Local unexpected food price volatility affects children's nutrition in sub-Saharan Africa

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Abstract

Food access can be affected by high and volatile food prices with potentially severe consequences for children’s nutrition. Local food price volatility is driven by international prices and local climate shocks, but little work explores how these price movements affect nutrition. Here, we decompose local maize price movements across 508 markets in 24 sub-Saharan African (SSA) countries to understand the sources of variation using econometric approaches. Our decomposition suggests that local price movements are strongly driven by global futures prices. Next, we compile DHS data over 19 years to measure how food price volatility affects children’s nutrition in SSA. We address endogeneity concerns and control for health-relevant weather shocks. Our results indicate that a 1 SD increase in unexpected price volatility in the year after birth increases the odds of stunting by 9%. These effects prevail more strongly among children in agricultural households without livestock.

Keywords: stunting, diet diversity, price volatility, weather shocks, econometrics

1. **Introduction**

Global political crises and consequences of climate change threaten food and nutrition security especially in lower income countries. One channel through which such global events affect local food systems are through food prices. Food price volatility is transmitted from international prices and climate shocks to local market prices, but evidence for how these factors affect subnational markets is scarce. High and volatile food prices affect households' access to food in sub-Saharan Africa (SSA), especially when food comprises a large fraction of household expenditure (Drammeh et al., 2019). If food access is reduced, food and nutrition insecurity can follow, leading to long-term consequences for health, developmental, and economic outcomes (Currie and Vogl, 2013; Engle et al., 2007; Hoddinott et al., 2013; Moradi et al., 2019).

Despite the United Nations' Sustainable Development Goal 2 (UN, 2015), which aims to end all forms of malnutrition by 2030 and to reduce stunting and wasting in children under 5 years of age by 2025, little progress has been achieved in SSA countries (Pomati and Nandy, 2020). Recent global political concerns such as the COVID-19 pandemic and the war in Ukraine have aggravated food supply shortage and food insecurity in SSA (Baptista et al., 2022). To improve nutrition outcomes, we need to better understand the drivers of food insecurity and the role played by volatile prices.

In this paper, we ask two related questions. First, what is the source of unexpected maize price volatility in SSA? Second, how does this price volatility affect children's nutrition? We begin by decomposing local food price volatility in SSA into variation driven by global maize futures and local weather shocks. Since global prices based out of a key market like the Chicago Board of Trade (CBOT) vary over time but not over space, we interact these prices with a measure of closeness to the nearest port to introduce cross-sectional variation that is meaningful in the sense that less remote places are likely more exposed to international price shocks than more remote ones.

Furthermore, we examine how local food price volatility affects nutrition outcomes for children under 5 years of age. The assessment focuses on stunting, a measure for low height given a certain age, that can result from chronic and recurrent undernutrition especially in utero and during the first two years of age (De Onis and Branca, 2016). Reasons for these undernutrition events are insufficient nutrition of the mother during pregnancy and breastfeeding, suspended breastfeeding, or insufficient protein supply to the child (Beal et al., 2018; Sebayang et al., 2020). Missing food access is a crucial underlying cause of malnutrition (Psaki et al., 2012). High food prices reduce affordability which threatens sufficient nutrient supply in children's diets (Ryckman et al., 2021). Besides high price levels, volatile prices might endanger a stable access to food, especially if households did not anticipate the price changes or have the capacities to prepare for these (Amolegbe et al., 2021; Cornia et al., 2016; Kornher and Kalkuhl, 2013).

Hitherto, only few studies explore the link between food prices and stunting in the literature (Lloyd et al., 2018; Woldemichael et al., 2022). We assess the effect of food price volatility in different stages of a child's life on stunting and control for a series of additional variables representing child-, parent-, and household-specific characteristics across SSA.

Our work contributes to two separate strands of literature. First, we complement existing research on the causes of local food price levels and volatility. Here, we focus on the contributions of weather shocks and international prices. Second, we contribute an extensive cross-country analysis of how changes in local staple food prices impact children's nutrition. Existing studies that assess the impact of food prices on the nutrition of children in SSA typically focus on one price measure and rarely provide inter-country comparisons. While limited, the evidence is suggestive. Arndt et al. (2016), for example, show that high food price inflation increases wasting and underweight conditions among children in Mozambique.

