Supply Chain Resilience to Extreme Weather: Evidence from Early Warning Systems

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Abstract

Anthropogenic climate change has accelerated the frequency and variability of extreme weather events. The impacts of these extreme weather events on food production systems are well documented; however, evidence regarding downstream impacts on transportation, storage, and markets, remains missing. Retail food prices provide a critical indicator of food system performance at the consumer end of supply chains. Quantification of the net welfare impacts of extreme weather events on bulky perishable foods can guide nutrition-sensitive interventions for climate adaptation and resilience planning. We utilize a novel global retail price dataset by combining monthly retail price observations from three early warning systems: FAO GIEWS, USAID FEWSNET, and WFP VAM. We then utilize market locations to extract constructed measures of heatwave, coldwave, flood, drought, and storm events using gridded data for study period of 2000 – 2022. We find that retail food prices are firmly resilient to extreme weather with some exceptions across regions and food groups. Supply reductions of Fruits and Vegetables indicate some vulnerability to storms in Asia. In Sub-Sahaharan Africa, small demand reductions for Breads and Cereals is associated with Floods, Coldwaves, and Heatwaves, and supply constriction is observed during seasonal drought months. These findings can inform targeted policies and programs to support healthy diets in the aftermath of extreme weather events.

Key words: Retail food prices, extreme weather events, diet quality, nutrition

Introduction

Weather extremes present critical threats to global food security and nutrition. Disaster-related losses in the agricultural sector totaled USD 280 billion between 2008 – 2018 with significant recent increases due to Covid-19 (FAO, 2021c). Rainfall shocks, droughts, and temperature extremes have been associated with substantial yield anomalies of major cereal crops (Lobell & Gourdji, 2012; Schlenker & Lobell, 2010; Ubilava & Abdolrahimi, 2019; Vogel et al., 2019). These production shortfalls strain households through direct damage to crops and assets as well as indirect pathways such as lost incomes, lowered household budgets, and impaired health (Green et al., 2013; Hallegatte et al., 2016). Greater frequency and variability of climate extremes in upcoming decades are expected to increase poverty rates, endangering global progress towards the Zero Hunger Sustainable Development Goal (FAO, IFAD, UNICEF, WFP, & WHO, 2021).

Food price volatility as a result of extreme weather also affects households at the regional scale. Global analyses have demonstrated the heterogeneity of price responses to weather shocks, particularly for maize, rice, wheat, and soybean (Chatzopoulos, Pérez Domínguez, Zampieri, & Toreti, 2020; Peri, 2017; Ubilava & Abdolrahimi, 2019). However, much of the evidence on food price volatility derives from commodity prices of staple grains and cereals during crisis periods (Cohen & Garrett, 2010; Cuesta, Htenas, & Tiwari, 2014; FAO et al., 2011; Headey & Fan, 2008). This focus is driven by the primacy of grains and cereals to the diets of poor people, as well as established global trade networks in non-perishable agricultural commodities (Moltedo, Troubat, Lokshin, & Sajaia, 2014). However, price changes in other food groups are relevant to poor peoples' health and nutrition status. The recent evolution of diet cost metrics underscores the need for price analysis of food groups such as fruits and vegetables and animal source foods (Herforth et al., 2020).

Retail prices better represent the additional cost paid by the consumer for transportation and storage of bulky, perishable food items (Takayama, 1971) and thus provide a critical data source for analyses of volatility. Retail food prices are often more responsive to local weather shocks and shocks at central wholesale markets than international price volatility (Brown & Kshirsagar, 2015; Minot, 2014). Small demand and supply elasticities also allow retail prices to be highly sensitive to supply shocks (FAO et al., 2011) and therefore incorporated in a wide variety of early warning systems (EWSs). Recent literature on the Covid-19 pandemic demonstrates this sensitivity as retail prices across various food groups were observed to be higher in countries with more stringent mobility restrictions and higher Covid-related morbidity and mortality (Akter, 2020; Imai, Kaicker, & Gaiha, 2021; Narayanan & Saha, 2021). Previous studies investigating retail food prices and extreme events have been spatially and temporally limited to particular geographies, record-breaking climate events, or particular humanitarian crises (Klomp & Bulte, 2013; Lawlor, Handa, Seidenfeld, & Zambia Cash Transfer Evaluation, 2019; Lazzaroni & Wagner, 2016; Mawejje, 2016; Maxwell & Fitzpatrick, 2012). Price observations from monitoring and early warning sources such as the Food and Agriculture Organization (FAO) Global Information and Early Warning System (GIEWS) (FAO, 2021b), the World Food Programme (WFP) Vulnerability Analysis and Mapping (VAM) (WFP, 2021), and the US Agency for International Development (USAID) Famine Early Warning Systems Network (FEWSNET) have also been used in localized models of fragility and food insecurity; however, structural analyses of retail price time series from these sources are notably lacking. Two existing studies have utilized early warning datasets to study price effects. Cedrez et al (2020) provide a time series analysis of compiled data to measure spatial and temporal price variation in 168 markets (Cedrez, Chamberlin, & Hijmans, 2020). Brown and Kshirsagar (2015) utilize a similar combined dataset of early warning systems market prices to investigate differential effects of weather in 2008 – 2012 using the Normalized Differenced Vegetation Index (NDVI) (Brown & Kshirsagar, 2015). Neither analysis specifically investigates extreme weather.

