I. Introduction

Global food prices have increased nearly 52 percent since 2019, driven by the global pandemic and shortages caused by the war in Ukraine.[1] High food prices fuel headline inflation and, if not curbed, may undermine macroeconomic stability. A sharp rise in food prices also erodes real incomes and impedes the continual access to sufficient and nutritious food for many households (Unsal et al. 2020). These effects are more acute for the lower end of the income distribution primarily because poor households spend large shares of their incomes on food consumption and many poor farmers are net buyers of staple food (Ivanic et al. 2012). Moving forward, climate change is forecast to make reliable access to food increasingly difficult, especially in Sub-Saharan Africa (Farid et al. 2022). This puts staple meals further out of reach for large swaths of the population in Sub-Saharan Africa, thereby threatening food security in a region where one in four people struggle with hunger (FAO et al. 2021).[2] In order to accurately forecast inflation and design policies to mitigate food insecurity, it is essential to first understand the drivers of food prices.

This paper explores the domestic and external determinants of the relative prices of staple foods in local markets in Sub-Saharan Africa (SSA). Our empirical strategy focuses on disaggregated food data to estimate the price elasticities of various drivers, yielding four main conclusions.

First, we estimate the food price effects of drivers such as the net import dependence, consumption share of staple foods, global food prices, and real effective exchange rates. Using a panel of domestic market prices of the five most consumed staple foods in 15 SSA countries, we find that these factors explain a sizeable share of the local food price variation, the effect of the consumption share being the largest.[3] Namely, SSA countries are highly vulnerable to global food price shocks, as the estimated pass-through from global to local food prices for highly imported staples is close to unity. Moreover, higher domestic production—reflected in lower net import dependence—and lower consumption shares correspond to lower food price inflation.

Second, we assess how the real costs of staples change in the wake of natural disasters and wars. Our estimates show that relative staple food prices rise sharply, by an average 1.8 percent after natural disasters, and 4 percent after wars hit, though the magnitude, direction, and persistence of the effects may depend on the nature of the shock (Dieppe et al. 2020; Kabundi et al. 2022). Similarly, the effects of the drivers on staple food prices were larger during the COVID-19 crisis, which coincided with the sharpest (19.3 percent) increase in staple food prices since the global financial crisis. For instance, our results suggest that a one percent depreciation in real effective exchange rate would have raised the real cost for highly imported staples by an average 0.7 percent more during

[1] The Food and Agriculture Organization real food price index climbed from 101.6 in December 2019 to 155.0 in April 2022. This index is accessible at https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

[2] The Food and Agriculture Organization (FAO) defines food security along four main dimensions: (i) availability of sufficient quantities of food from domestic production or net imports, (ii) access to nutritious food through adequate resources and well-functioning markets, (iii) appropriate utilization of food through non-food inputs such as clean water, sanitation, and health care, (iv) stable access to adequate food at all times.

[3] Local factors (net import dependence, consumption share) explain about 65 percent of the baseline model fit. However, a model fit decomposition should be interpreted with caution due to potential confounding effects of exports on net import dependence and possible omitted variables. For more details, see discussions in the econometric results section.

the pandemic, as the COVID-19 crisis triggered massive disruptions of global food markets along with exchange rate depreciations in some countries. Within countries, relative staple food prices are on average 2.4 percent lower in large cities, and this urban-rural price gap is wider (3 percent) for highly imported staples. This mainly reflects very low levels of physical infrastructure and related high transaction costs—transport, electricity, market access—in rural SSA areas, where about 60 percent of the population live and the majority of households depend on subsistence agriculture (Gollin and Rogerson 2016).

Third, we explore the country characteristics that contribute to cross-country differences in food price increase. Monetary policy framework, fiscal management, per capita income, and geographic challenges contribute to substantial differences in staple food prices across SSA countries. Countries with stronger monetary policy frameworks and income growth tend to have lower relative food prices, reflecting better control of inflation and smaller share of spending on staple foods when households' incomes rise, respectively. By contrast, food prices are higher in countries with elevated debt-to-GDP ratios and those that are more geographically challenged, as weaker fiscal management and transport challenges tend to inflate the cost of staples.[4]

Other authors have analyzed the link between external factors and local food prices. Early evidence suggested a predominant positive effect of global food price shocks on domestic inflation in advanced economies (Blinder 1982, DiCecio and Nelson 2009). However, this positive link between global food prices and domestic inflation has faded over time, while remaining larger in developing economies than in advanced economies (Furceri et al. 2016). This may reflect a smaller weight of food in the consumption baskets, larger domestic consumption of local products, and better anchoring of inflation expectations in advanced than developing economies. While external factors drive food price inflation, our analysis suggests that domestic factors such as consumption shares and local production—through the net import dependence—explain a substantial share of staple food price variations in local SSA markets.

Another strand of the literature investigates food price volatility. Large swings in food prices may come from unexpected changes in food supply and/or demand. On the supply side, food prices may vary substantially because of net import restrictions or shocks to production. Supply-side shocks often stem from sudden yield variations, unfavorable weather conditions, surges in energy and fertilizers costs, low inventories, limited storage capacity, and transport constraints (Tadesse et al. 2014). On the demand side, food price variations typically reflect shifts in consumption that arise from changes in incomes and tastes (Christiaensen 2009). Exchange rate fluctuations, policy shocks, and conflicts may also accentuate food price volatility (McGuirk and Burke 2020, Unsal et al. 2020). The far-reaching macro-economic and distributional effects of high food prices have ignited a debate on the policy actions needed to ensure food price stability. To stabilize food prices, Kornher and Kalkuhl (2013) argue for building public staple food reserves and promoting well-functioning markets. Combes et al. (2014) contend that remittances and foreign aid can cushion the corrosive effects of food price volatility on real

[4] We use lagged regressors to mitigate endogeneity issues in our panel estimations. However, lagged regressors are not strictly exogeneous and may not fully guard from endogeneity concerns, for instance when the lagged explanatory variables and unobserved characteristics have the same temporal dynamics (Bellemare et al. 2017; Leszczensky and Wolbring 2019). Therefore, we caution against interpreting our estimation results as pure causal effects.

household consumption. Portillo et al. (2016) analyze optimal monetary policy adjustments using a new-Keynesian equilibrium model with flexible food prices and sticky non-food prices. To curb inflationary pressures, the authors suggest anchoring inflation expectations and targeting core inflation rather than headline inflation.

Taking a long run perspective, a strand of the literature investigates the food price elasticities of income growth, subject to storage constraints (Roberts and Schlenker, 2013). One may argue that a rapid income growth could boost the demand for food and put upward pressures on food prices. On the other hand, Engle's law states that wealthier households spend a smaller proportion of their income on food than their poorer counterparts. In growing developing countries, a decline in the share of demanded foods in the consumption basket would lead to lower relative food prices (Baffes and Etienne 2016). It also means that the terms of trade will follow a downward path because of a smaller demand increase in domestic food and primary commodities than manufacturing products, in line with the Prebisch-Singer hypothesis (Arezki et al. 2014).

Our analysis also relates to the broad literature on food security. A few papers have coalesced around the macro-economic variables that affect food insecurity. Timmer (2000) contends that food price inflation, income and social transfers affect per capita daily caloric intake—a proxy for food security. Using a self-assessed indicator of food insecurity, Headey (2013) concludes that GDP growth reduces food insecurity, but food price inflation has no significant impact. Fukase and Martin (2020) argue that faster income convergence rates across countries are expected to boost food demand more than supply, leading to upward pressures on global food prices. Using a an open-economy spatial multi-sector macro-model, Baptista et al. (2022) show that a large negative shock to agricultural productivity can lead the economy into a lower productivity steady state and poverty trap, entailing policy response trade-offs.

The literature so far, however, has mostly focused on the food component of the Consumer Price Index (CPI), a specific food commodity, or a narrow set of countries. Analyzing food price data involves important trade-offs between data availability, the degree of granularity, and the selection of food items. On the one hand, while the food component of CPI offers an aggregate view of food price variations, it doesn't allow for a deep dive analysis by staple food item or within country locations. On the other hand, the sheer size of market-level food prices data often compels researchers to select in an ad hoc way a narrow set of staples or focus on a specific country. Instead, we use the contribution of each staple food to daily diets—a useful criterion from a food security perspective—to guide our selection of the most consumed staples. Thus, our paper contributes to the literature on food security by exploiting, based on a food security relevant criterion, the richness of local market-level data to explain the price changes of the major staple foods in a large set of SSA countries.

The rest of the paper is organized as follows. Section 2 presents some descriptive statistics on staple foods in SSA. Section 3 briefly reviews the main drivers of food prices. Section 4 introduces our empirical model and outlines the estimation strategy. In Section 5, we discuss the empirical results and assess the food price effects of various drivers. We report some robustness exercises in Section 6. Section 7 concludes.

II. Data and Context

A. Identifying staples in SSA

The staple foods are identified based on their average contribution to individual diets. Our analysis focuses on staple foods across a diverse group of 15 Sub-Saharan African countries (Table 1). This set of countries—home to approximately 70 percent of the population in the region—includes low-income countries, as well as frontier and emerging economies.[5] Due to data limitations, a larger set of Sub-Saharan countries was not included in the analysis.