Amolegbe et al. (2021) assess the impact of rice price volatility on diet diversity and food expenditure shares for Nigeria. Grace, Brown and McNally (2014) conclude that increasing maize prices before pregnancy correlate with low birth weights in Kenya. For Malawi and Niger, Cornia et al. (2016) show that the trend, seasonal, and famine components of food prices significantly affect child admissions to feeding centers.

We contribute to the existing literature by analyzing local market price data for maize in 24 SSA countries to compose and compare multiple price indicators (i.e., price level, price volatility, unexpected price volatility) and estimate their effect on nutrition in children under the age of 5. In particular, we compare the effects of price volatility in rural, local markets and more centralized, urban centers to capture the effect of prices faced by both urban and rural populations.

We use nutrition indicators provided by the Demographic Health Survey (DHS) and compile data on more than 300,000 children over 19 years and 24 SSA countries. Due to data gaps in relevant covariates, the number of observations drops to below 100,000 in the full model specifications. We make use of the variation in our data over time and space and disentangle the effects on different household types, to better understand the heterogeneity of findings for rural vs. urban and rich vs. poor family types.

Local market prices and nutrition outcomes are potentially subject to endogeneity concerns as local production shocks and policies can affect both nutrition and prices. Also, household decisions to buy or sell on the local market can be determined by their children's nutrition and thus simultaneously affect local food prices. To address these issues, we use global prices, a measure of closeness to the nearest port and local agriculturally-relevant weather shocks to predict local price volatility.

Weather shocks do not only affect children's nutrition through their impact on food availability and access. There can also be a link through direct health effects caused by heat stress or disease spreading, that influences children's nutrient uptake and parents' productivity and income opportunities (Engle et al., 2007; Hoddinott et al., 2013). We account for these direct channels of weather on health by controlling for explicitly health-relevant weather variables such as wet-bulb temperature for a subset of our data.

The research data and methods are described in Section 2. The results of the price decomposition and the nutrition–price analyses are presented in Section 3 and discussed in Section 4. Concluding remarks are provided in Section 5.

2. **Research data and methodology**

2.1. **Price decomposition**

We employ monthly maize price data consolidated from the Global Information and Early Warning System on Food and Agriculture (GIEWS)[1], the World Food Program (WFP)[2], and the Famine Early Warning Systems Network (FEWS)[3] for 508 local markets across all investigated SSA countries and matched survey years. For each market we determine the dominant maize price based on the longest data series available among the different sources. Rolling mean prices for each market serve as price levels $\overline{P_{m,t}}$ varying by market m, and time t. We compose a general price volatility measure $V_{m,t}^{g}$ following Kornher and Kalkuhl (2013) based on the standard deviation of the difference of logarithmic monthly price changes over the preceding twelve months.

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[1] https://fpma.apps.fao.org/giews/food-prices/tool/public/#/home

[2] https://data.humdata.org/dataset/wfp-food-prices

[3] https://fews.net/fews-data/337

$$V_{m,t}^{g} = \sigma_{m,t} = \sqrt{\frac{\sum_{t-11}^{t}\left(\log\,\Delta p_{mt} - \overline{\log\,\Delta p_{m}}\right)^{2}}{N-1}}$$

In contrast to price levels or seasonally reoccurring price movements, unexpected price volatility is presumably more difficult for a household to prepare for. To compute the unexpected nonseasonal price volatility $V_{m,t,s}^{u}$ for each market m and in time t, we follow the approach described by Amolegbe et al. (2021) to strip out seasonal variation and price trends. We use non-deflated prices converted to USD cents based on available exchange rates to compute price variables in a comparable unit across markets and countries. In addition, the month after harvest H is included as dummy when regressing the price against a continuous time variable C

$$P_{m,t,s} = \alpha_{m} + C_{t,s}\beta_{m} + H + \varepsilon_{m,t,s}$$

to detrend the price

$$P_{m,t,s}^{det} = P_{m,t,s} - \widehat{P_{m,t,s}}$$

Then, we calculate the unexpected nonseasonal price variation as the difference between the deflated, detrended price and its market- and season-specific average:

$$A_{m,t,s}^{u} = P_{m,t,s}^{det} - \overline{P_{m,s}^{det}}$$

We create the rolling 12-months standard deviation of this unexpected price variation, which we furthermore refer to as unexpected volatility.

$$V_{m,t,s}^{u} = \sqrt{\frac{\sum_{t-11}^{t}(A_{m,t,s}^{u} - \overline{A_{m,t,s}^{u}})^{2}}{N}}.$$

Before assessing the effects of price volatility on children's nutrition, we like to understand how much of it is driven by local versus global shocks. Therefore, we decompose our price variables to assess how much these are driven by the corresponding global price movements, and – in lieu of missing yield data – local weather shocks.