In this paper, we aim to describe retail price changes by food group and urbanicity as they respond to a suite of five contemporaneous and recent extreme weather events: heatwaves, coldwaves, storms, floods, and droughts. We focus on net price changes as our outcome of interest rather than market efficiencies to exploit a global dataset of market-level price observations derived from early warning systems. The magnitude and direction of retail price changes are affected by the disruption itself, the impacted supply chain, and the mechanism of downstream impacts throughout the food system. Market locations allow us to utilize the quasi-random nature of extreme events for this analysis. We further disaggregate this study by food groups to identify differential impacts of these hazards on perishable and nonperishable food groups. For example, upward price shifts for perishable and nutrient-dense foods such as dairy and meats may indicate supply constrictions due to shocks impacting a supply chain with higher storage and transportation costs. Alternatively, downward price shifts for the same food group would indicate demand reduction potentially due to widespread loss of income across a region (Bai, Alemu, Block, Headey, & Masters, 2021). These correlations are further distinguished by markets' classification as rural, urban, or peri- and sub-urban to better represent global variability in market connectivity, integration, and population density (Minten, Koru, & Stifel, 2013; Shively & Thapa, 2016; Thapa & Shively, 2018). Quantification of these heterogenous impacts can inform long-term climate adaptation as well as rapid interventions to mitigate diet disruptions due to extreme weather events. This analysis also provides a critical input for simulation studies of global food insecurity and climate which are constrained by limited data about price impacts on livestock, fruits, and vegetables (Hasegawa et al., 2021; Mbow et al., 2019). As the food system intensifies to feed 9.7 billion people by 2050 despite higher likelihood of weather-related disasters (FAO et al., 2021), understanding the impacts of extreme weather events on various food groups is critical to building resilience in the food system and protecting affordability of healthy diets.

Data Sources and Processing

Retail food prices

Monthly retail food item prices were obtained from early warning system (EWS) databases published by three different international agencies: the Global Information and Early Warning System (GIEWS) by the Food and Agriculture Organization (FAO) of the United Nations (UN); the Famine Early Warning System Network (FEWSNET) produced by USAID; and the Vulnerability Analysis and Mapping (VAM) system from the World Food Programme (WFP). All available data were extracted, and a continuous study period of 2000 – 2022 was utilized for this analysis. Each price observation was then adjusted for its country's inflation using a combined database of monthly consumer price indices for food items from the IMF (IMF, 2021) and the FAO (FAOSTAT, 2021). All prices in local currency units were then adjusted for international comparisons using purchasing power parity prices to a reference period of June 2017 using the World Bank's purchasing power parity (PPP) conversion factor for private consumption (International Comparison Program & World Bank, 2021).

All retail price data were then cleaned to remove outliers. Plausible errors in data entry were defined as values of each market-item time series greater than or less than 3 standard deviations in units of 2017 USD/kCal which could be corrected to fall within the time series range by multiplying or dividing by a power of 10. These *order of magnitude outliers* were corrected to restore the price value to within plausible range. A total of 104 (0.08% of the dataset) order of magnitude outliers were corrected. The winsor2 Stata package was then used to trim the top and bottom 0.5% of price observations within each food group category to remove extreme values most likely due to data entry errors. After trimming, a total of 2,172,210 price observation were available from 3,053 markets in 78 countries.