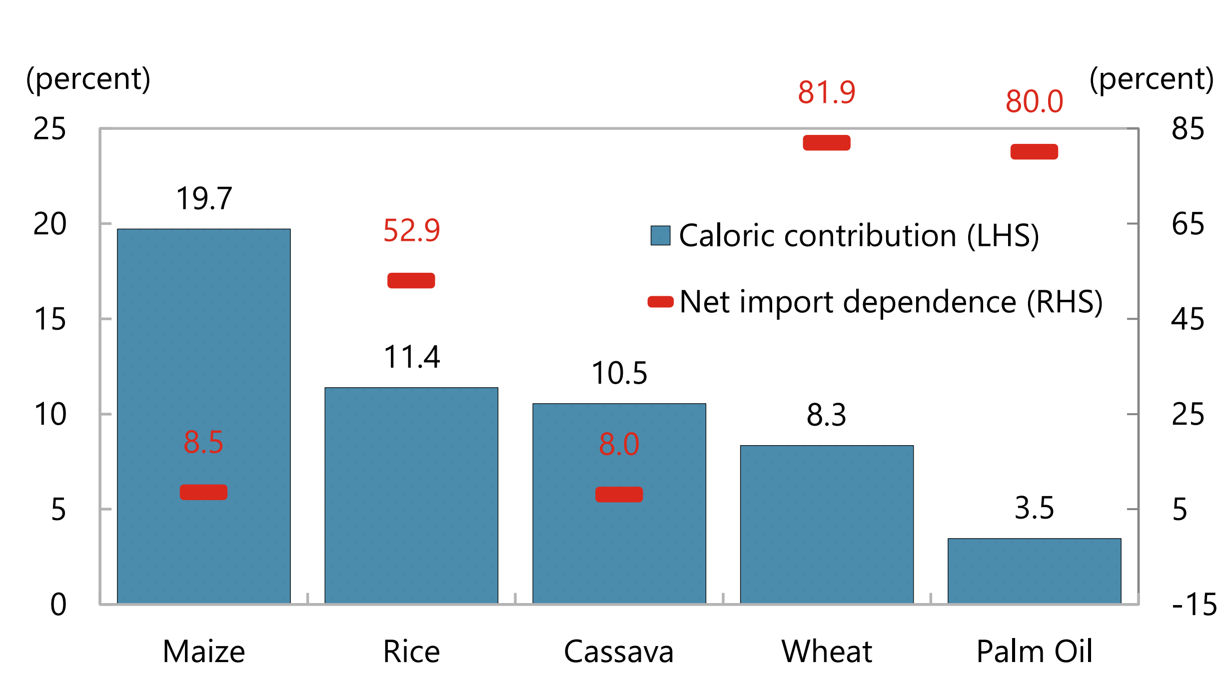
Using consumption data from FAO food balance sheets, the most consumed staple foods are selected by averaging the daily per capita caloric intake of each staple across countries. A typical consumption basket in the region is broadly made up of two types of staples: cereals and starchy roots. On average, cereals—such as maize, rice, and wheat—and starchy roots—such as cassava, sweet potatoes, and potatoes—account for almost two thirds of daily caloric intake. The other third of daily food consumption is mainly comprised of vegetable oils, sugar, fruits, meat, and pulses. The five most consumed staples in SSA are maize, rice, cassava, wheat, and palm oil, which contribute to about 54 percent of the average daily per capita caloric intake (Figure 1).[6] Within the region, maize—19.7 percent of the daily per capita caloric intake—is the top staple in Eastern and Southern Africa, while rice—11.4 percent of the daily per capita caloric intake—is widely consumed in Western Africa. The consumption of cassava, wheat, and palm oil—which account for around 10.5, 8.3, and 3.5 percent of the daily per capita caloric intake, respectively—seems more homogeneous across the region, albeit with some differences between certain countries. For instance, the top 5 staples make up more than 65 percent of total daily caloric contribution in Angola and Mozambique, whereas they account for less than 40 percent in Ethiopia, Namibia, or Rwanda, reflecting differences in diet composition and missing data in some countries. In Ethiopia, other cereals (15.3 percent) such as teff, sorghum (9.6 percent), and roots (6.0 percent) are largely consumed staples alongside maize (19.3 percent) and wheat (13.3 percent). In Namibia, wheat (17.3 percent) and maize (16.9 percent) are the top 2 staples, followed by roots (11.5 percent), sugar (9.1 percent), and milk (7.8 percent). In Rwanda, the top staples are beans (14.6 percent), cassava (11.8 percent), sweet potatoes (10.1 percent), maize (8.8 percent) and potatoes (8.6 percent). The percent caloric contribution of each staple to the daily diet has remained virtually unchanged over the last 5 years of the sample period, suggesting a limited temporal substitution between these top five staples in the food consumption basket.[7]

[5] The sample includes market-level data on staple foods from Angola, Cote d'Ivoire, Ethiopia, Ghana, Kenya, Malawi, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Uganda, United Republic of Tanzania, and Zambia.

[6] The daily caloric intake for each staple food is computed using FAO food balance sheets data from 2019. The market-level price data for sugar (raw and equivalent), which makes up nearly 5 percent of the daily caloric diet in SSA, were not widely available in our dataset.

[7] The daily per capita consumption shares of maize (19.3-20.4 percent), rice (10.8-11.1 percent), cassava (9.7-10.3 percent), wheat (8.2-9.0 percent), and palm oil (3.1-4.0 percent) have been almost flat over the last 5 years of the sample period.

Figure 1. Daily caloric contribution and net import dependence of top 5 staples



Source: FAOSTAT Food Balances and authors' calculations.

There is substantial cross-country heterogeneity in the domestic production and net import dependence of staple foods.[8] For example, Côte d'Ivoire is a net exporter of palm oil—with a net import dependence of -73.5 percent, whereas Ghana is a net importer—with a net import dependence of 36.4 percent (Table 2). About three-quarters of Ghana's annual imports of palm oil come from Malaysia and Indonesia—two leading global producers—and only 13 percent from Côte d'Ivoire.[9] Despite this heterogeneity, reliance on domestic production in the region is broadly low for wheat, palm oil, and rice, reflected in relatively high net import dependence of 81.9, 80, and 52.9 percent, respectively. As regards import trading partners, Russia is the dominant source for wheat (34.7 percent), while palm oil and rice mainly come from Malaysia (47.8 percent) and India (36.3 percent), respectively (Table 3). By contrast, maize and cassava, which are mainly domestically sourced subsistence crops, have low net import dependence ratios at 8.5 and 8 percent, respectively.[10] The main regional suppliers of maize and cassava

[8] Net import dependence is defined as $(100 \times (imp - exp)/(prod + imp - exp))$ and computed using FAO food balance sheet data from 2019.

[9] The new Africa Continental Free Trade Agreement (AfCFTA) that came into force in January 2021 is expected to stimulate inter-African trade of services and goods, including staple foods.

[10] The simple average net import dependence of the top five staples is 46.3 percent. The average net import dependence weighted by the consumption shares of the top five staples is 34 percent. The majority of the top five staples are heavily imported in Angola, Kenya, Mozambique, Namibia, Senegal, and South Africa. However, in Côte d'Ivoire, Ethiopia, Ghana, Malawi, Nigeria, Uganda, Zambia, the majority of the five most consumed staples are produced locally.

are Uganda and Tanzania, accounting for 33.8 and 41.2 percent of imported maize and cassava, respectively.[11] The net import dependence of a staple food, which reflects its supply composition in terms of net imports versus domestic production, is expected to play a crucial role in shaping local staple food prices and food security in the region.

B. Overview of staple food price developments during COVID-19

Global food prices have increased substantially during the COVID-19 crisis, as the pandemic dealt a massive humanitarian and economic blow to countries worldwide. The upward trend in global food prices, which rose 25 percent over 2020-21, coincided with higher relative staple food prices—nominal food prices deflated by general CPI—in local markets in SSA (Figure 2.A-B). In SSA, where food makes up nearly 40 percent of the consumption basket, the local relative prices of staples surged by an average 19.3 percent in 2020-21 (Figure 2.C).[12] This was the sharpest increase in the staple food prices since the global financial crisis.

The recent step change in the local costs of staple foods was broad-based, albeit of varying magnitudes. The largest real price increases were seen for cassava (83.2 percent), wheat (18.6 percent) and maize (11.3 percent). The average price changes for rice and palm oil have been more muted. When consumption shares are factored in, there is a 8.5 percent real increase in the cost of a typical food consumption basket in the region (Figure 2.D).

While mainly imported staple food prices have risen more than the costs of domestically produced staples over the last decade (2012-21), the prices of locally sourced staples have spiked during the pandemic (2020-21) in some countries. For example, the prices of both cassava and maize (mainly produced locally) in Nigeria have more than doubled. In Ghana, the relative prices of cassava and maize have surged by 78 and 66 percent, respectively.

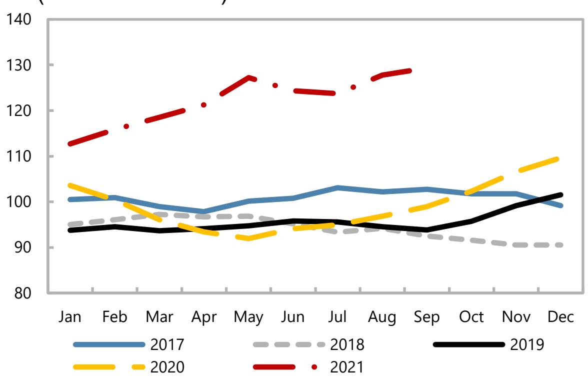
Stricter mobility restrictions in groceries and pharmacies, retail facilities, and workplaces during the pandemic have disrupted local food markets and accentuated the dual shock of rising food prices and falling incomes (Figure 2.E). Countries in the region have gradually eased these mobility restrictions towards the end of the period. Within countries, market-level data reveal different staple food price dynamics between urban and rural areas (Figure 2.F). The relative prices of maize and cassava—predominantly produced domestically in rural areas—have become more expensive in urban than rural areas. In contrast, the cost of wheat and rice—mostly imported staples—have been relatively cheaper in urban than rural local markets. This partly reflects better infrastructure and lower transport costs of imported goods in urban areas. On balance, the costs of the five most consumed staples are on average cheaper in urban area than rural area—see subsequent discussions of estimation results by location.

[11] While the main import sources of rice (India and Thailand) and palm oil (Malaysia and Indonesia) to SSA have remained unchanged since 2010, the prominence of import trading partners for other staples has varied over time. For instance, China has become the fourth largest exporter of rice to the region, raising its share of imported rice from 1.6 to 7.1 percent over the past decade. Similarly, the share of wheat imports from Russia has more than tripled over the past decade, from 10.5 to 34.7 percent.

[12] Food price increases in SSA are expected to contribute more to headline inflation, partly because the consumption spending on food in the region (which has many low-income countries) is about twice (39.9 percent) that in high income countries (21.6 percent).

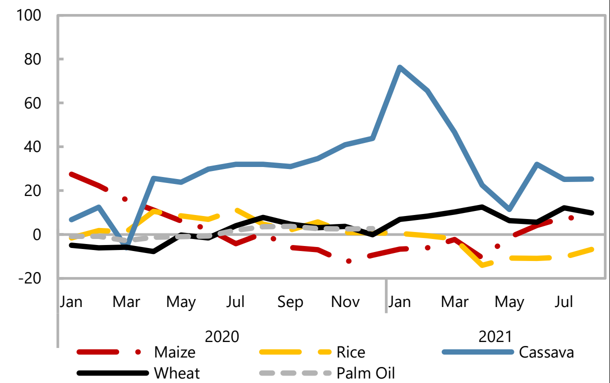
Figure 2. Evolution of Staple Food Prices

2.A: Global food price index, 2017-2021
(2014=2016=100)



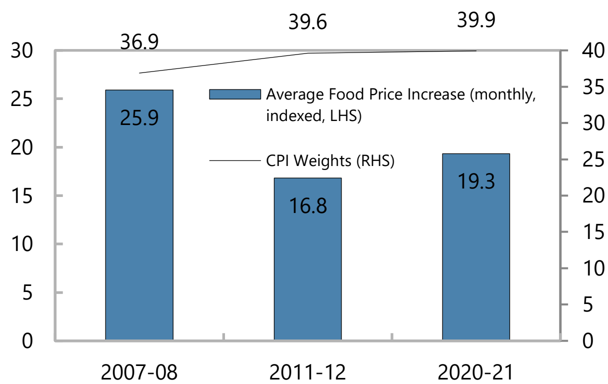
Sources: FAOSTAT Global Food Price Index and authors'

2.B: Change in real local prices of staples, 2020-21
(y-o-y, percent)



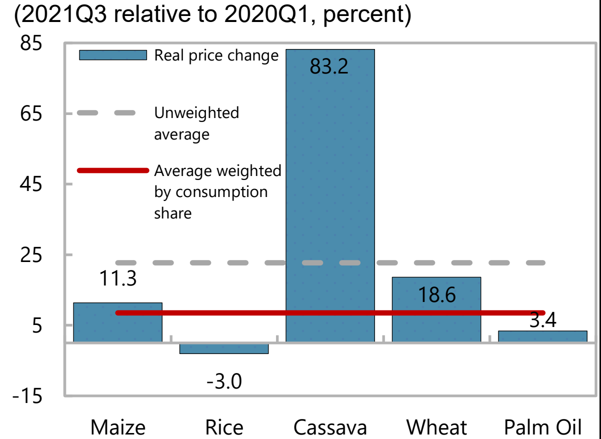
Sources: FPMA GIEWS Tool and authors' calculations

2.C: Relative price increase of staples in food crises
(percent)



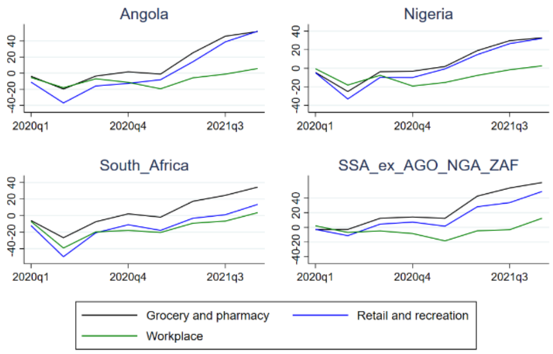
Sources: FPMA GIEWS Tool and authors' calculations.
Notes: Simple averages of monthly real price increase of staples during 2007-08, 2011-12, and 2020-21 global food crisis periods. Real prices are indexed at the start of each crisis period (January 2007=January 2011=January 2020=100).