To create market-specific and agriculturally relevant weather data, we determine nearby maize-growing regions and extract temperature and precipitation during the relevant prior crop growing season. Nearby maize-growing regions are identified based on production quantity raster data from FAO's Global Agro-Ecological Zones (GAEZ) International Institute for Applied Systems Analysis (IIASA)[4]. Within each maize-growing region random points are drawn for which weather information is collected. Daily rainfall data is retrieved from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015). Mean monthly temperature data are taken from the National Centers for Environmental Information (NCEI)'s Global Historical Climatology Network (GHCN)[5].

To capture the international market price for maize, we use daily CBOT nearby corn futures prices (closing price) between 1990 and 2019[6]. We aggregate these to monthly average prices. Price levels, general futures volatility and unexpected futures volatility are constructed analogously to the market price indicators.

International market prices are interacted with a measure of market integration I_m to create spatial variation in this variable. We use travel time to the nearest medium or large port (Nelson et al., 2019), scale and reverse it to create a weight that reflects proximity to the nearest port.For the decomposition exercise, we estimate linear regressions controlling for fixed effects for markets M, years Y, and months O (Eq. I). Since monthly variation has already been stripped out in the unexpected volatility variable, we do not include month fixed

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[4] https://iiasa.ac.at/models-and-data/global-agro-ecological-zones

[5] https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-monthly

[6] CME Group. (2019). CBOT corn futures contract prices (Daily data, Sep 2009–Oct 2019). https://bba.bloomberg.net

effects there. The analogous international price indicators F and the weather variables W (and their polynomial transformations) are included as explanatory variables. Eq. I can also be regarded as the first stage of our two-stages instrumental variable approach.

$$V_{m,t,s}^{j} = \omega W_{m,r} + \gamma I_m \times F_{t,s}^{j} + Y + M + O + \varepsilon_{m,t,s} \qquad \text{(I)}$$

$with\ V_m^j = \{P_{m,t,s}, V_m^u, V_m^g\},\ F_m^j = \{F_{m,t,s}, F_m^u, F_m^g\},$
$W_{m,r} = Weather\ in\ previous\ crop\ season\ (r)\ around\ nearby\ market\ (m)$
$(i.e., mean\ temperature, total\ rainfall, mean\ temperature\ squared,$
$total\ rainfall\ squared)$

3. Nutrition–price analysis

To assess children's food security and nutrition, we use DHS[7] data, which are nationally representative. For stunting, we use the height-for-age z-score (haz),)[8]. For this binary indicator, we refer to a two standard deviations threshold below the mean based on the WHO Child Growth Standards implying moderate or severe nutritional deficiencies. We calculate the diet diversity score ranging between 0 and 10 following Niles et al. (2021) as another control variable. Our data cover 24 SSA countries and survey rounds between 1998 and 2020. Food security and price data are matched on the basis of geo-locations of surveyed households and markets[9] subject to annual data availability (Figure 1).
As the main explanatory variable of interest, the fitted values for mean price levels, general volatility and unexpected volatility are included in these models. Since shocks during the prenatal period and early childhood can be decisive for nutrition outcomes, we analyze price changes in different periods of a child's life. Nutrition outcomes can accumulate over a child's lifetime and are thus not necessarily the result of (only) short-term price shocks.
We control for variables relevant to the child's nutrition (e.g., sex, birth order, siblings) and related to the household's characteristics (e.g., parents' education, mother's age and height, assets, wealth, ruralness). As fixed effects we consider the survey year and the matched market to which the price data relates. The remaining variation explained by the coefficients should therefore be independent of time-invariant market characteristics and location-invariant annual specifics.

