more responsive to changes in local food prices than elsewhere, perhaps at the cost of long term production and farm development strategies. Third, food markets SSA are very heterogeneous with regards to both key figures. Thus, with regards to agricultural market policy, aside from measures to incentivize stock piling, there are no on-size-fits all instruments but rather specific interventions that could mitigate region and crop specific food market shocks.

The remainder of this paper proceeds as follows. Section 2 revisits the commodity storage theory and discusses low or zero storage opportunities. Section 3 proposes the model to estimate food supply elasticities and the impact of climate shocks and subsequently, section 4 presents the dataset compiled for this paper. The results are presented and discussed in 5 while 6 concludes the paper.

2 Prices, food supply and commodity storage

Numerous studies have pointed out the vulnerability of (i) food markets in SSA to production (e.g. Buhaug et al., 2015; Devereux, 2016) and (ii) price shocks (e.g Dalheimer et al., 2021; Minot, 2014). The most prevailing driver that has been analyzed in the literature are poor integration of SSA food markets with world markets that might stem from relatively low trade flows (Hatzenbuehler et al., 2017; Pierre and Kaminski, 2019; Baffes and Haniotis, 2010; Minot, 2014, 2010; Conforti, 2011, e.g.), relatively low-yielding and non-resilient production technologies (e.g. Bonilla-Cedrez et al., 2021; McKenzie and Williams, 2015) and institutional factors (von Cramon-Taubadel, 2017; Pinstrup-Andersen, 2015; Timmer, 2012; Byerlee et al., 2006; Coulter and Onumah, 2002). All of these factors or in many cases the combination of them results in SSA food markets being vulnerable predominantly to local production shocks stemming form both social as well as natural events[1]

While food markets in high-income countries are usually integrated with world markets resulting in some degree of market resilience, such markets also build in some cases public but in all cases at least private inventories (Serra and Gil, 2013). Commodity storage theory states that stocks are key to the the resilience of food markets which includes both stability of prices and consumption over time (e.g. Bobenrieth et al., 2021; Cafiero et al., 2015; Wright, 2011; Deaton and Laroque, 1996). In presence of non-zero stocks, consumption is smoother than production. Prices are not a reflection of a consumption (z_t)-production equilibrium at one point in time, but rather depict domestic supply which - aside from production - includes carryover quantities (x_t) from the previous period(s). Thus,

$$c_t = z_t + x_t, \tag{1}$$

which is the identity of commodity storage proposed in Wright (2011) and the basis of other works that focus on food demand and supply estimation (Ghanem and Smith, 2020; Hendricks et al., 2015; Roberts and

[1]Indeed, Dalheimer et al. (2021) argue that global demand shocks, such as the food price crisis of 2007/08 are relatively small in extend compared with global levels and compared with other local supply-side shocks in SSA.

Schlenker, 2013). In particular, Scheinkman and Schechtman (1983) and Bobenrieth H. et al. (2002) suggest a model in which producers and storers face two decisions. The first decision relates to ho much of the current supply should be consumed or marketed ($z_t - x_t$) and how much should be stored and thus ponders the marginal cost of storing ($\phi(x_t)$) against the expected change in future prices. The second decision relates to how much effort (λ_t) in terms of resources and inputs should be put towards production for the next period and thus pondering the marginal effort against a marginal change in future prices. The corresponding social maximization problem, as reported in Roberts and Schlenker (2013) is

$$\begin{aligned} v(z_t) = \max_{x_t, \lambda_t} \quad & \{u(z_t - x_t) - \phi(x_t) - g(_t) + \delta E[v(z_{t+1})]\} \\ \text{s.t.} \quad & z_{t+1} = x_t + \lambda_t \omega_{t+1} \\ x_t \geq x_t + \lambda \omega_{t+1}, \quad & z_t - x_t \geq 0, \quad \lambda \geq 0. \end{aligned} \tag{2}$$