2.D: Relative price change of top five staples
(2021Q3 relative to 2020Q1, percent)



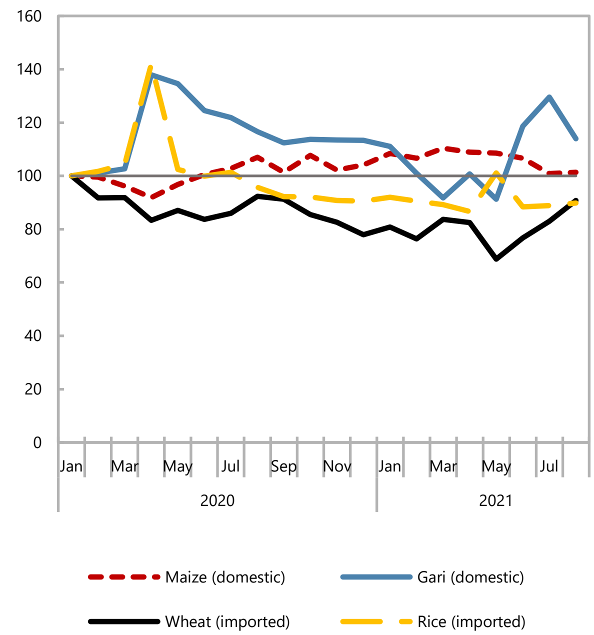
Sources: FAOSTAT Food Balances and authors' calculations.

Figure 2.E: Mobility during COVID-19 crisis, 2020-21
(change from baseline day, percent)



Source: Google Maps.
Notes: Mobility refers to percent changes in visits to (or time spent in) grocery and pharmacy, retail and recreation facilities, and workplaces compared to a baseline day. The baseline day is a "normal" value of visits for that day of the week, computed as the median value for the 5-week period from January 3 to February 6, 2020. Grocery and pharmacy facilities include grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. Retail and recreation facilities include restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Workplaces include places of work.

Figure 2.F: Urban-rural staple price ratios, 2020-21
(urban/rural price ratio, percent)



Sources: FPMA Giews Tool and Author's calculations.

III. A Primer on the Drivers of Staple Food Prices

Many domestic and external factors are related to food prices in Sub-Saharan African economies (Alper et al. 2016). Supply factors such as domestic food production, net imports, and transport constraints affect the cost of staple foods in local markets. On the demand side, staple food prices vary, owing to changes in food consumption and incomes. Moreover, elevated world food prices, and exchange rate depreciations often contribute to higher domestic food prices.

A. Supply

Local production. The domestic food production is a key component of staple food supply in SSA, where the agricultural sector makes up about one-fifth of the value added (Fuglie et al. 2020). Food production in the region is predominated by small-scale farming—it absorbs 80 percent of all farmers and accounts for 90 percent of food production (Unsal et al. 2020). Smallholder farmers typically operate small-scale farms and resort to unmechanized labor-intensive production (Lowder et al. 2021). Despite recent headways, agricultural (land and labor) productivity in SSA has remained low and lagged other regions (Gollin 2010). Over the last half century, the increase in crop yields in Sub-Saharan Africa has been muted, on average at 1.5 tons per hectare (t/ha), whereas yields have tripled to 3 t/ha in South Asia and jumped six-fold to 6 t/ha in East Asia (Fuglie et al. 2020). Moreover, there is limited storage capacity in SSA despite recent progress, which prevents many countries from maintaining sufficient food inventories. In some areas, this leads to sizeable food losses and limits the ability of countries to cushion supply disruptions and food price volatility that are exacerbated by frequent natural disasters and conflicts (ECOWAS 2020, Tadesse et al. 2014). The post-harvest handling and storage food losses in the region have been estimated at about 15 percent of total production (Affognon et al. 2015; Hodges et al. 2010).

The knock-on effects of the rising costs of food production inputs—fertilizers used to improve crop yields and fuel, combined with localized seed shortages have contributed to bouts of food price volatility in some countries (Schmidhuber et al. 2020). Input and production subsidies also shape the supply of staple foods. These production subsidies aim at raising agricultural production and supporting the price competitiveness of domestic food products by dampening production costs, and therefore, reducing import demand. From a food security perspective, governments have used subsidies to boost food availability, provide a form of social assistance to farmers, facilitate the access of vulnerable people to basic staple foods, and limit food price volatility (Morris et al. 2007). Despite their good intentions, ill-designed, broadly targeted, and prolonged subsidies can lead to bad outcomes. Poorly targeted food subsidies often distort productive investments toward low-productivity agriculture sector, imply high fiscal costs, and crowd out pressing public spending in priority sectors such as education, health, and infrastructure. Many subsidy programs are also socially regressive, that is, they actually benefit the rich much more than the poor (Coady et al. 2004). Recognizing these potentially negative outcomes, some countries have taken steps to reduce or remove subsidies, while improving their targeting and efficiency.

Net imports. In SSA, net imports complement the domestic production to ensure a sufficient supply of staple foods in local markets. Some countries rely more heavily on imports to bridge the food supply and demand gap

of certain staples such as wheat and rice. The net import dependence—net food imports as a share of total food supply—synthesizes the information about net imports and local production. A high net import dependence for some staples potentially entails two opposite effects. On one hand, international trade disruptions can accentuate the risk to food security in high food import dependent countries. This was particularly critical in the context of COVID-19, as the pandemic-related restrictions have disrupted midstream and downstream components of the food supply chains and compressed the imports of some foodstuffs (Mogues 2020). For instance, export restrictions by the region's main food trading partners (e.g., the European Union, Pakistan, Thailand) may have contributed up to 25 percent decline in food imports into the region (Zeufack et al. 2020). On the other hand, countries with access to global food markets can hedge against domestic food supply-side shocks, such as extreme weather conditions and insect infestations that damage harvests and dent food production (Nchanji et al. 2021). The net effect may depend on the degree of net import dependence of a country, diversification of supply sources, and substitutability of imported staples.

Transport and geographic challenges. Transport costs affect the quantity and quality of domestically available food items. Logistical constraints including weak transport infrastructures and geographical challenges—e.g., mountainous or rough terrain—weigh on the ability of market intermediaries to ship food at reasonable costs (Burke and Myers 2014, Nunn and Puga 2012). There are various transport costs, including international shipping costs and domestic distribution costs. These frictions add to staple food prices in local markets and can contribute to inflationary pressures (Gollin and Rogerson 2016). Typically, the closer the consumption centers to the main supply points—farms for locally sourced foodstuffs or borders for imported staples—the lower the logistical costs. This could imply cheaper transport costs for highly imported staples in large SSA cities where transport infrastructures are often better. By contrast, the transport costs for locally produced staples would be cheaper in rural areas where most farms are situated.

B. Demand

Consumption. The demanded quantities of staples are influenced by local dietary habits. These are reflected in the caloric contribution of staple food items to individuals' daily diets—measured by their consumption shares—and shape prices in local markets (Timmer 2000). Data from FAO food balance sheets show that a typical consumption basket in SSA countries is predominantly comprised of cereals—maize, rice, and wheat—and starchy roots—cassava, sweet potatoes, and potatoes. Cereals and starchy roots make up nearly two-thirds of the daily per capita caloric intake, while other staples such as vegetable oils, sugar, fruits, meat, and pulses account for the rest. Moreover, substitutability among demanded staples allows consumers to switch from expensive products to cheaper ones, which in turn can help ease price pressures (Haggblade et al. 2017). Over the last 5 years, the share of each of the top five staples in the daily caloric intake has remained almost unchanged, pointing to limited substitution effects for the five most consumed staples.

Income. The purchasing power of consumers also affects food demand and prices. Households at the lower end of the income distribution spend a larger share of their incomes on food (Arezki et al. 2014, Ehui 2020). The very poor typically live from hand to mouth and devote a substantial part of their incomes to buy subsistence foods

(Timmer 2010). An erosion of income, as seen during the pandemic, imposes a heavy cost on poor households and further hinders their access to sufficient and nutritious staple foods in SSA (World Bank 2021). By contrast, better-off households can afford more diverse diets and tend to spend more on non-food items. Thus, food consumption shares subsume the information on income differences and dynamics.

C. Global food prices and exchange rates

Global food prices. Net imports shape the pass-through of global food prices to domestic food prices. There are both direct and indirect effects. The direct effect occurs through wholesale purchases of foodstuffs on international markets. Indirectly, global food prices affect prices in local food markets through purchases of agricultural inputs—fertilizers, fuels, seeds, etc.—on global markets. In the absence of subsidies and tariffs, the higher the net import dependence, the stronger the link between global and domestic food prices. In practice however, policy interventions affect the pass-through from international market prices to domestic consumers prices. For instance, import tariffs aimed at insulating domestic producers from foreign competition can weaken the price transmission from international to local markets. By contrast, export tariffs are often used to ensure sufficient supply of locally sourced staples and alleviate price pressures on domestic markets. There have been significant price pressures during the pandemic, which contributed to the sharpest increase in staple food prices since the global financial crisis. In 2020-21, global food prices have risen sharply by 25 percent, alongside a nearly 20 percent jump in local staple food prices. Despite some heterogeneity across countries, staple food markets in SSA experienced dramatic price increases for major staples, in particular cassava (83.2 percent), wheat (18.6 percent) and maize (11.3 percent).