[7] https://dhsprogram.com/Methodology/Survey-Types/DHS.cfm

[8] https://dhsprogram.com/data/Guide-to-DHS-Statistics/Nutritional_Status.htm

[9] Matching in R based on distm and distHarversine, market with minimum distance to a household chosen among markets within a respective country for which price data are available for relevant matching years

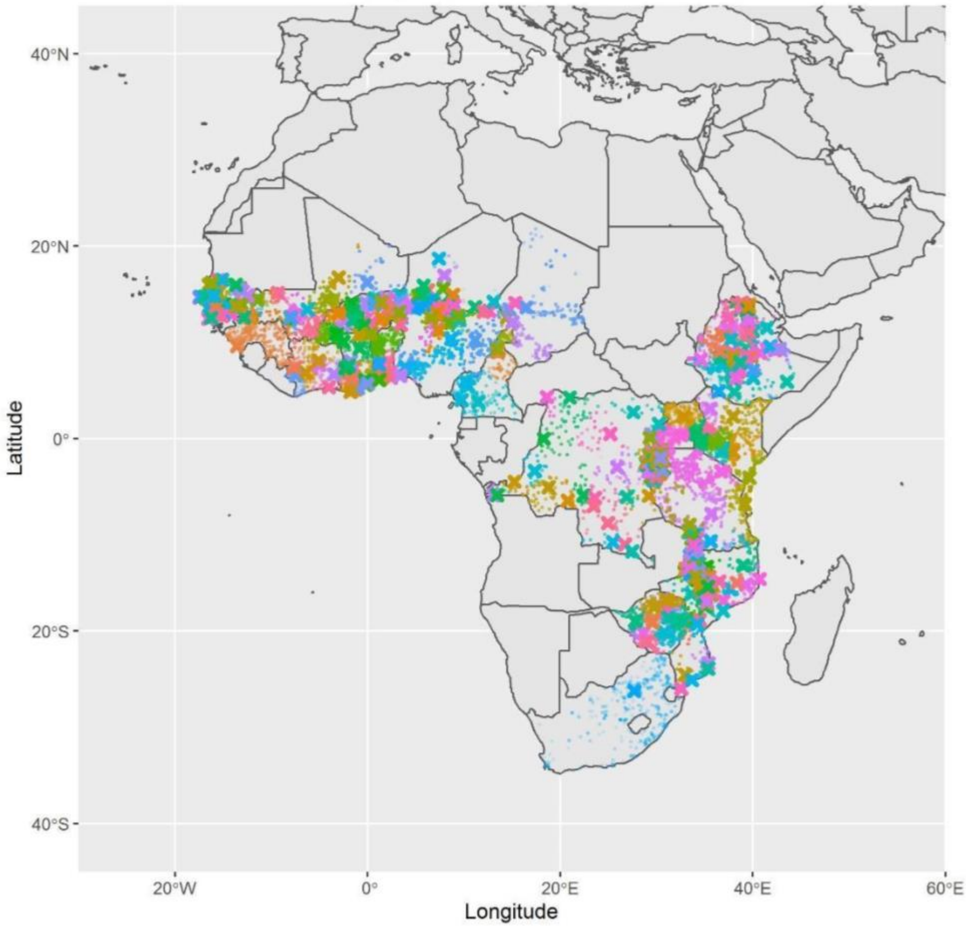

Figure 1 Household – market mapping shown for all survey years and markets with price data for the preceding 12 months.

In addition, we control for direct channels of weather on health by adjusting for explicitly health-relevant weather shocks based on wet-bulb globe temperature (built with CHIRTS daily Tmax data and downscaled daily RHmin (Tuholske et al., 2021; Verdin et al., 2020). Wet-bulb globe temperature indicates humid-hot air which causes heat-stress in humans and is especially dangerous for health as the humidity inhibits the human body's ability to cool down (Parsons, 2006). We include the count of days where maximum wet-bulb globe temperature exceeded a biologically relevant threshold (i.e., 28C (Parsons, 2006)) during the child's life in our model.

$$S_c^i = \alpha(V_{m,t}^j \times L_{c,t}) + \beta X_c + \theta T_{m,r} + Y + M + \varepsilon_c \quad \text{(II)}$$

With

S_c^i = Stunting,

$V_m^j = \left\{\widehat{P_{m,t}}, \widehat{V_{m,t}^u}, \widehat{V_{m,t}^g}\right\}$,

$L_{c,t} = Life\ stage\ of\ a\ child,$

$X_c = child-, parental-, household - specific\ variables,$

$T_c = health - relevant\ wet - bulb\ globe\ temperature,$

$Y = survey\ year\ fixed\ effects, M = market\ fixed\ effects$

We estimate this as a fixed effects maximum likelihood model of the family *logit* using R's *fixest* package (Berge, 2018) and cluster standard errors at the market level. Price variables are converted to z-scores to facilitate coefficient interpretation as the result of a 1 standard deviation increase. Moreover, it is assumed that the fitted values are exogenous to the local market and capture the variation in price volatility that is driven by international futures prices and local weather shocks.