Food group classification and food composition

All food items in the combined EWS dataset were classified into eight categories and two groups. The *Non-Perishable* category includes the following food groups: Breads and Cereals; Legumes, Nuts, Seeds; Oils and Fats; and Sugar and Confectionary. The *Perishable* category included: Dairy and Eggs; Fish and Seafood; Fruits and Vegetables; and Meat food groups. This classification is based on the UN Classification of Individual Consumption According to Purpose (COICOP) system (Bai et al., 2021a, 2021b). To allow for comparison across food groups, each food item was also matched to the USDA Standard Reference 28 Food Composition Table (US Department of Agriculture Agricultural Research Service, 2016) or the West African Food Composition Table where appropriate (Vincent et al., 2020). 98% of all items in the larger dataset were successfully matched, and kilocalories in each item as purchased was calculated using the edible fraction of the matched item. Any prices for live animals were dropped due to the lack of food composition data. EWS retail prices were thus standardized to 2017 USD/kcal of item.

Extreme Weather Events

Gridded data were utilized to derive extreme weather events matched to the GPS location of each market location in the EWS dataset. Maximum and minimum temperature anomalies were extracted from the Terraclimate dataset (Abatzoglou, Dobrowski, Parks, & Hegewisch, 2018). Maximum temperature anomalies greater than 2 SD were classified as heatwaves, and minimum temperature anomalies less than -2 SD were classified as coldwaves. Tropical cyclones and storms within 200 km of a market were calculated using the International Best Track Archive for Climate Stewardship (IBTrACS) storm track database (Knapp, Kruk, Levinson, Diamond, & Neumann, 2010). A market was classified as having experienced a storm or tropical cyclone in a month if it experienced at least one tropical cyclone of Category 3 or higher on the Saffir-Sampson scale, corresponding to wind speeds of at least 178 km/h or 96 knots (Bell et al., 2000). Floods and droughts were characterized using the Standardized Precipitation Index (SPI) and Standardized Evapotranspiration Index (SPEI) respectively (Beguería, Vicente-Serrano, & Angulo-Martínez, 2010; Beguería, Vicente-Serrano, Reig, & Latorre, 2014). 6-month SPEI values less than or equal to -1.5 were classified as having experienced Drought (Bischiniotis et al., 2018), and 1-month SPI values greater than or equal to 1.5 (corresponding to Severe or Extreme conditions) were classified as having experienced Flood conditions

Global Prices

The FAO monthly food price index (FPI) for the commodity group corresponding to each food item was utilized as a proxy of average global price levels during each month (FAO, 2021a). These FAO commodity groups include: Cereals, Vegetable Oils, Dairy, Meat, and Sugar. These commodity groups correspond to the modified COICOP categories of Breads and Cereals, Fats and Oils, Dairy and Eggs, Meats, and Sugar and Confectionery respectively. Two food groups (legumes, nuts, and seeds; fruits and vegetables) lack a comparable FPI category and are therefore omitted from specifications including the FPI variable.

Urbanization

Each market was assigned an urban classification corresponding to the Global Human Settlement Layer (GHSL) Degree of Urbanization classification in the years 2000 and 2015 (Florczyk A.J., 2019; Pesaresi, Florczyk, Schiavina, Melchiorri, & Maffenini, 2019). Classification for both years derives from the GHSL Settlement Model Grid (SMOD), and the high-level categories of Urban, Suburban, and Rural were used. Changes in urbanization classification over time were examined to identify urbanization dynamics during the study period. Markets classified as Urban in 2000 and Rural in 2015 were dropped from the analysis[1]. Based on combinations of remaining transitions, all markets were initially classified into typologies of Urban, Rural, Suburban, and Transitional. A balance table comparing characteristics of sample markets to rest of world allowed for merging of the latter two categories to generate the final typology of Urban, Rural, and Peri- and Sub-Urban markets.

Table 1 Urbanization categories of EWS markets per DEGURBA classification

Class in 2000	***Class in 2015***	***Typology***	***% of Markets***
Urban (any density)	Urban (any density)	Urban	64.4%
Rural (any density)	Rural (any density)	Rural	28%
Suburban	Suburban	Suburban	1.4%
Suburban	Urban (any density)	Intensifying Suburb	1.2%
Rural (any density)	Urban (any density) Suburban	Urbanizing Rural	4.6%
Urban (any density)	Suburban Rural	De-Urbanizing City	0.4%
Suburban	Rural	-	0%

[1] Dropped markets experienced significant conflict or migration during the study period. The14 markets comprising this category are located in northern Sri Lanka, parts of Rwanda, central Mali, southern Malawi, and one market in Mozambique. Two non-conflict related examples were found in Nepal and Cambodia, potentially driven by migration or sprawl.