Exchange rates. The change in local prices may also reflect the relative changes in exchange rates. The relative strength of a country's currency with respect to its trading partners affects the costs of imported food items in domestic markets. This effect depends on the exchange rate pass-through to domestic prices for tradable staple foods (Alper et al. 2016). After the onset of the pandemic, there were initially sharp broad-based currency depreciations in 2020 in our sample, followed by different speed recoveries (Unsal et al. 2020).

D. Adverse events

Adverse events such as natural disasters and wars exacerbate food price volatility. These events often cause severe human (deaths, injuries, displacements), physical (destruction of infrastructures, assets, etc.), and economic damages, and inflict deep scars on the affected countries (Dieppe et al. 2020). Absent public or international assistance, these shocks typically compress food production (disruption of planting and harvesting cycles, destruction of crops, etc.), dislocate supply chains, and degrade the living conditions in affected areas. Recurring bouts of violence in some areas (e.g., insurgencies in the Sahel) and armed conflicts push food prices higher by putting stress on food security from both supply and demand sides (McGuirk and Burke 2020, van Weezel 2016). Of particular concern is the greater frequency of natural disasters, especially climate disasters that are increasingly fueled by climate change.

IV. Empirical Strategy and Specification

A. Baseline specification

This section describes the empirical specification and estimation approach used to analyze the factors driving the observed change in the relative price of food staples. The analysis starts with the following baseline linear specification:

$$y_{cmi,t} = \beta_1 NID_{ci,t-1} + \beta_2 CS_{ci,t-1} + \beta_3 \Delta GFPI_{i,t-1} + \beta_4 y^{high}_{cmi,t} + \alpha_{cmi} + \varepsilon_{cmi,t}, \qquad (1)$$

where $y_{cmi,t}$ is the annualized (monthly year-on-year) change in the relative price (nominal prices deflated by general CPI) of staple food i, in market m, country c, month t, NID is the net import dependence defined as (imports – exports)/(production + imports – exports) in percent, CS is the consumption share reflecting the percent contribution of a staple food in the daily diet, $\Delta GFPI$ is the annualized (monthly year-on-year) change in the global food price index in real term, y^{high} is a dummy that takes 1 if the change in staple food price exceeds 50 percent and 0 otherwise, α_{cmi} stands for the country-market-item fixed effects, and ε is the error term.[13] Note that for the dependent, we use the retail prices of staples in local markets.[14] The model includes lagged net import dependence, consumption share, and change in the global real price to mitigate the bias from potential endogeneity and reverse causality. Following Calderón and Schmidt-Hebbel 2010, we control for episodes of high food price increases (y^{high}). Linear models tend to overestimate the effects when based on samples that include high food price episodes compared to estimations based on samples without these extreme episodes (Fischer et al. 2002). Thus, controlling for episodes of food price surges helps circumvent the exclusion bias of coefficients estimates for other determinants of food price inflation and improves the overall fit.[15] However, it is

[13] All variables, expect high food price dummy y^{high}, are lagged and expressed in percent. The global food price index in real term is the FAO global nominal food price index based in 2014-16 and deflated by the World Bank Manufactures Unit Value Index.

[14] Missing retail prices are replaced by wholesale prices when available to get a more balanced panel.

[15] Episodes of high food price increases ($y^{high} = 1$ if the change in staple food price exceeds 50 percent) account for about 7.5 percent of local food price data. The model specification doesn't include lags of the dependent variable as regressors (dynamic panel model) because local staple food prices are highly volatile and weakly persistent.

important to stress that while lagged regressors are commonly used instruments in panel regressions, they may not fully guard from endogeneity concerns in reduced form estimations. For instance in cases where the lagged explanatory variables and unobserved characteristics have the same temporal dynamics, changes in local relative food prices could affect consumption and imports, and using lagged regressors would not ensure strict exogeneity (Bellemare et al. 2017; Leszczensky and Wolbring 2019). Therefore, our estimation results should be interpreted with care, as the estimated coefficients are not pure causal effects from strictly exogenous factors (Arellano and Bond 1991; Imbens 2014).

Equation (1), which assumes slope homogeneity across food staples, is estimated using fixed effects panel data regressions, which account for time-invariant unobserved heterogeneity across food items.[16]

B. Extensions

The baseline model in Equation (1) is augmented to encompass the changes in real effective exchange rate for highly imported staples, natural disaster and war shocks, location, along with interaction terms. The extended specification writes:

$$y_{cmi,t} = \beta_1 NID_{ci,t-1} + \beta_2 CS_{ci,t-1} + \beta_3 \Delta GFPI_{i,t-1} + \beta_4 y_{cmi,t}^{high} + \mathrm{B}' * \overline{M}_{c,t-1} + \alpha_{cmi} + e_{cmi,t}, \qquad (2)$$

where $\overline{M}_{c,t}$ is a vector of additional variables including the percent change in the real effective exchange rate ΔREER, dummies for COVID-19, natural disaster, war, and location (largest city), and interaction terms. The binary COVID-19 variable takes 1 during the pandemic from January 2020 through the end of our sample period in September 2021. Natural disasters dummies are defined based on adverse events comprising climate, biological, and geophysical disasters recorded in the Emergency Disasters Database. Using the Correlates of War (COW) and Peace Research Institute Oslo (PRIO) databases, wars are identified as civil and inter-state armed conflicts with at least 1,000 battle-related deaths over the entire episode. We refer the reader to Dieppe et al. (2020) for detailed definitions of COVID-19, natural disaster, and war dummies.[17] An increase in the real effective exchange rate level (ΔREER>0) indicates a real appreciation, reflecting a loss in price competitiveness in the home country vis-à-vis its trade partners. Simply put, an increase in effective exchange rate implies that the home country's exports become more expensive while imports become cheaper. An uptick in real effective exchange rate is expected to lower the real price of highly imported staples whereas a real effective exchange rate depreciation is expected to raise the real cost of highly imported staples. Therefore, we expect the coefficient

[16] Fixed effects help control for unobserved individual characteristics or omitted variables that presumably remain constant over time, such as historical, cultural, or culinary preference for each type of food. We test the validity of the fixed effects estimation against random effects estimation for the baseline specification. Table A2 in the Appendix shows that a Hausman test favors the fixed effects estimation over the random effects regression.

[17] The EMDAT uses the following criteria to identify natural disasters: (i) 10 or more people reported killed; (ii) 100 or more people affected, (iii) an official declaration of a state of emergency; or (iv) a call for international assistance. Affected people include injured, homeless, and those who required immediate assistance during the state of emergency. Wars are identified based on the situation in the home country but do not account for the conflict situation in trading partners where staple foods are sourced.

of the interaction between ΔREER and $NIDhigh$—a dummy for highly imported staples that takes 1 if the net import dependence of a staple food exceeds 75 percent and 0 otherwise—to be negative. Moreover, the coefficients associated with COVID-19, natural disaster, and war dummies are expected to be positive because these shocks typically entail large-scale disruptions in the supply and consumption of staple foods. For location effects, we expect relatively lower average staple food prices in largest cities, as better infrastructure in largest cities facilitates food transport, in particular the shipping of imported staples.

V. Econometric Results

A. Baseline estimations

The empirical estimations use an unbalanced panel of 15 countries covering the period January 2012 to September 2021. The sample selection was guided by data availability. The primary sources of data used are the FAO FPMA and food balance sheets, IMF AREAER, Emergency Events Database, Correlates of War and Peace Research Institute Oslo armed conflicts database, IMF World Economic Outlook, and World Bank WDI (Table A1).[18] The regressions are conditioned on lagged regressors to mitigate the bias from potential endogeneity and reverse causality. Nonetheless, the estimated coefficients should not be interpreted as pure causal effects from strictly exogenous regressors.

Empirical assessment of food price determinants in SSA

What key factors drive staple food prices in local markets in SSA? Taking Equation (1) to data, we run our baseline specification using fixed effects estimations. The two columns in Table 4 show fixed effects estimations of the baseline model excluding and including a dummy for high food price increases.[19] As discussed after Equation (1), we control for episodes of high food price increases to limit the exclusion bias of coefficient estimates (Calderón and Schmidt-Hebbel 2010). This is confirmed by the large and significant coefficient values and the substantial improvement in the model fit. Conditional on other regressors, the real cost of staples rises by an average 89.2 percent in periods of food price surges (Table 4, column 2). The net import dependence has a positive and significant coefficient as expected. A one standard deviation increase in net import dependence from the panel sample mean of 24 percent to about 59 percent, would raise the relative prices of local staple foods by 3.9 percent (Figure 3.A).[20] As expected, the consumption share is also associated significantly, both in statistical and economic terms, with higher staple food prices. Following a one percent increase in the consumption share of a staple food, the corresponding relative prices in local markets are expected to rise, on

[18] Table 1 presents the countries covered by the analysis. The panel data sample (n=98, T=116) covers 5 food staples (Cassava, Maize, Palm Oil, Rice, Wheat) across 68 local markets in 15 SSA countries (Angola, Côte d'Ivoire, Ethiopia, Ghana, Kenya, Malawi, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Uganda, United Republic of Tanzania, and Zambia), from January 2012 to September 2021. Table A1 contains the data descriptions, summary statistics, and sources for all variables.

[19] Coefficient estimates are shown with clustered (market-level) robust standards errors. Driscoll and Kraay's (1998) standard errors, not presented here to save space, yield similar results.

[20] Figure 3 shows coefficient estimates and 95 percent confidence intervals.

average, by 0.7 percent. Turning to global food prices, the results show a positive and significant effect in line with our prior. A one standard deviation uptick of about 8.6 percent in the global food price index would increase the average real cost of staples by 1.3 percent. In the baseline specification, domestic factors (net import dependence and consumption share) contributed more (65 percent) to model fit than the external factor (global food prices).[21]

Next, the baseline model is extended to include other variables such as the change in the real effective exchange rate ∆REER, dummies for COVID, natural disaster, war, and location (largest city), and interaction terms.

B. Exchange rates effects for imported staples

We now turn to the price effects for imported food staples (Alper et al. 2016). The extended specification includes the change in REER interacted with a dummy for highly imported staples, that takes 1 if the net import dependence of a staple exceeds 75 percent and 0 otherwise. As expected, the estimated coefficient of $\Delta REER * NIDhigh$ is significantly negative, as shown in Table 5. The estimate in column 1 in Table 5 suggests that a one percent appreciation in the REER—making imports cheaper and exports more expensive—is associated with about 0.3 percent decline in the relative price of imported staple foods in local markets.

The other columns (2-4) in Table 5 show interactions for the baseline drivers.[22] The positive and significant interaction coefficients suggest that the average price effects are broadly higher for highly imported staples than locally produced food items. Simply put, an increase in consumption shares and global food prices would raise the relative price of highly imported staples more than those produced locally. Rescaling the estimated interaction coefficients by the standard deviations of the regressors reveals that the change in global food prices has the largest effect on the price of highly imported staples (Figure 3.B). Pass-through estimates in column 4 of Table 5, show that increases in global staple food prices could bring almost one-to-one (0.966=0.189+0.777) increases in the local relative prices of highly imported staples.[23] Thus, there are potential gains in promoting a competitive domestic production of highly imported staple foods in SSA countries.