4. **Results**

Results of the price decomposition (4.1) and the nutrition-price analysis (4.2) are presented in the following. Both analyses are connected since the fitted values of the price decomposition inform the nutrition-price analysis.

4.1. **Price decomposition**

We aim to get a better understanding of the underlying drivers of local market price volatility. In Figure 2, the variables underlying our price decomposition are shown as averages across local markets between January 1994 and December 2017. For most of this period, maize futures and average local maize market prices move in similar directions. Spikes and drops are more amplified in the global futures market. The spread of local market prices has increased since 2008. Regarding weather variables, the average mean temperature remains comparably constant over this period. However, already small differences in temperature might affect crop yields (Faye et al., 2023; Waha et al., 2013). Total rainfall reveals larger variability over time and strong differences across markets. To account for this variability in long-run local climate in our price decomposition, we control for market-, year-, and month-fixed effects in the econometric models.

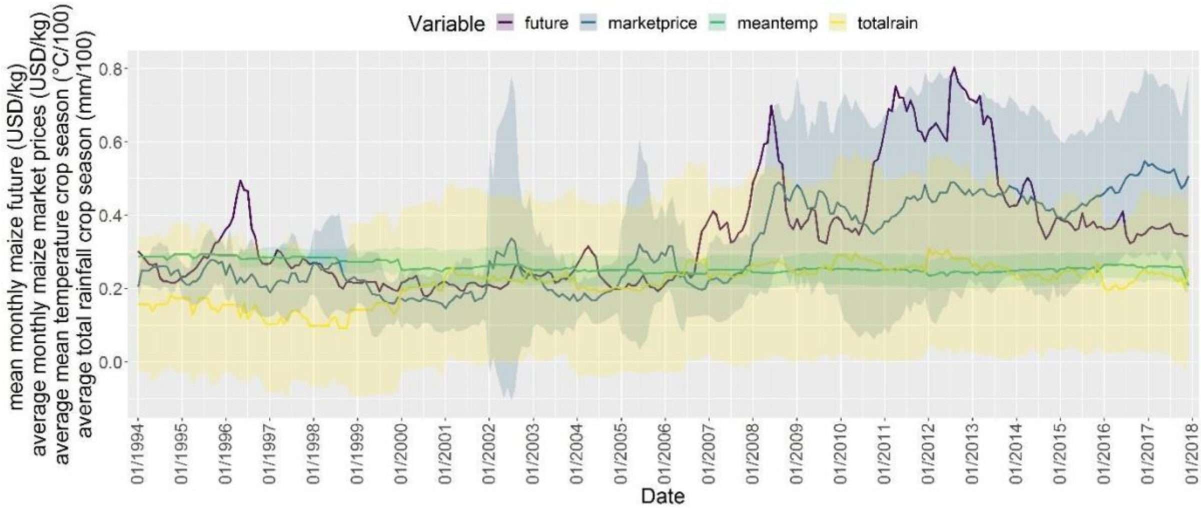

Figure 2 Ithaca, NY 14853-6201

Table 1 shows how three different price variables are affected by local weather changes and their respective international futures market prices weighted by closeness to the nearest port.

Table 1 Decomposition of local market price movements

	local market (USD cents)		
	price level	**volatility**	**volatility unexpected**
price_level_int:port_closeness	**-0.011**		
	(0.004)		
volatility_int:port_closeness		**0.146**	
		(0.064)	
volatility_unexp_int:port_closeness			**0.038**
			(0.017)
temp	0.101	0.404	**2.433**
	(0.141)	(1.214)	(0.671)
rain	-0.666	2.062	-0.346
	(0.429)	(1.836)	(0.843)
temp_sq	-0.004	-0.001	**-0.037**
	(0.003)	(0.024)	(0.013)
rain_sq	0.369	-0.088	**1.065**
	(0.331)	(1.372)	(0.580)
Num. obs.	42373	42373	42373
Num. groups: year	24	24	24
Num. groups: month	12	12	
Num. groups: market	508	508	508
R^2 (full model)	0.963	0.419	0.564
R^2 (proj model)	0.000	0.001	0.007
Adj. R^2 (full model)	0.963	0.411	0.558
Adj. R^2 (proj model)	0.000	0.001	0.007

We find positive effects of general and unexpected futures volatility on the respective local price volatility. The negative effect on price levels might indicate an "iceberg transport cost" (Bosker and Buringh, 2020) relationship, though this requires further investigation. The weather-related coefficients suggest temperature and rainfall are affecting local price volatility in complex ways. A linear model might be limited in capturing the pathways of influence on local market price volatility. Therefore, in future research we will test the sensitivity of our results with respect to model specification and choice of functional form.