Optimal supply in t is thus a function of the utility of current consumption minus convex costs of storing and production efforts plus the expected expected utility of supply in the next period. However, the future supplies are also subject to random production shocks ω. Stockpiling is competitive when production x_t is large and thus the price is low. As a consequence of withholding supply as inventory, the price in the current period rises and the price in the following period decreases. In equilibrium[2], the discounted future price net of storage equals the current price. The exogenous weather shock leads to a decrease in z_t and thus reduces the competitiveness of stockpiling and increases the likelihood of stock withdrawals. The social optimization problem leads to a situation in which (i) consumption is smoother than production over time, and (ii) prices are stable in that the change in production will be distributed across periods and thus the change in price will always be smaller than the production shock. Conversely, the supply and production response, will also be buffered by stocks and distributed across periods which will be reflected in the elasticity of supply. At infinite (high) stock levels, effects of production shocks may net out entirely and production responses to shocks are minimal. Conversely, at depleted inventories, a relative change in price is equal to the production shock and the supply response of producers will fully reflect the production shock.

However, there are at least two further assumptions implied in order o stock and store production of the current period to carryover to the next period. First, in terms of technology stocking and inventory require infrastructure. In agricultural production sectors where storage facilities are absent or the cost of storing are exceedingly high such that stockpiling is technically not feasible, stocks may net to zero. This differs by commodity and the production technology. Rice, for instance, is relatively cheaper and less technology demanding than storing meats or dairy.

Second, in context of equation 2, z_t must be *sufficiently* large to build up stocks. This implies that z_t is larger than the demand in the current period D_t. With regards to food, it must be at least larger than minimum requirements. In other words, as long as minimum food requirements are not met, storage is not competitive. In regions with high prevalence of food insecurity, poverty and general economic volatility, the

[2]The first order conditions are that consumption sis strictly, storage and effort both weakly increasing in production (z_t)

marginal utility of stock piling might be severely compromised by the uncertainty that extends beyond just future yields.

While most of the literature around commodity storage analyzes either global food markets or markets in developed countries (e.g. Bobenrieth et al., 2021; Cafiero et al., 2015, 2011; Serra and Gil, 2013), little is known about the dynamics of food storage and corresponding supply responses in regions where storage technology is low. Yet, in precisely these regions, food inventories could have largest marginal benefit in reducing market stability and consumption smoothing. A notable exeption is (Larson et al., 2014) simulate various stockpiling scenarios in the Middle East and North Africa and conclude that net food importers can particularly benefit from policy efforts that target the build up of food inventories.

3 Model

In order to model the elasticity of supply - which is subject to commodity storage - Roberts and Schlenker (2013) propose to estimate supply equations. In this framework, the exogenous market shock captures the effect of weather on supply, reflecting the level of inventories. Moreover, the exogenoeus shocks serve as an IV variable to identify the supply equation where production and price are subject to simultaneity. (Hendricks et al., 2015) argue that the IV approach is a natural derivative of commodity storage theory as eather shocks exogenously determine inventories that affect futures prices which conversely determine production responses. Thus, in this framework past shocks serve as an instrument for futures prices. by contrast, (Ghanem and Smith, 2020) take a time series-based route and use a Structural Vector Autoregression models to identify supply and demand elasticities. Both approaches employ FAO data on production, consumption and stocks at global aggregates.

We adopt the supply-side equations of the model in (Roberts and Schlenker, 2013) to formulate the empirical model

$$\begin{aligned} q_t &= \alpha + \beta p_t + \gamma \omega_t + f_1(t) + u_t \\ p_t &= \delta + \mu_1 \omega_t + \mu_2 \omega_{t-1} + f_2(t) + \epsilon_t. \end{aligned} \tag{3}$$

Where p_t is the logarithmized supply quantity and reflects both ${}_{t-1}$ and ω_t. The first equation is the supply function where the price p_t is the log of the price in the precious period. The second equation is the first stage of the IV problem and identifies price based on past and current production shocks. α and δ are intercepts which vary over time via the the time trends $f_1(t)$ and $f_2(t)$. Roberts and Schlenker (2013) use land and yield variables separately in their model. They express supply as a function of area planted and yield, which in turn reflects weather shocks. As our data is not on national but on the regional level, we do not have region specific plantation area available. However, we implement supply as the production total and define the production shock in two different ways. First, instead of proxying weather shocks as a deviation from time-trending average yields we define a climate-related production shock directly as a function of both precipitation and temperature in the marketing area. Second, we use deviations of the time-trending production level to describe production shocks that may originate from any event. This is particularly useful in the context of SSA since many food production shocks in the region stem from extraordinary social conflict or political events. Thus, in our model we can separate climate related effects from other - social effects, at the disadvantage of specifically model area planted - which is a decision of the producer in response to price signals, and random shocks.