Estimation Strategy

Extreme event dummies were first defined as above. The association between retail food prices and each of the five extreme events were examined using a baseline ordinary least squares (OLS) regression specification shown in Equation 1.

$$\mathrm{P_{ijt}} = \beta_0 + \beta_1 \text{Extreme Event}_{\mathrm{j,t-n}} + \gamma_j + \lambda_{jm} + \theta_{jy} + \tau_i + \varepsilon \qquad \textit{Equation 1}$$

In this equation, *i* refers to food item, *j* refers to market location, *t* refers to continuous time, *n* refers to lagged month, *m* refers to month, and *y* refers to year of price observation. P_{ijt} indicates one of two outcomes: the natural log of retail price in 2017 USD/1000 kCal, and the difference from the average price of each food group during each market and month of analysis. $\text{Extreme Event}_{\mathrm{j,t-n}}$ is a dummy variable which represents one of Flood, Drought, Storm, Heatwave, or Coldwave. Each extreme event was lagged by up to three months prior to the month of price observation (*n* = 1, 2, 3) to test for potential persistence. We also include market location fixed effects γ_j to account for unobserved heterogeneity over space, market-month fixed effects λ_{jm} to account for seasonal price fluctuations, market-year fixed effects θ_{jy} to account for year-to-year changes, and item fixed effects τ_i to account for differences in product characteristics such as item packaging and storage requirements. Equation 1 was sequentially applied to the pool of available retail prices, and subsequent subsets by food group, urban category (rural, urban, peri- and sub-urban), and both food group and urban category respectively. A Bonferroni correction was applied by dividing the p-value thresholds for statistical significance by the total number of comparison groups to adjust for multiple comparisons.

Alternate specifications of Equation 1 explore the robustness of observed coefficients to the inclusion of differentially lagged retail food prices and covariates representing average weather including average temperature and precipitation at location *j* and time *t*. The effect of world retail prices was also explored through the inclusion of the FAO commodity group price index for the food category corresponding to retail item *i* of interest during time *t*.

Results

Summary statistics

A summary of dataset characteristics is provided in Table 2. A grand total of 2,172,210 observations are utilized, with 69.1% of observations in Urban markets, 20.0% in Rural markets, and

10.8% in Peri- and Sub-Urban markets. Approximately 59% of the EWS data is sourced from WFP VAM, with GIEWS contributing 36% of the dataset and FEWS contributing approximately 5%. Food price monitoring has improved steadily during the study period; the first decade of the study period contributed only 2.8% of the complete dataset, and the share of observations grew to 25.5% in 2010 – 2014. Food price monitoring has also improved during the Covid-19 pandemic of 2020 – 2022; the greater share of observations during these years comprises approximately 23.1% of the dataset. To account for this improvement in price monitoring during the study period, we utilize market-month and market-year fixed effects to further absorb any seasonality in the retail price signal.

The geographic distribution of market locations in EWS is heavily skewed towards low and middle income countries (LMICs) in the global south. Price observations in Sub-Saharan African markets represent 58.6% of the dataset, and the East Asia & Pacific, Latin America & Caribbean, and South Asia regions represent 9-10% each. Along the income dimension, 91% of price observations in the EWS dataset are collected from markets in Low and Lower Middle income categories per the World Bank's country classification by income group during the year of price observation.

Table 3 presents summary statistics by food group and market type. Prices in weight (2017 USD/kg) and caloric units (2017 USD/1000 kCal) are presented for the purpose of discussion; however, the remainder of the paper discusses only outcome units of 2017 USD/kCal. Breads and Cereals comprise the largest food group for which retail prices are observed (53.0%), followed by Fruits and Vegetables (18.0%) and Pulses, Nuts, and Seeds (9.9%). There is considerable diversity in food items within these food groups as well; a list of unique items by food group is provided in Supplemental Materials. Breads and Cereals are the cheapest food group at USD 1.59/kg. This food group is USD 0.13 cheaper per kg in rural markets compared to urban markets. Fruits and Vegetables are the next cheapest food group at an average price of USD 1.91/kg, followed by Sugar and Confectionary at USD 2.53 on average. The urban-rural gradient is particularly stark for Sugar and Confectionery, as average prices in rural markets are USD 1.06 higher per kg compared to Urban markets. Rural markets are also observed to have cheaper prices on a weight basis for perishable food groups compared to urban markets, with an average difference of USD 0.85/kg.