4.2. Nutrition–price analysis

High and volatile staple food prices assumingly affect food access and nutrition outcomes. In the following it will be assessed, in how far our data supports this relationship on the basis of maize prices for sub-Saharan Africa.

Table 2 summarizes the regressions for stunting as dependent variable including the predicted values of either the mean price, general or unexpected volatility in separate regressions. We control for child-, parent-, and household-characteristics.

Table 2 Estimation results for stunting

	stunting		
	Price level	**Volatility**	**Unexpected volatility**
$\widehat{V^J}.z$:in utero	0.144	0.034	0.038
	(0.318)	(0.040)	(0.048)
$\widehat{V^J}.z$:year1	0.167	**0.097**	**0.092**
	(0.320)	(0.046)	(0.048)
$\widehat{V^J}.z$:year2	0.157	**0.085**	0.062
	(0.318)	(0.038)	(0.044)
$\widehat{V^J}.z$:year3	0.163	0.037	0.064
	(0.316)	(0.049)	(0.044)
$\widehat{V^J}.z$:year4	0.187	-0.045	0.050
	(0.316)	(0.078)	(0.053)
Wet bulb hot days (number)	**0.020**	**0.018**	**0.019**
	(0.011)	(0.010)	(0.011)
Diet diversity	**0.016**	**0.015**	**0.016**
	(0.007)	(0.007)	(0.007)
Age child months	**-0.586**	**-0.535**	**-0.555**
	(0.327)	(0.309)	(0.321)
Urban	**-0.189**	**-0.188**	**-0.189**
	(0.033)	(0.033)	(0.033)
Poor (omitted: middle)	**0.079**	**0.080**	**0.079**
	(0.036)	(0.035)	(0.036)
Rich (omitted: middle)	**-0.240**	**-0.240**	**-0.239**
	(0.034)	(0.034)	(0.034)
Male child	**0.225**	**0.225**	**0.226**
	(0.023)	(0.023)	(0.023)
Birth order	**0.056**	**0.056**	**0.056**
	(0.010)	(0.010)	(0.010)
Child is twin	**0.814**	**0.814**	**0.815**
	(0.080)	(0.080)	(0.080)
Age mother	**-0.024**	**-0.024**	**-0.024**
	(0.004)	(0.004)	(0.004)
Mother no education (omitted: high)	**0.742**	**0.741**	**0.741**
	(0.108)	(0.108)	(0.108)
Mother primary education (omitted: high)	**0.669**	**0.669**	**0.668**
	(0.103)	(0.104)	(0.103)
Mother secondary education (omitted: high)	**0.486**	**0.486**	**0.485**
	(0.110)	(0.110)	(0.109)
Mother works in agriculture	**0.062**	**0.063**	**0.063**
	(0.034)	(0.034)	(0.034)
Floor unfinished	0.072	0.072	0.072

	stunting		
	Price level	**Volatility**	**Unexpected volatility**
	(0.045)	(0.045)	(0.045)
Height mother	**-0.004**	**-0.004**	**-0.004**
	(0.001)	(0.001)	(0.001)
Has livestock	**-0.093**	**-0.093**	**-0.094**
	(0.023)	(0.023)	(0.023)
Has agricultural land	**0.063**	**0.063**	**0.062**
	(0.033)	(0.032)	(0.033)
Num. obs.	128364	128364	128364
Num. groups: year	11	11	11
Num. groups: market	325	325	325
Log Likelihood	-78895.100	-78870.828	-78889.431
Pseudo R^2	0.080	0.080	0.080

Despite being mostly statistically insignificant, the full model specifications disentangle a positive link between price levels, general and unexpected volatility, and stunting. Volatile staple food prices appear to be especially problematic in the first year after birth. Our results indicate that a 1 SD increase in unexpected price volatility in the first year of life increases the odds of stunting in children by 9%.