Our empirical model to be estimated is

$$\begin{aligned} q_t &= \alpha + \beta p_t + \gamma_1 P_t + \gamma_2 T_t + \gamma_{12} P_t^2 + \gamma_{22} T_t^2 = u_t \\ p_t &= \delta + \mu_1 P_{t-1} + \mu_2 T_{t-1} + \mu_{12} P_{t-1}^2 + \mu_{22} T_{t-1}^2 + \epsilon_t, \end{aligned} \tag{4}$$

where the weather shocks are modeled in terms of temperature (T) and precipitation (P) and their squared terms to capture non linear effects as both temperature and precipitation effects are likely to have an inverted U-shape functional form. The main parameter of interest is the elasticity of supply β, which is identified using the 4 weather variables as an IV in the first stage regression. The first equation in uses the fitted values of p_t retrieved from the second equation in the equation system of 4. The error terms u_t and ϵ_t are i.i.d. by assumption.

4 Data

We compile a novel dataset that comprises two overarching sources. First, we rely on the data provided in Porteous (2019) for production data and prices. The dataset consists of a compilation of FAO, USDA and WFP data. While FAO (2020) and USDA (2022b) provide data at national levels, Porteous (2019) uses remote sensing data to calculate regional production shares of gross agricultural output by commodity. These data are then in line with regional price information which stems from FAO (2022), USDA (2022a) and WFP (2022) databases. The data cover 6 commodities The data cover the period from January 2002 to December 2013 at a monthly frequency.

Second, we use weather data from TerraClimate Abatzoglou et al. (2018), accessed through the R package *climateR* (Johnson, 2021). We create a buffer around each market region of 100 km and capture average precipitation and temperature to compile both a temperature and precipitation indicator for each market regions and append it to the production and price data obtained in the first step. Altogether our dataset emcompasses 173 maize, rice and wheat markets in 34 SSA markets and total 1,389 observations. The food market locations are depicted in Figure 1.

Figure 1: Map of food market locations in SSA

5 Results

Table 1 reports the results from estimating the IV regression detailed in Equation 4[3]. The model controls for unobservables at country, crop and market levels by means of fixed effects and standard errors are clustered at the country level.

The first stage regression reveals strong effects of the weather variables on prices. The period of $t-1$ describes the weather conditions before harvest in $t-1$ and we observe rather strong coefficient estimates, compared with the global estimates reported in (Roberts and Schlenker, 2013). In the second stage of the model, we estimate a supply estimate of .32, indicating that for every percentage increase of food prices, production will rise by .32% in the following period.

A direct comparison between the estimates of the first stage of our model and the one in Roberts and Schlenker (2013) warrants some caution as they specify their model at a calorie per person level. To that end their price variable is an index that expresses the calorie-equivalent price of maize, wheat, rice and soybean. The size of our coefficient estimates of past temperature and past precipitation are substantially larger than those of global food production, by factors of about 200 for temperature and about 5 for precipitation. This implies, that food price levels in SSA are substantially more responsive to weather than global prices are. With regards to the food supply elasticity, our estimate of is about 3 times as high as those reported in Roberts and Schlenker (2013) and Ghanem and Smith (2020) at the global level. Thus, food production is about three times more price elastic in SSA than in the rest of the world. While no comparable study to validate these results is available, to some extend they are comparable to the effects found in , who also report a supply elasticity of similar order.