C. Largest cities

The price of a commodity should be the same across frictionless markets. However, frictions such as transport costs typically lead to price differentials across food markets and location.[24] In SSA, the infrastructure gap is particularly acute in rural areas. Underdeveloped road networks complicate the access to many rural areas and

[21] One should interpret the model fit contribution of global versus local factors with caution because (i) the net import dependence is not strictly a local factor, as it embeds exports, and (ii) the reduced form specification in Equation (1) could omit other factors, despite controlling for episodes of high food price.

[22] The interaction between high staple food price and highly imported staple food (NIDhigh) dummies is not included to avoid multicollinearity, as the regression includes many fixed effects dummies.

[23] The estimated pass-through from global to local staple food prices may vary across countries depending on policy conditions. In particular, subsidies and tariffs tend to weaken the global to local prices pass-through estimates.

[24] The urban-rural price gaps may also reflect other factors such as subnational spatial differences in the consumption of subsidized staples.

very few rural residents have access to electricity or piped water. This pushes transport and market access costs higher in rural areas where about 60 percent of the population live and depend on subsistence agriculture (Gollin and Rogerson 2016). The first column of Table 6 shows that the average real cost of staple foods is 2.4 percent lower in largest cities. This points to better infrastructures in largest cities that facilitate food transport. Interestingly, the reduction in staple food prices in largest cities is smaller (1.9 percent in column 3 vs. 2.4 percent in column 1) in more geographically challenged countries—identified by an index which measures how rough in elevation is the terrain in a country. Nunn and Puga (2012) use this index of terrain ruggedness as an exogenous proxy for geographic isolation and transport challenges in Africa.[25] In more geographically challenged areas, food prices are often higher because transportation over irregular terrain is slower and more expensive and crop production is more difficult (Allen, Bourke, and Gibson 2005). Indeed, steep slopes hinder the transportation of crops to markets and make earthwork, seeding, watering, and harvesting more costly (FAO 1993). For highly imported staples in the second column of Table 6, the average relative price differential is larger: relative prices are 3 percent lower in largest cities. The standardized price effects are shown in Figure 3.C. These findings are in line with the implications of the spatial macro-model of Baptista et al. (2022). Although our analysis does not explicitly explore this channel, real income gaps between (urban and rural) areas could also entail differences in consumption shares and explain spatial differences in the relative prices of staple foods. Because wealthier households can afford more diversified diets, a larger concentration of affluent households in large cities may entail smaller consumption shares, and thus, lower relative prices of the top staple foods in urban areas than in rural areas.

D. Natural disasters and wars

We analyze what happens to staple food prices when countries are hit by natural disasters and wars. These adverse events often leave short-term socio-economic impacts and long-term scarring effects on the affected countries (Marto et al. 2018; Dieppe et al. 2020). The estimation results are reported in Table 7 and shown in Figure 3.D. Following natural disasters (climate, biological, and geophysical) and wars (intra, extra, and inter), the relative prices of staples in local markets surge by 1.8 and 4 percent, respectively, conditional on other variables. McGuirk and Burke (2020) and van Weezel (2016) document similar food price spikes in the aftermath of natural disasters and conflicts. Wars also exhibit more persistent effects on local staple food prices than natural disasters. Columns 1-3 in Table 8 show that the effects of natural disasters on the relative prices of staples taper-off to about 0.4 percent and become statistically insignificant after 3 months. By contrast, wars (columns 4-7) have more protracted effects on relative staple food prices, as reflected by the statistically significant coefficient of 1.5 percent associated with the 2-year lagged war dummy.[26] It is worth stressing that our estimations bundle various types of natural disasters together. While we leave finer analyses of the impact of different types of natural disasters for future work, let’s stress as in Dieppe et al. (2020) that the definition and type of a natural disaster

[25] Puga and Nunn (2012) show that while the average terrain ruggedness in Africa is slightly lower than outside the region, Lesotho, Rwanda, and Seychelles are among the countries with the roughest topography in the world.

[26] Alternatively, the persistence of the effects of natural disasters and wars on local staple food prices could be estimated using reduced-form vector autoregression or local projections models (Dieppe et al. 2020, Kabundi et al. 2022).

matters because different categories of natural disasters (type, magnitude, frequency) can entail various price effects. For instance, Kabundi et al. (2022) argue that droughts tend to push staples inflation higher whereas floods tend to have deflationary impacts.[27] Moreover, attrition around natural disasters and wars entails that data might not be collected in affected food markets at times where staple food prices could rise the most. As a result, our estimated effects of natural disasters and wars on the local relative prices of staples could be interpreted as lower bounds.

E. Effects of the COVID pandemic

Focusing on COVID-19—a large-scale biological disaster—we assess to what extent the relative price effects of the drivers may have changed during the pandemic (Bogmans et al. 2021; Unsal et al. 2020). To this end, we interact our explanatory variables and a dummy for the COVID period. In Table 9 and Figure 3.E, the interaction coefficients for NID, CS, and $\Delta GFPI$ are all positive and significant. The negative coefficient associated with $\Delta REER * NIDhigh * COVID$ suggests that a one percent depreciation in REER would have raised the real cost for highly imported staples by 0.7 percent more during the pandemic, conditional on other variables. Thus, the price effects of these factors have been amplified during the pandemic, which led to massive disruptions of global and domestic food supply chains, unprecedented policy support, and currency depreciations in some countries.

F. Drivers of cross-country food price differences

To explore the country characteristics that may explain the differences in staple food prices across SSA countries, we fit the following model:

$$\tilde{y}_{cmi,t} = \gamma_1 MPF_{c,t-1} + \gamma_2 Debt_{c,t-1} + \gamma_3 \Delta GDPPC_{c,t-1} + \gamma_5 GEO_{c,t} + \gamma_5 y_{cmi,t}^{high} + \tau_t + \alpha_{cmi} + u_{cmi,t} \quad (3)$$

where $\tilde{y}_{cmi,t} = y_{cmi,t} - \left(\sum_{cm} y_{cmi,t}\right)/N_{cm}$ is the deviation of the relative food price change of staple i, in market m, and country c from the regional average, observed for each month *t*. N_{cm} stands for the number of country-market pairs. For the monetary variable, we use a dummy reflecting the quality of the monetary policy frameworks MPF. In each time period, we create a dummy that takes 1 if the Independence, Accountability, Policy and Operational Strategy, and Communications (IAPOC) index of monetary policy frameworks of a country is above the median and 0 otherwise (Unsal et al. 2022).[28] Our fiscal variable *Debt* is the debt-to-GDP ratio. $\Delta GDPPC$ is the change in GDP per capita (constant 2010 USD). GEO is an index measuring the roughness of the landscape in a country (Nunn and Puga 2012), and we expect food transport to be more difficult and expensive in geographically challenged countries. In Equation (3), GEO is not lagged because the overall roughness of a country's terrain is

[27] There are at least two possible explanations for the deflationary effects of floods. First, low intensity floods tend to bring nutrients to the soil, which could increase yields and boost crop production, in particular in areas where fertilizers are scarcely used (Dieppe et al. 2020). Second, high intensity floods tend to destroy production capacity, which could reduce income and food demand more than induced supply disruptions, and hence dampen inflation (Kabundi et al. 2022).

[28] The sample includes 3 inflation targeters (Ghana, South Africa, Uganda) and 10 countries (Ethiopia, Ghana, Kenya, Malawi, Mozambique, Nigeria, Rwanda, South Africa, Uganda, Zambia) with floating exchange rate regimes. Floating exchange rate regimes comprise free floating and other managed arrangements.

expected to be nearly time-invariant and would likely not change in the short run. y^{high} is a dummy (1 if y > 50% and 0 otherwise), τ and α are time and item fixed effects, u is the error term.

Table 10 reports the estimates coefficients and Figure 3.F shows the standardized price effects. On average, the real cost of staple food is about 2.5 percentage points lower for countries above the median of monetary policy framework index.[29] This suggests that central banks can effectively curb food price inflationary pressures, and in turn control general inflation, by making strides to establish credibility, fostering independence, enhancing operational strategy, and improving communication (Unsal et al. 2022). Moreover, monetary authorities, should monitor and credibly calibrate their actions to account for both direct and second-round inflationary effects—through non-food item prices—of food price increases. This is of prime importance for low-income SSA countries which have faced higher inflation relative to richer countries, owing to less developed monetary policy frameworks, larger share of food in the consumption basket, and higher exposure to volatile food prices (World Bank 2021).[30] On the fiscal side, a one percent increase in debt to GDP ratio, would raise relative staple food prices by about 0.1 percent. A higher debt in percent of GDP may reflect weaker fiscal management and/or heavy debt burden, which could weaken the domestic currency in SSA countries. In this case, the relative prices of staple foods would rise in local markets, as nominal staple food prices—boosted by more expensive imported staples—increase faster than non-food components of the CPI.

Turning to income per capita—a proxy for overall economic development, a one percent increase is associated with 1.2 percent lower relative food prices, consistent with the findings in Calderón and Schmidt-Hebbel (2010). This negative and significant effect of income growth on real food prices is consistent with Engle's law, which hinges on the view that wealthier households spend a smaller proportion of their income on food than their poorer counterparts. Thus, in growing developing countries, the relative decline in the demand for food would lead to lower relative food prices (Baffes and Etienne 2016).

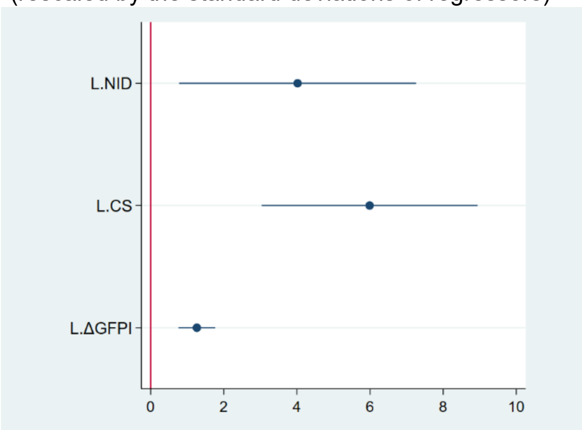
Finally, a country with one-point higher geographic challenge index—or 100 meters higher terrain elevation, e.g., from Zambia-0.5 to Ethiopia-1.6—has, on average, 2.5 percent higher relative food prices. Typically, food transport is more challenging in countries where the terrain is very rugged (e.g., Rwanda, Ethiopia).

[29] At the end of the sample, South Africa, Uganda, Ghana, Kenya are above the median of the monetary framework index.

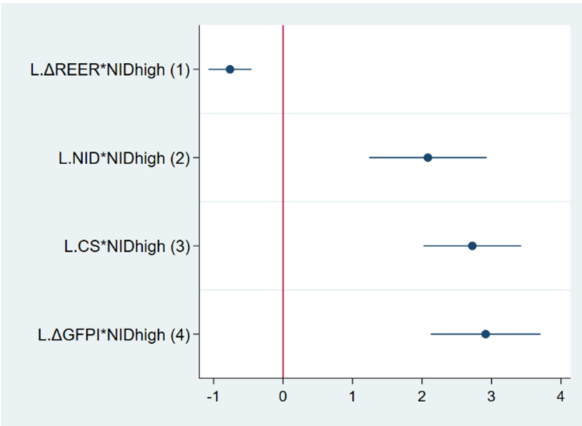
[30] Equation (3) is also estimated using a dummy for inflation targeting (IT) regime in lieu of a monetary policy framework dummy (MPF). Results suggest that IT lowers relative staple food prices by about 3 percent across countries, conditional on other variables. The full estimation table for the specification including IT dummy is not reported for the sake of brevity but is available from the authors upon request.