Other control variables consistently show that being urban, comparably rich and owning livestock reduces the occurrence of stunting, whereas being a twin, living in a household that owns agricultural land, and having a mother with little education increases the likelihood of stunting in a child. While it reduces the odds of stunting to live in a household that owns livestock, an important direct source of protein, higher diet diversity increases the probability of stunting. This outcome contradicts findings in previous research (Darapheak et al., 2013). Diet diversity might be inversely linked to breastfeeding, which is regarded an important component in a healthy nutrition of children especially during the months after birth (Arimond and Ruel, 2004; Sebayang et al., 2020). The effect of experiencing one more hot-humid day than average during childhood increases the odds of stunting by 2%.

If we compare the marginal effects by markets (Figure 3), some variation becomes apparent. In tendency, the influence of price volatility seems to be lowest in some markets in West Africa. The regional heterogeneity and resulting policy implications require further investigation.

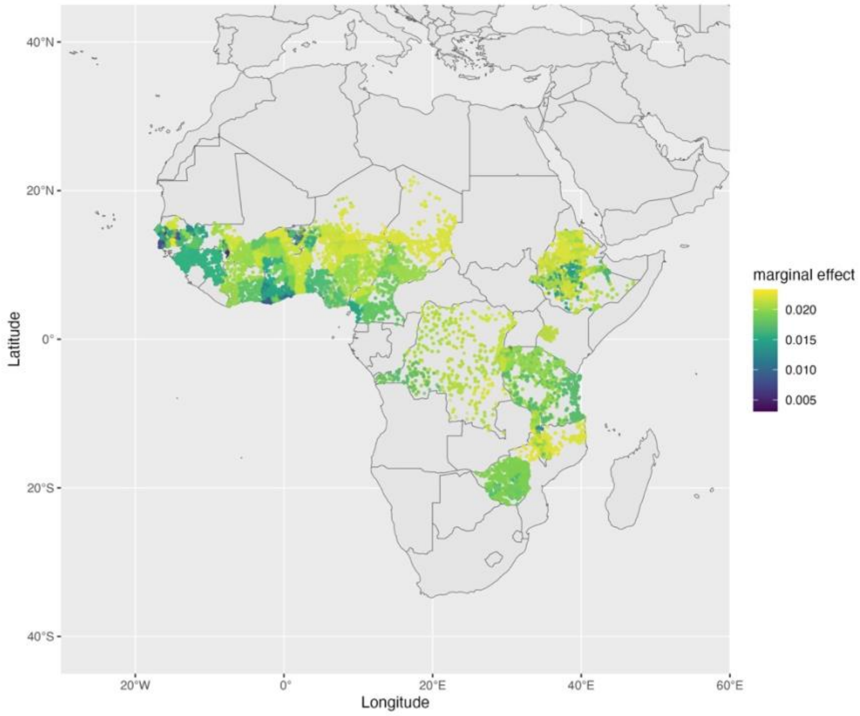

Figure 3 Marginal effect of unexpected volatility on stunting in year 1 after birth (grouped by market)

A heterogeneity analysis is provided in Table 3. Effects of unexpected volatility by life period are disentangled for rural vs urban households, by wealth level and agricultural involvement. The largest and most significant effects of unexpected maize price volatility on stunting are found in the first year of life across subgroups. Larger effects of price volatility on stunting for rich compared to poor households are surprising, still, the overall odds of being stunted are considerably smaller for children in rich households. It is striking, that having access to livestock does not only reduce the odds of stunting by itself, but additionally through mediating effects of price volatility. While differences between rural and urban or rich and poor households turn out to be minor, children in households that own agricultural land face higher odds of stunting in any life period as consequence of an increase in unexpected price volatility. Nonseasonal weather shocks and price transmission of volatile international prices might meet crop producers unprepared. Owning livestock versus cropland influences how unexpected maize price volatility affects stunting in opposing ways. Both effects will be underlying the estimate for children in overall rural households and to some degree cancel out.