[3]These are preliminary results

Table 1: Food Supply Elasticity in Sub-Sahara Africa

	p_t	q_t
IV stages	First	Second
	(1)	(2)
Variables		
p_t		0.32^{*}
		(0.16)
Temperature T_{t-1}	742.5^{**}	
	(279.5)	
Precipitation P_{t-1}	-0.32^{***}	
	(0.10)	
Temperature T_{t-1}^2	-16.8^{**}	
	(6.3)	
Precipitation P_{t-1}^2	0.003^{***}	
	(0.0009)	
t	0.14^{*}	
	(0.08)	
Precipitation P_t	0.08	0.01
	(0.07)	(0.01)
Temperature T_t	-29.8	-31.3^{***}
	(26.8)	(9.7)
Precipitation P_t^2	-0.0004	-8×10^{-5}
	(0.0005)	(8.2×10^{-5})
Temperature T_t^2	0.67	0.71^{***}
	(0.61)	(0.22)
Fixed-effects		
country	Yes	Yes
crop	Yes	Yes
market	Yes	Yes
Fit statistics		
Observations	1,389	1,389
R^2	0.74798	0.91851
Within R^2	0.27098	-0.05335

Clustered (country) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

As both a check of robustness and to shed more light on the elasticity of food supply in SSA on the commodity level we estimate the model using a sample split by crop, the results of which are reported in Table 2. The elasticity of supply is both statistically most powerful as well as largest in terms of coefficient for rice, where - however - effects of temperature and precipitation on price in the first stage are considerably smaller than in the aggregate model. Instead, temperature effects are driving a substantial higher variation in prices of maize while the food supply elasticity of maize production is smaller at .17 and statistically less significant. The wheat model exhibits no meaningful effects in terms of coefficient size and statistical power. One potential explanation is wheat is perhaps the least important staple food compared with the other two commodities under consideration and thus the number of observations of 65 in this model is rather small compared with the other models.

Nevertheless, in all three models we observe substantial heterogeneity in sample size, statistical power and size of the coefficients of the supply elasticities. Some confirmation of these results may be found in Colen et al. (2018), who investigate food demand elasticies in SSA reported in the literature and find remarkable differences across regions and crops. Also with regards to effects and drivers of food prices, a rich body of literature show that food prices in SSA are heterogeneous in terms of their response to exogenous market drivers (Dalheimer et al., 2021; Hatzenbuehler et al., 2020; Pierre and Kaminski, 2019; von Cramon-Taubadel, 2017; Minot, 2014).

Table 2: Supply Elasticity by crop in Sub-Sahara Africa

	p_t	q_t	p_t	q_t	p_t	q_t
crop	Maize		Rice		Wheat	
IV stages	First	Second	First	Second	First	Second
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
p_t		0.17		0.47*		0.02
		(0.17)		(0.25)		(0.13)
Temperature T_{t-1}	1,299.1***		432.5		-3,116.3	
	(241.8)		(424.3)		(853.4)	
Precipitation P_{t-1}	-0.64***		-0.14**		0.98	
	(0.14)		(0.06)		(0.21)	
Temperature T_{t-1}^2	-29.5***		-9.8		70.6	
	(5.5)		(9.6)		(19.3)	
Precipitation P_{t-1}^2	0.005***		0.001*		-0.009	
	(0.001)		(0.0006)		(0.002)	
t	0.14*		0.11		-0.22	
	(0.07)		(0.11)		(0.08)	
Precipitation P_t	0.29***	0.01	-0.08	0.02	-0.21	-0.03
	(0.07)	(0.01)	(0.06)	(0.02)	(0.05)	(0.03)
Temperature T_t	-43.3	-27.1**	-56.3*	-46.0***	240.7	-0.11
	(40.3)	(12.1)	(27.1)	(15.7)	(62.7)	(51.8)
Precipitation P_t^2	-0.002***	-0.0001	0.0007	-0.0001	0.0010	0.0002
	(0.0005)	(7.8×10^{-5})	(0.0004)	(0.0001)	(0.0005)	(0.0003)
Temperature T_t^2	0.95	0.62**	1.3*	1.0***	-5.5	0.002
	(0.91)	(0.27)	(0.62)	(0.36)	(1.4)	(1.2)
Fixed-effects						
country	Yes	Yes	Yes	Yes	Yes	Yes
crop	Yes	Yes	Yes	Yes	Yes	Yes
market	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	832	832	492	492	65	65
R^2	0.72706	0.98736	0.71303	0.98504	0.70492	0.99141
Within R^2	0.44980	0.05899	0.31125	0.27727	0.60549	0.05346