As indicated by Table 3, the vast difference in food composition across groups necessitates caloric adjustment for comparison across food groups. On a weight basis, Dairy and Eggs is only 3.7x as expensive as Breads and Cereals; however in calorie terms, the Dairy and Eggs and Fruits and Vegetables food groups are approximately 10x more expensive than Breads and Cereals. Within perishable food groups, rural markets on average appear to be more effective at provisioning Dairy and Eggs and Fish and Seafood whereas urban markets appear to be more effective at provisioning Fruits and Vegetables and Meat, as evidenced by comparatively lower prices per kilocalorie. Retail prices of perishable food groups are also poorly represented and monitored in EWS, with the exception of Fruits and Vegetables. Perishable food groups represent less than 30% of the complete dataset, indicating a critical gap in price monitoring of foods needed for a balanced and healthy diet.

Table 2 Summary of dataset characteristics by data source, year, and World Bank Region, across market urbanization typologies

	Pooled	*Urban*	*Rural*	*Peri- and Sub-Urban*
Total Observations	2,172,210	1,500,656	435,022	236,532
Total Items	105	105	97	98
Total Unique Products	141	141	117	112
Total Countries	78	76	57	51
Total Markets	3053	1742	933	378
% of Observations by Data Source				
FEWS	4.88	5.38	5.56	0.47
GIEWS	36.13	41.84	22.1	25.71
VAM	58.99	52.78	72.34	73.81
% of Observations by Year				
2000 - 2004	2.82	3.19	1.67	2.64
2005 - 2009	11.05	11.96	8.69	9.63
2010 - 2014	25.53	25.22	25.97	26.65
2015 - 2019	37.48	36.99	38.58	38.56
2020 - 2022	23.12	22.64	25.1	22.51
% of Observations by WB Region				
East Asia & Pacific	9.59	10.14	7.88	9.27
Europe & Central Asia	7.75	8.8	1.44	12.69
Latin America & Caribbean	9.96	13.78	1.4	1.45
Middle-East & North Africa	4.29	4.28	4.46	4.03
South Asia	9.77	12.38	5.76	0.59
Sub-Saharan Africa	58.64	50.63	79.05	71.97
% of Observations by WB Income Group				
High Income	0.54	0.78		
Upper Middle Income	8.45	9.2	5.23	9.59
Lower Middle Income	42.29	44.09	42.29	30.86
Low Income	48.72	45.93	52.47	59.56

Table 3 Share of observations, average price per kg, and average price per kCal by food group across market typologies

	Pooled			*Urban*		
	%	*Avg. Price (2017 USD/kg)*	*Avg. Price (2017 USD/kCal)*	*%*	*Avg. Price (2017 USD/kg)*	*Avg. Price (2017 USD/kCal)*
Breads & Cereals	53.0	1.59	0.23	52.5	1.61 *(t = 15.01, p = 0)*	0.23 *(t = 16.78, p = 0)*
Fats & Oils	6.0	4.83	0.27	6.2	4.72 *(t = -7.55, p = 0)*	0.27 *(t = -7.74, p = 0)*
Pulses, Nuts, & Seeds	9.9	3.12	0.46	9.6	3.15 *(t = 4.61, p = 0)*	0.46 *(t = -2.11, p = 0.04)*
Sugar & Confectionery	1.3	2.53	0.33	1.6	2.37 *(t = -13.53, p = 0)*	0.30 *(t = -13.53, p = 0)*
Dairy & Eggs	3.1	5.84	2.35	3.3	5.83 *(t = -0.14, p = 0.89)*	2.42 *(t = 3.32, p = 0)*
Fish & Seafoods	2.1	10.96	5.01	2.0	11.00 *(t = 0.45, p = 0.65)*	5.03 *(t = 0.48, p = 0.63)*
Fruits & Vegetables	18.0	1.91	2.25	17.9	1.91 *(t = -0.82, p = 0.41)*	2.15 *(t = -14.27, p = 0)*
Meats	6.6	11.60	3.05	6.8	11.67 *(t = 3.30, p = 0)*	2.96 *(t = -13.36, p = 0)*