Figure 3. Estimated effects

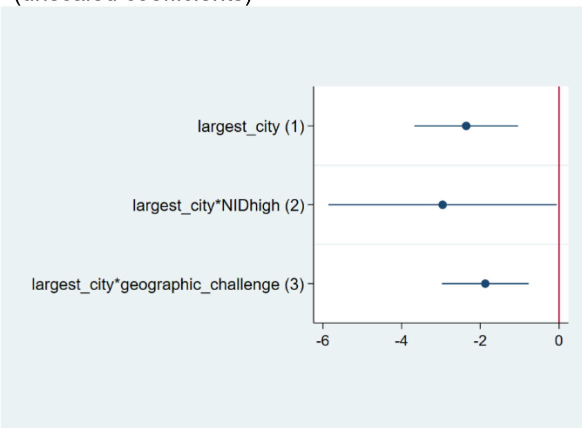
3.A: Baseline model, Eq. 1
(rescaled by the standard deviations of regressors)



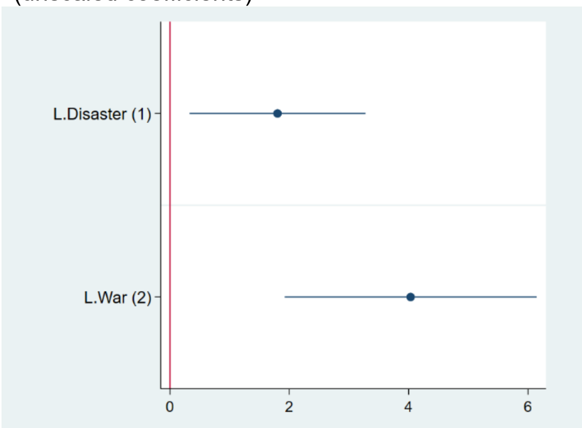
3.B: Highly imported staples, Eq. 2
(rescaled by the standard deviations of regressors)



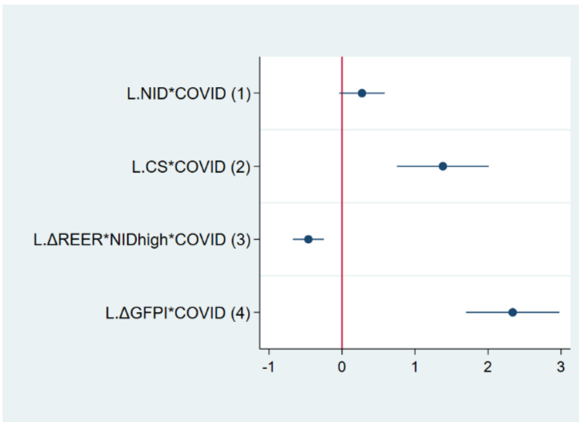
3.C: Location, Eq. 2
(unscaled coefficients)



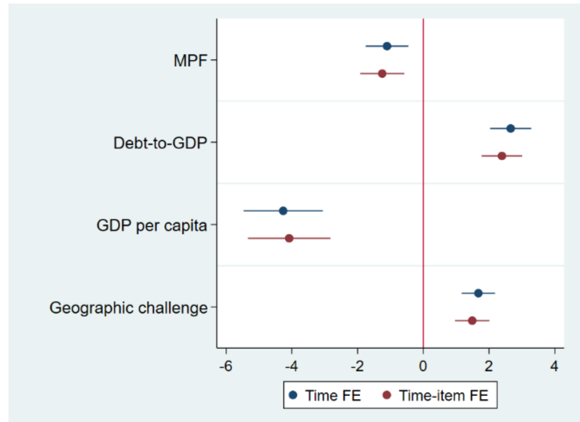
3.D: Disasters and wars, Eq. 2
(unscaled coefficients)



3.E: COVID period, Eq. 2
(rescaled by the standard deviations of regressors)



3.FCountry characteristics, Eq. 3
(rescaled by the standard deviations of regressors)



Source: COW, EMDAT, FAOSTAT food balance sheets, FPMA GIEWS Tool, IMF WEO and AREAER, Nunn and Puga (2012), PRIO, Unsal et al. (2022), World Bank WDI, and authors' calculations.
Notes: The round markers show coefficient estimates and horizontal bars represent 95 percent confidence intervals. The vertical red line draws a reference line at zero.

VI. Robustness

Several robustness exercises are undertaken to further establish the empirical validity of the estimated effects of global and local factors on staple food prices in SSA markets. To this end, we re-estimate our model specifications using different thresholds for episodes of high food price increases (y^{high}) and highly imported staples ($NIDhigh$). The estimated effects remain significant and broadly in line with the results discussed in previous sections, further granting credibility to our empirical assessment.

A. High food price increase

We start by assessing the sensitivity of our estimations to episodes of high food price increases. To do this, we define the episodes of staple food price surges using a higher threshold. Tables 11 and 12 show the estimated models in Equations (2) and (3), where y^{high} is a dummy that takes 1 if the change in staple food price exceeds 75 percent and 0 otherwise.[31] As expected, the coefficient estimates of y^{high} is higher in Table 11 than Table 9. In Table 11, the sign and magnitude of the coefficients (e.g., in column 1) associated to NID (0.348 from 0.143), CS (0.846 from 0.558), $\Delta GFPI$ (0.334 from 0.393), and $\Delta REER * NIDhigh$ (-0.248 from -0.222) are similar to those from Table 9—where y^{high} is defined using a lower threshold of 50 percent. Similarly in column 2 of Table 12, the coefficients of MPF (-1.807 from -2.504), $Debt$ (0.122 from 0.113), $\Delta GDPPC$ (-1.990 from -1.200), and GEO

[31] Episodes of high food price increases ($y^{high} = 1$ if the change in staple food price exceeds 75 percent) account for about 4 percent of local food price data.

(2.523 from 2.532) are in line with their estimated values in Table 10. This demonstrates the robustness of the estimated effects to the choice of the threshold of price surges.

B. Net import dependence

To further establish the robustness of our analysis, we take an extra step to estimate the sensitivity of the price effects of the drivers to different levels of net import dependence. Table 13 reports the estimation of Equations (2) using a lower threshold of net import dependence to define the dummy for highly imported staples—here, $NIDhigh$ takes the value of 1 if the net import dependence of a staple exceeds 50 percent and 0 otherwise. These robustness results are reported in Table 13 and are similar to the estimates in Table 9. In particular, the estimated coefficients associated with NID ranges from 0.099 in column 1 of Table 13 to 0.143 in column 1 of Table 9. Our robustness exercises lend additional confidence in the estimated effects of these factors on local staple prices.

VII. Discussions and Conclusion

This paper provides new empirical evidence on the drivers of staple food prices in local markets in SSA. High food price inflation may lead to macro-critical issues and severe distributional effects in a region where one in four people are food insecure. Our analysis uses a panel of domestic market prices of the five staple foods that contribute the most to local diets across 15 SSA countries to estimate the relative price elasticities of various drivers. We find that the net import dependence, consumption share of staples, global food prices, and real effective exchange rates are key factors that govern changes in local staple food prices. Among these drivers, the consumption share of each staple has the largest price effect. A one percent increase in the consumption share of a staple food is expected to raise its relative price by an average 0.7 percent. Similarly, local relative staple food prices are expected to edge up by 3.9 and 1.3 percent following a one standard deviation increase in net import dependence and global food prices, respectively. A one percent depreciation in real effective exchange rates would increase the price of highly imported staples by an average 0.3 percent. Pass-through from global to local staple prices is estimated to be a near one-to-one (0.97) in countries which import at least three-quarters of their consumption, suggesting potential gains in fostering a competitive domestic production of highly imported staple foods in SSA. Adverse events such as natural disasters and wars also matter. We show that relative staple food prices typically rise sharply after natural disasters and wars, on average by 1.8 and 4 percent, respectively. The food price effects of natural disasters taper-off after one quarter, whereas the effects of wars are more prologued and remain statistically significant after 2 years. Of course, different types of natural disasters—e.g., droughts versus floods—or wars—e.g., internal versus external—could imply different or even opposite impacts, depending on their definition, magnitude, frequency, duration, and location (Kabundi et al. 2022). The price effects of these drivers have been amplified during the COVID-19 period. In particular, a one percent depreciation in real effective exchange rate would have raised the real cost for highly imported staples by an average 0.7 percent more during the pandemic.

Within countries, we observe differences in staple food prices between urban and rural areas (Gollin and Rogerson 2016). The average real cost of staple foods is 2.4 percent lower in large cities and the urban-rural price gap is wider for highly imported staples. Acute infrastructure gaps and binding transport bottlenecks in friction-prone markets push transport and market access costs higher, and in turn, inflate staple food prices in rural SSA areas.

Looking across countries in the region, our results suggest that differences in monetary policy frameworks, fiscal management, per capita income and geographic challenges explain a large share of the cross-country variation in staple food prices. While countries with stronger monetary policy frameworks have better tools to curb food inflationary pressures, weaker fiscal management tends to push food prices higher in countries with elevated public debt. Faster growing countries have lower staple food prices, suggesting that households spend a smaller fraction of their incomes as they become richer (Calderón and Schmidt-Hebbel 2010). Moreover, staples are on average more expensive in geographically challenged countries, again pointing to higher logistical costs.

From a food security perspective, these results suggest a mix of fiscal, monetary, and structural policies. On the fiscal side, strengthening public finance management seems critical. This can be done by improving the efficiency of public spending, enhancing domestic resource mobilization, and maintaining a credible medium term fiscal framework to anchor public debt on a sustainable path (Farid et al. 2022). Improving public finance management would allow countries to build adequate fiscal buffers, free up resources to invest in resilient infrastructure such as roads, irrigation, water, and sanitation systems, implement well-targeted social assistance programs for the most vulnerable people, and ease the availability, accessibility, utilization, and price stability of staple foods (Baptista et al. 2022). On the monetary side, central banks should closely monitor food price inflation to mitigate its corrosive effects on real incomes. Central banks should also remain independent and build credibility by implementing well-designed and effective policy, operation, and communication strategies, in particular in disaster-prone countries where the risk of food insecurity is prevalent.[32] Structural and regulatory reforms to promote fair competition could enable domestic food producers and consumers to buy cheaper inputs (seeds, fertilizers, fuel, etc.) and staple foods on local, regional, and international markets. These reforms could include streamlining agricultural trade procedures, leveraging research and development to promote agricultural innovation and food product quality. In this regard, the full implementation of the Africa Continental Free Trade Agreement (AfCFTA) is expected to boost inter-African trade of services and goods, including staple foods. Obviously, the policies discussed here are rather indicative but not exhaustive and should be tailored to the specific circumstances of each country.