Clustered (country) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Altogether, the results of the baseline model of (i) substantially more elastic food supply and (ii) substantially stronger weather effects on prices in SSA are generally in line with the theory of commodity storage. If the assumptions of low to zero stocks - either because of absence of storage technology or minimum requirement constraints - hold, at least to the extend that they are lower than global food stocks, the relatively higher food supply elasticity reflect the stronger response to exogenous production shocks that can not be shifted across periods through carryovers. Producers have no utility from supply in the next period and thus decide placing efforts in production solely based on current prices that are a function of production shocks. This implies that exogenous shocks to production translate only to prices and production of the current period and either consumption nor price effects are distributed across periods. In other words, prices have stronger signalling effects in year-to-year production decisions in SSA.

From a broader perspective, these results help explain both the higher food price volatility in SSA, which is consistently reported in SSA (e.g. Minot, 2014), and to some extend also the larger fluctuations in production (Buhaug et al., 2015). While volatility in production certainly is subject to weather shocks, the comparably more elastic supply will amplify rather than remedy the problem. Since production shock can only be buffered by stocks and not with production capacities of the next period each period will either have comparably large negative effects from an exogenous production shock or a positive effect from a price response and only coincidentally perceive both effects jointly - which would stabilize production levels and prices over time.

With regards to policy implications, our results indicate that food markets in SSA work will in the sense that price signals are transmitted into production decisions. The main implication of the results is that policy that targets either storage infrastructure or stockpiling behaviour of producers could mitigate production risks and price volatility to eventually smoothen consumption levels. Hence, we join (Larson et al., 2014) and (Coulter and Onumah, 2002) in arguing that increased inventory building in SSA will lead to stabilized food markets and improved food security. One option is promoting adoption and procurement of storage facilities, for instance through dedicated investment support, or specific training programs. Moreover, national inventory programs are also relatively scarce in SSA, revealing a strong potential to mitigate the problem of low food stocks and associated market instability.

One problem that remains are stocks that are not held simply because of minimum requirement constraints. In these instances, policy efforts that are targeting storage and stockpiling behaviour will only be effective if production increases. In light of current population growth rates, increasing agricultural productivity remains imperative in the region to raise food supply sustainably. Nevertheless, stocks can also be built based on imports. Stabilizing trade flows and promoting storage behaviour and decisions using imports are equally effective in ensuring more stable supply and price developments. In the longer term, stability in both prices and supply lead to improved and meaningful long term production strategies.

6 Conclusion

In this paper we analyze the food supply elasticity in SSA. SSA exhibits comparably high volatility in food prices and production levels, resulting in a strong vulnerability to exogeneous weather shocks. At the same time the region also exhibits rising rates of food insecurity and particularly high poverty and prevalence of undernourishment. Building up on the theory of competitive storage, our analysis investigates food supply and prices over time in absence of storage activity that might be due to lack of storage technology or minimum requirements constraints. We compile a dataset of food production, food prices and climate data on a regional level of maize, rice and wheat of 173 markets in 34 countries in SSA. Using an IV model in which we use temperature and climate as instruments, we estimate and identify the food supply elasticity in SSA.

Our results suggest that (i) food supply in SSA is more elastic than global food supply, and (ii) prices are much more subject to exogenous weather events than global prices are. Moreover, we find substantial heterogeneity of food market responses to weather shocks and price developments by crops. These results are in line with commodity storage theory as in absence of opportunities to build inventories, producers will not shift supplies across time periods. Thus, exogenous production shocks will translate fully to both supply and price levels, resulting on overall more volatile prices and production levels over time.

Given that markets are functioning in the sense that producers respond to price signals in the region, promoting stockpiling in SSA is thus a promising a policy avenue. Such measures include investment programs, training and outreach as well as public inventory agencies. Even in cases where low productivity or low levels of production remain the root-cause of food insecurity in SSA, food stocks are major opportunities to stabilize prices and supplies also by means of imports.

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