Table 3 Heterogeneity analysis for stunting and unexpected volatility

Stunting	Price variable related to life period:				
	In Utero	**Year1**	**Year2**	**Year3**	**Year4**
$\widehat{V^u}.z$:rural	0.02	**0.09**	0.06	0.07	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
$\widehat{V^u}.z$:urban	0.09	**0.11**	0.07	0.05	0.07
	(0.06)	(0.06)	(0.05)	(0.06)	(0.07)
$\widehat{V^u}.z$:poor	0.03	**0.10**	0.08	**0.09**	0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
$\widehat{V^u}.z$:middle	-0.00	0.05	0.04	0.04	0.01
	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
$\widehat{V^u}.z$:rich	**0.09**	**0.11**	0.05	0.02	0.03
	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
$\widehat{V^u}.z$:No agric. land	0.04	0.09	0.04	0.01	0.01
	(0.06)	(0.06)	(0.05)	(0.06)	(0.07)
$\widehat{V^u}.z$:Has agric. land	0.04	**0.10**	0.07	**0.08**	0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
$\widehat{V^u}.z$:No livestock	0.06	**0.14**	**0.08**	0.09	0.07
	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
$\widehat{V^u}.z$:Has livestock	0.03	0.07	0.05	0.05	0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Further covariates			Yes		
Num. obs.			128364		
Num. groups: year			11		
Num. groups: market			325		

5. Discussion

Our price decomposition reveals that unexpected local market price volatility is significantly driven by futures volatility, subject to closeness to the nearest port, and local weather shocks. Our findings are in line with Brown and Kshirsagar (2015) who show that international prices and domestic weather disturbances affect local market prices.

Previous research shows that food price inflation during pregnancy and infancy increases the risk of stunting significantly (Woldemichael et al., 2022). In contrast, Grace et al. (2014) find a positive correlation between pre-pregnancy maize prices and birthweight.

For the time during pregnancy, our results do not allow a clear conclusion regarding the effect of price levels and volatility on stunting. High and volatile food prices could cause families to delay pregnancies or miscarriage (Grace et al., 2014). In this case, our results for the price effects around birth could be driven by households with generally lower risk of food insecurity. A similar logic could be underlying the effects related to hot humid days, in cases where heat stress during pregnancy induces miscarriage. Moreover, our linear model specification might be limited in its ability to disentangle the relationship between weather shocks and nutritional outcomes that is, for example, fitted to a fourth order polynomial model or other model types (Baker and Anttila-Hughes, 2020; Sweeney et al., 2013). A more in-depth exploration of

weather variables e.g. making use of machine learning techniques could help disentangling these relationships as these data-driven approaches are able to capture non-linearities without imposing a functional form (Storm et al., 2020).
Our data hardly allows us to differentiate between net food producing households, including sellers and subsistence farmers, and food purchasing households, to a limited extent. We distinguish between rural and urban households and include information about the possession of agricultural land and livestock and about the employment in agriculture. However, a clear distinction between net producers and buyers is impossible, wherein the resulting effects could still be the outcome of opposing mechanisms of both household types. Nonetheless, livestock ownership is nutrition improving across models, which agrees with previous research (Khonje et al., 2022).
Despite that maize is the main staple food across SSA, nutrition outcomes are especially dependent on dietary diversity and sufficient protein consumption. Therefore, the presented analysis is limited by its focus on maize prices. Nevertheless, given its important role in diets, maize price volatility likely has a direct effect on the consumption of other food products as well.
Our underlying nutrition and price data originate from different sources. The matching of households to the nearest market is based on the geolocations provided in the two data sources. Our market price data is limited; thus, the matches might not represent the actually relevant market for each household. Nevertheless, infrastructure, market integration, and weather shocks might be comparable to the true market in many cases. Moreover, owing to confidentiality reasons, the DHS household locations are shifted by up to 10 km, which adds further error to our geo-matching approach.

6. Conclusions

High and volatile staple food prices are often regarded as threats to food security. In particular, nonseasonal unexpected price volatility can reduce food access, because households might not have the chance to adjust their food production, purchases, storage, and subsistence behaviors accordingly. Climate change and related weather shocks can affect crop yields and, via market effects and related expectations, food prices. Increasingly integrated global value chains and trade relations cause the transmission of international price changes to local market levels.
We complement existing research (i) by investigating price volatility drivers in a decomposition analysis, and (ii) by getting a step closer toward causally estimating the effect of price volatility on nutrition.
The findings of this paper clearly suggest that price volatility is transmitted from international to local markets in SSA. The effect direction of weather shocks on unexpected price volatility are less clear and require further investigation. Our results indicate that unexpected price volatility in the first year after birth increases the odds of stunting in children significantly. While net producers and consumers are hard to differentiate based on the available dataset, the results suggest that unexpected price volatility imposes a greater risk of stunting among children in agricultural households unless these have access to livestock.

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