[32] In disaster-prone countries, Cantelmo et al. (2022) show that monetary policy is commonly tightened to contain inflationary pressures after a natural disaster and argue for a flexible inflation targeting regime—allowing inflation to deviate from target in the short run—rather than strict inflation targeting or hard pegs. Moreover, while many net food importing countries adopted fixed exchange rates to limit the impact of global food inflation, a transition to flexible exchange rate regimes could support the competitiveness of food and other exports, help build foreign exchange buffers, and allow for a gradual adjustment to global food price shocks.

Tables

Table 1. Sample of countries and number of makets included in empirical exercises

Country	Code	Markets
Angola	AGO	2
Côte d'Ivoire	CIV	2
Ethiopia	ETH	7
Ghana	GHA	6
Kenya	KEN	4
Malawi	MWI	2
Mozambique	MOZ	7
Namibia	NAM	8
Nigeria	NGA	6
Rwanda	RWA	2
Senegal	SEN	10
South Africa	ZAF	2
United Republic of Tanzania	TZA	4
Uganda	UGA	4
Zambia	ZMB	2
SSA (total)	15	68

Source: Authors' calculations.

Table 2. Consumption share and net import dependence of the top 5 staples

Country	Maize		Rice		Cassava		Wheat		Palm Oil	
	CS	NID	CS	NID	CS	NID	CS	NID	CS	NID
AGO	16.9	8.1	5.5	**98.3**	25.4	0.0	10.2	**99.8**	7.8	**80.1**
CIV	5.4	2.5	26.7	53.8	14	0.0	6.3	**100**	6.6	-73.5
ETH	19.3	0.7	1.6	**78.9**	N/A	0.0	13.3	21.1	2.0	**100**
GHA	7.5	0.5	9.5	59.9	26.4	-0.1	4.1	**100**	1.7	36
KEN	27.6	6.3	6.2	**85.5**	2.1	0.1	12.2	**84.6**	1.7	**100**
MWI	44.1	0.1	1.9	6.3	7.6	0.0	1.9	**99.2**	0.5	**100**
MOZ	28.7	11.4	12.2	**81**	14.6	0.0	7.6	**97.3**	4.3	**100**
NAM	16.9	68.8	3.1	**100**	N/A	0.0	17.3	**95.8**	N/A	**100**
NGA	12.3	2.7	10.9	1.1	11.4	0.0	7.9	**98.7**	7.2	51.2
RWA	8.8	8.1	3.5	36.2	11.8	14.7	3.4	**88.5**	3.2	**100**
SEN	7.6	41.8	29.8	49.7	3.3	1.0	12.9	**100**	4.5	**91.1**
ZAF	28.9	-10.5	4.8	**99.8**	N/A	**100**	16.9	51.7	2.9	**100**
TZA	19.7	-1.7	3.1	31.5	15.6	-0.3	2.8	**95.4**	5.5	**100**
UGA	21.4	-3.4	13.3	7.1	7.8	-3.2	5.6	93.5	3.7	**99**
ZMB	50.4	-2.1	1.1	45.5	16.4	0.0	3.0	-13.4	2.7	**100**

Source: FAOSTAT New Food Balances and authors' calculations.

Notes: Consumption shares (CS) are calculated as percent of average daily per capita caloric contribution data from 2019. Net import dependence (NID) = 100*(imports – exports)/(production + imports – exports) data from 2019. Bold indicates net import dependence greater than 75 percent.

Table 3. Top 5 import trading partners of SSA

Maize		Rice		Cassava		Wheat		Palm Oil	
Trading partner	Share of quantity imported (percent)	Trading partner	Share of quantity imported (percent)	Trading partner	Share of quantity imported (percent)	Trading partner	Share of quantity imported (percent)	Trading partner	Share of quantity imported (percent)
Uganda	33.8	India	36.3	Tanzania	41.2	Russia	34.7	Malaysia	47.8
Argentina	27.6	Thailand	24.0	Uganda	40.5	Canada	10.2	Indonesia	42.8
Zambia	11.8	Pakistan	13.2	Thailand	14.8	USA	10.1	Côte d'Ivoire	1.2
South Africa	8.6	Vietnam	9.8	Vietnam	1.4	Argentina	6.8	South Africa	1.2
Tanzania	6.0	China	7.1	India	0.7	Ukraine	6.4	UAE	1.2
SSA (all)	63.7	SSA (all)	1.7	SSA (all)	82.1	SSA (all)	2.3	SSA (all)	4.6

Source: FAOSTAT Trade Matrix and authors' calculations.

Table 4. Drivers of relative staple food prices

Dependent variable: relative food price change	(1)	(2)
L.NID	0.275***	0.112**
	(0.0659)	(0.0461)
L.CS	0.422*	0.664***
	(0.239)	(0.167)
L.ΔGFPI	0.395***	0.153***
	(0.0442)	(0.0310)
High food price increase (dummy)		89.24***
		(1.050)
Country-market-item FE	Yes	Yes
Observations	6970	6970
Adj. R^2	0.126	0.500

Source: FAO FPMA and authors' calculations.

Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise). Fixed effects regressions with lagged regressors are run. Clustered robust standard errors in parentheses. *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 5. Effects of high net import dependence

Dependent variable: relative food price change	(1)	(2)	(3)	(4)
L.NID	0.168***	0.120**	0.0968**	0.184***
	(0.0446)	(0.0490)	(0.0491)	(0.0470)
L.CS	0.564***	0.540**	0.522**	0.571***
	(0.215)	(0.215)	(0.215)	(0.216)
L.ΔGFPI	0.180***	0.182***	0.182***	0.189***
	(0.0378)	(0.0378)	(0.0378)	(0.0391)
High food price increase (dummy)	93.16***	93.22***	93.26***	93.01***
	(1.522)	(1.521)	(1.520)	(1.522)
L.ΔREER*NIDhigh	-0.335***	-0.130**	-0.0305	-0.262**
	(0.0695)	(0.0551)	(0.0536)	(0.109)
L.NID*NIDhigh		0.0998***		
		(0.0207)		
L.CS*NIDhigh			0.726***	
			(0.0955)	
L.ΔGFPI*NIDhigh				0.777***
				(0.107)
Country-market-item FE	Yes	Yes	Yes	Yes
Observations	6313	6313	6313	6263
Adj. R^2	0.569	0.570	0.570	0.569

Source: FAO FPMA and authors' calculations.
Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>75%, 0-otherwise), and other interaction terms between lagged regressors and NIDhigh dummy. Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 6. Prices in largest cities

Dependent variable: relative food price change	(1)	(2)	(3)
L.NID	0.0947**	0.0916**	0.0979**
	(0.0380)	(0.0381)	(0.0381)
L.CS	0.396***	0.438***	0.400***
	(0.0966)	(0.0963)	(0.0965)
L.ΔGFPI	0.145***	0.144***	0.144***
	(0.0276)	(0.0276)	(0.0276)
High food price increase (dummy)	72.52***	72.68***	72.53***
	(0.842)	(0.841)	(0.842)
L.ΔREER*NIDhigh	-0.131**	-0.138**	-0.131**
	(0.0611)	(0.0612)	(0.0611)
largest_city	-2.359***		
	(0.672)		
largest_city*NIDhigh		-2.958**	
		(1.479)	
largest_city*geographic_challenge			-1.874***
			(0.562)
Country-item FE	Yes	Yes	Yes
Observations	5068	5068	5068
Adj. R^2	0.695	0.695	0.695

Source: FAO FPMA and authors' calculations.
Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>75%, 0-otherwise), largest city dummy, and interaction terms between largest city dummy, highly imported staples dummy and geographic challenge proxied by a country's terrain ruggedness index (hundreds of meters of terrain elevation, Nunn and Puga 2012). Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 7. Effects of natural disasters and wars

Dependent variable: relative food price change	(1)	(2)	(3)
L.NID	0.114***	0.119***	0.123***
	(0.0428)	(0.0428)	(0.0428)
L.CS	0.309*	0.362**	0.367**
	(0.170)	(0.170)	(0.170)
L.ΔGFPI	0.229***	0.201***	0.197***
	(0.0293)	(0.0306)	(0.0306)
High food price increase (dummy)	81.06***	80.69***	80.66***
	(1.410)	(1.413)	(1.412)
L.ΔREER*NIDhigh	-0.186***	-0.160**	-0.155**
	(0.0680)	(0.0685)	(0.0685)
L.Disaster (dummy)	1.831**		1.704**
	(0.752)		(0.752)
L.War (dummy)		3.967***	3.852***
		(1.076)	(1.077)
Country-market-item FE	Yes	Yes	Yes
Observations	6091	6091	6091
Adj. R^2	0.418	0.419	0.419

Source: FAO FPMA, EMDAT, COW, PRIO, and authors' calculations.

Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Regressions include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>75%, 0-otherwise), natural disaster dummy, and war dummy. Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 8. Persistence of the effects of natural disasters and wars

Dependent variable: relative food price change	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.NID	0.114***	0.109***	0.114***	0.119***	0.125***	0.150***	0.178***
	(0.0428)	(0.0382)	(0.0384)	(0.0428)	(0.0435)	(0.0493)	(0.0591)
L.CS	0.309*	0.392**	0.434**	0.362**	0.511***	0.702***	2.064***
	(0.170)	(0.176)	(0.183)	(0.170)	(0.181)	(0.240)	(0.316)
L.ΔGFPI	0.229***	0.215***	0.202***	0.201***	0.164***	0.195***	0.122***
	(0.0293)	(0.0331)	(0.0329)	(0.0306)	(0.0311)	(0.0328)	(0.0349)
High food price increase (dummy)	81.06***	81.23***	81.38***	80.69***	80.72***	80.74***	80.66***
	(1.410)	(1.740)	(1.756)	(1.413)	(1.472)	(1.530)	(1.553)
L.ΔREER*NIDhigh	-0.186***	-0.176***	-0.185***	-0.160**	-0.154**	-0.173**	-0.179**
	(0.0680)	(0.0453)	(0.0460)	(0.0685)	(0.0673)	(0.0682)	(0.0738)
L.Disaster (dummy)	1.831**						
	(0.752)						
L2.Disaster (dummy)		1.046*					
		(0.534)					
L3.Disaster (dummy)			0.371				
			(0.542)				
L.War (dummy)				3.967***			
				(1.076)			
L3.War (dummy)					4.722***		
					(1.110)		
L12.War (dummy)						2.397***	
						(0.262)	
L24.War (dummy)							1.459***
							(0.138)
Country-market-item FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6091	5787	5615	6091	5615	4848	4126
Adj. R^2	0.418	0.424	0.426	0.419	0.428	0.455	0.511

Source: FAO FPMA, EMDAT, COW, PRIO, and authors' calculations.

Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Regressions include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>75%, 0-otherwise), natural disaster dummy, and war dummy. Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 9. Effects of COVID

Dependent variable: relative food price change	(1)	(2)	(3)	(4)
L.NID	0.143***	0.159***	0.142***	0.171***
	(0.0393)	(0.0392)	(0.0393)	(0.0394)
L.CS	0.558***	0.571***	0.553***	0.532**
	(0.212)	(0.211)	(0.212)	(0.210)
L.ΔGFPI	0.393***	0.324***	0.398***	0.165***
	(0.0411)	(0.0430)	(0.0397)	(0.0488)
High food price increase (dummy)	91.58***	91.40***	91.61***	91.73***
	(1.548)	(1.552)	(1.547)	(1.552)
L.ΔREER*NIDhigh	-0.222***	-0.195***	-0.214***	-0.163***
	(0.0528)	(0.0522)	(0.0527)	(0.0522)
L.NID*COVID	0.0307*			
	(0.0178)			
L.CS*COVID		0.365***		
		(0.0847)		
L.ΔREER*NIDhigh*COVID			-0.666***	
			(0.156)	
L.ΔGFPI*COVID				0.626***
				(0.0872)
Country-market-item FE	Yes	Yes	Yes	Yes
Observations	6594	6594	6594	6594
Adj. R^2	0.572	0.574	0.573	0.576

Source: FAO FPMA and authors' calculations.

Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>75%, 0-otherwise), and interaction terms between lagged regressors and COVID period (2020m1-2021m9) dummy. Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 10. Deviations of relative food price change from SSA country group average

Dependent variable: deviation of relative food price change	(1)	(2)
L. Monetary policy framework (dummy)	-2.210***	-2.504***
	(0.664)	(0.686)
L.Government gross debt (% of GDP)	0.126***	0.113***
	(0.0151)	(0.0149)
L.ΔGDPPC	-1.253***	-1.200***
	(0.181)	(0.188)
Geographic challenge	2.850***	2.532***
	(0.440)	(0.453)
High food price increase (dummy)	67.21***	67.86***
	(1.483)	(1.486)
Time FE	Yes	Yes
Item FE	No	Yes
Observations	4968	4968
Adj. R^2	0.454	0.457

Source: IMF WEO, World Bank WDI, and authors' calculations.

Notes: The dependent variable is the monthly deviation (in percentage points) of real food price change from the group average of 15 Sub-Saharan African (SSA) countries. Regressions include lagged dummy for the Independence, Accountability, Policy and Operational Strategy, and Communications (IAPOC) index of monetary policy frameworks (1- if IAPOC index > median IAPOC index, 0-otherwise), government gross debt (% of GDP), GDP per capita growth (ΔGDPPC), geographic challenge proxied by a country's terrain ruggedness index (hundreds of meters of terrain elevation, Nunn and Puga 2012), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), and control for time and item fixed effects. Clustered robust standard errors in parentheses. *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 11. Robustness: price effects, y^{high}>75%

Dependent variable: relative food price change	(1)	(2)	(3)	(4)	(5)
L.NID	0.348***	0.290***	0.316***	0.292***	0.325***
	(0.0510)	(0.0897)	(0.0935)	(0.0898)	(0.0912)
L.CS	0.846***	0.770	0.795	0.780	0.749
	(0.230)	(0.485)	(0.475)	(0.487)	(0.485)
L.ΔGFPI	0.334***	0.594***	0.481***	0.608***	0.326**
	(0.0403)	(0.124)	(0.120)	(0.120)	(0.154)
High food price increase (dummy)	109.6***	107.9***	107.9***	108.0***	108.4***
	(2.039)	(5.493)	(5.511)	(5.498)	(5.229)
L.ΔREER*NIDhigh	-0.248***	-0.240	-0.199	-0.247	-0.176
	(0.0654)	(0.156)	(0.149)	(0.160)	(0.152)
L.NID*COVID		0.0650*			
		(0.0363)			
L.CS*COVID			0.607***		
			(0.224)		
L.ΔREER*NIDhigh* COVID				-0.400	
				(0.283)	
L.ΔGFPI*COVID					0.753***
					(0.161)
Country-market-item FE	Yes	Yes	Yes	Yes	Yes
Observations	6594	6594	6594	6594	6594
Adj. R^2	0.470	0.482	0.485	0.482	0.487

Source: FAO FPMA and authors' calculations.
Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 75%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>75%, 0-otherwise), and interaction terms between lagged regressors and COVID period (2020m1-2021m9) dummy. Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 12. Robustness: deviations of relative food price change from SSA country group average, y^{high}>75%

Dependent variable: deviation of relative food price change	(1)	(2)
L. Monetary policy framework (dummy)	-1.656	-1.807**
	(2.040)	(0.705)
L.Government gross debt (% of GDP)	0.139***	0.122***
	(0.0374)	(0.0154)
L.ΔGDPPC	-1.978**	-1.990***
	(0.788)	(0.195)
Geographic challenge	2.729***	2.523***
	(0.785)	(0.504)
High food price increase (dummy)	66.21***	67.92***
	(9.155)	(3.167)
Time FE	Yes	Yes
Item FE	No	Yes
Observations	4672	4672
Adj. R^2	0.222	0.234

Source: IMF WEO, World Bank WDI, and authors' calculations.

Notes: The dependent variable is the monthly deviation (in percentage points) of real food price change from the group average of 15 Sub-Saharan African (SSA) countries. Regressions include lagged dummy for the Independence, Accountability, Policy and Operational Strategy, and Communications (IAPOC) index of monetary policy frameworks (1- if IAPOC index > median IAPOC index, 0-otherwise), government gross debt (% of GDP), GDP per capita growth (ΔGDPPC), geographic challenge proxied by a country's terrain ruggedness index (hundreds of meters of terrain elevation, Nunn and Puga 2012), high food price increase dummy (1-if food price increase > 75%, 0-otherwise), and control for time and item fixed effects. Clustered robust standard errors in parentheses. *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table 13. Robustness: price effects, $NIDhigh$>50%

Dependent variable: relative food price change	(1)	(2)	(3)	(4)	(5)
L.NID	0.0985**	0.126**	0.142***	0.127**	0.156***
	(0.0481)	(0.0513)	(0.0526)	(0.0513)	(0.0516)
L.CS	0.595***	0.577	0.587	0.580	0.549
	(0.215)	(0.492)	(0.488)	(0.493)	(0.496)
L.ΔGFPI	0.245***	0.417***	0.350***	0.423***	0.193
	(0.0437)	(0.110)	(0.115)	(0.106)	(0.132)
High food price increase (dummy)	93.11***	91.50***	91.34***	91.50***	91.66***
	(1.537)	(3.779)	(3.802)	(3.787)	(3.640)
L.ΔREER*NIDhigh	-0.135***	-0.342*	-0.313*	-0.339*	-0.281
	(0.0476)	(0.185)	(0.182)	(0.187)	(0.179)
L.NID*COVID		0.0252			
		(0.0299)			
L.CS*COVID			0.340**		
			(0.164)		
L.ΔREER*NIDhigh* COVID				-0.222	
				(0.273)	
L.ΔGFPI*COVID					0.602***
					(0.133)
Country-market-item FE	Yes	Yes	Yes	Yes	Yes
Observations	6594	6594	6594	6594	6594
Adj. R^2	0.578	0.573	0.574	0.573	0.577

Source: FAO FPMA and authors' calculations.

Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise), percent change in real effective exchange rate (ΔREER) interacted with a dummy for highly imported staples (NIDhigh=1-if NID>50%, 0-otherwise), and interaction terms between lagged regressors and COVID period (2020m1-2021m9) dummy. Clustered robust standard errors in parentheses; *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Appendix

Further details on data

Table A1. Data definitions, sources, and descriptive statistics

Variable	Description	Source	Mean	Standard deviation	Min	Max
Staple food prices (change, %)	Market-level relative prices	FAO FPMA	4.1	31.0	-79.2	293.4
Net import dependence (%)	(imports – exports)/(production + imports – exports)	FAO FBS	24.0	35.2	-73.5	100.0
Consumption share (%)	Contribution to daily per capita caloric intake	FAO FBS	17.8	8.9	0.5	58.6
Global food price index (change, %)	Real index based in 2014-16	FAO World Food Situation	-1.4	8.5	-13.8	38.4
High food price increase	Dummy variable (1-if food price increase > 50%)	FAO FPMA and authors' calculations	0.08	0.26	0	1
Real effective exchange rate (change, %)	Weighed average exchange rates deflated by index of costs	IMF AREAER	-0.54	10.6	-44.7	37.2
Largest city	Dummy variable	UN data	0.27	0.44	0	1
Natural disaster	Dummy variable	EMDAT	0.81	0.39	0	1
War	Dummy variable	COW, PRIO	0.06	0.30	0	1
COVID	Dummy variable	Authors' calculations	0.08	0.28	0	1
IAPOC index of monetary policy frameworks	Index of independence and accountability, policy operation and strategy, and communication	Unsal, Papagerogiou, and Garbers (2022)	0.50	.06	0.34	0.68
Debt (%)	Gross government debt/GDP	IMF WEO	46.0	21.4	17.5	136.5
GDP per capita (change, %)	GDP per capita (constant 2010 USD)	World Bank WDI	1.5	3.4	-9.7	8.0
Geographic challenge	Index of average terrain elevation between a point and each of the 8 nearest points on a 30-by-30 arc-seconds cells grid.	Nunn and Puga (2012)	0.76	0.59	0.22	3.3

Source: AREAER = Annual Report on Exchange Arrangements and Exchange Restrictions, IMF; COW = Correlates of War; EMDAT = Emergency Events Database, Université Catholique de Louvain; FBS = Food Balance Sheets, FAO; FPMA = Food Price Monitoring and Analysis, FAO; PRIO = Peace Research Institute Oslo; WEO = World Economic Outlook, IMF; WDI = World Development Indicators, World Bank; and authors' calculations. The sample period is from January 2012 to September 2021.

Fixed versus random effects

Table A2. Fixed effects versus random effects estimations

	(1)	(2)
Dependent variable: relative food price change	FE	RE
L.NID	0.112**	0.0809***
	(0.0461)	(0.0116)
L.CS	0.664***	0.104**
	(0.167)	(0.0434)
L.ΔGFPI	0.153***	0.155***
	(0.0310)	(0.0308)
High food price increase (dummy)	89.24***	88.35***
	(1.050)	(1.030)
Country-market-item FE	Yes	No
Observations	6970	6970
Adj. R^2	0.500	0.523
Hausman test (FE vs RE) p-value	0.000	

Source: FAO FPMA and authors' calculations.
Notes: The dependent variable is the percent change in real food price (monthly, y-o-y). Explanatory variables include lagged net import dependence in percent (NID), consumption share in percent (CS), the percent change in the real global food price index (ΔGFPI), high food price increase dummy (1-if food price increase > 50%, 0-otherwise). Fixed effects (FE) and random effects (RE) regressions with lagged regressors are run; the Hausman test favors FE estimations. Clustered robust standard errors in parentheses. *p < .10; **p < .05; ***p < .01. The sample includes panel data on 15 Sub-Sharan African countries (see country list in Table 1) from 2012m1-2021m9.

Table A2 reports the fixed effects and random effects estimation results of the baseline model in Equation 1. At the bottom of Table A2, a Hausman test favors the fixed effects estimation over the random effects regression.

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