	Rural			*Transitional*		
	%	*Avg. Price (2017 USD/kg)*	*Avg. Price (2017 USD/kCal)*	*%*	*Avg. Price (2017 USD/kg)*	*Avg. Price (2017 USD/kCal)*
Breads & Cereals	54.9	1.48 *(t = -49.46, p = 0)*	0.21 *(t = -54.43, p = 0)*	52.1	1.66 *(t = 26.71, p = 0)*	0.24 *(t = 25.81, p = 0)*
Fats & Oils	6.0	5.04 *(t = 7.87, p = 0)*	0.28 *(t = 6.92, p = 0)*	5.0	5.20 *(t = 8.23, p = 0)*	0.30 *(t = 9.87, p = 0)*
Pulses, Nuts, & Seeds	11.2	3.08 *(t = -4.75, p = 0)*	0.45 *(t = -8.16, p = 0)*	9.0	3.02 *(t = -7.11, p = 0)*	0.51 *(t = 12.65, p = 0)*
Sugar & Confectionery	1.0	3.43 *(t = 22.78, p = 0)*	0.44 *(t = 22.85, p = 0)*	0.0	2.55 *(t = 0.24, p = 0.82)*	0.33 *(t = 0.24, p = 0.82)*
Dairy & Eggs	2.3	4.74 *(t = -15.43, p = 0)*	1.98 *(t = -11.85, p = 0)*	2.8	7.54 *(t = 9.92, p = 0)*	2.45 *(t = 2.22, p = 0.03)*
Fish & Seafoods	2.5	9.81 *(t = -12.33, p = 0)*	4.25 *(t = -14.13, p = 0)*	2.4	12.91 *(t = 13.07, p = 0)*	6.31 *(t = 14.66, p = 0)*
Fruits & Vegetables	16.4	1.88 *(t = -3.92, p = 0)*	2.49 *(t = 21.38, p = 0)*	21.7	1.98 *(t = 6.04, p = 0)*	2.41 *(t = 12.27, p = 0)*
Meats	5.8	10.59 *(t = -21.89, p = 0)*	3.29 *(t = 17.15, p = 0)*	6.9	12.64 *(t = 22.37, p = 0)*	3.30 *(t = 19.09, p = 0)*

Frequency of Extreme Events

Figure 1 presents the frequency of extreme event occurrence by month and year in the study period, for the complete panel of market-months in this dataset. Extreme temperature deviations from normal occur commonly throughout the world, whereas tropical regions are particularly prone to seasonal flooding and storm events. Due to the extremely different climatologies of markets in the EWS sample, the timing of each event within a calendar year holds little meaning; however, event frequencies can still be analyzed. Heatwaves are the most frequently occurring event during the study period (4.3% of market-months), followed by floods (2.99%) and droughts (1.98%). Coldwaves (0.35%) and storms (0.31%) occur least frequently, and storm occurrence is limited to 38.7% of study markets. While floods occur consistently during the study period, increasing occurrence of heatwaves and droughts are observed in the recent decade.

Figure 1 Number of markets affected by extreme events (flood, drought, storm, heatwave, and coldwave) by month and year, 2000 – 2022

Contemporaneous Extreme Events

Figure 2 presents estimated coefficients per Equation 1 applied to split samples by extreme event and food groups for both price by weight and price by calorie outcomes. On average, Heatwaves and Coldwaves are associated with net reductions in retail prices, whereas Storms and Droughts are associated with net increases in retail prices. Statistically significant effects are similar across both weight (top row) and calorie (bottom row) price outcomes; therefore, focusing on only statistically significant effects paints a clearer picture of these relationships. Differential responses are observed between food groups in response to extreme events. Although no clear pattern is discernible across non-perishable and perishable food groups, food group-level responses are notable. Storms are associated with a 7% increase in price per 1000 kilocalories of Fruits and Vegetables (β_1 = 0.068 ± 0.016) and Droughts are associated with a 5.2% increase in prices of Breads and Cereals (β_1 = 0.051 ± 0.008). The magnitude of most effects is similar across price outcomes in weight and calorie units; therefore, the remainder of this paper reports coefficients of price in calorie units (USD 2017/1000 kCal). Although Fats and Oils appears to respond to Coldwaves, the small sample sizes of this category and lack of plausible physical mechanism for this effect call into question the observed association.

Figure 2 Change in retail price (%) during extreme events (flood, drought, storm, heatwave, and coldwave) by price type (price per kg and price per 1000 kCal).

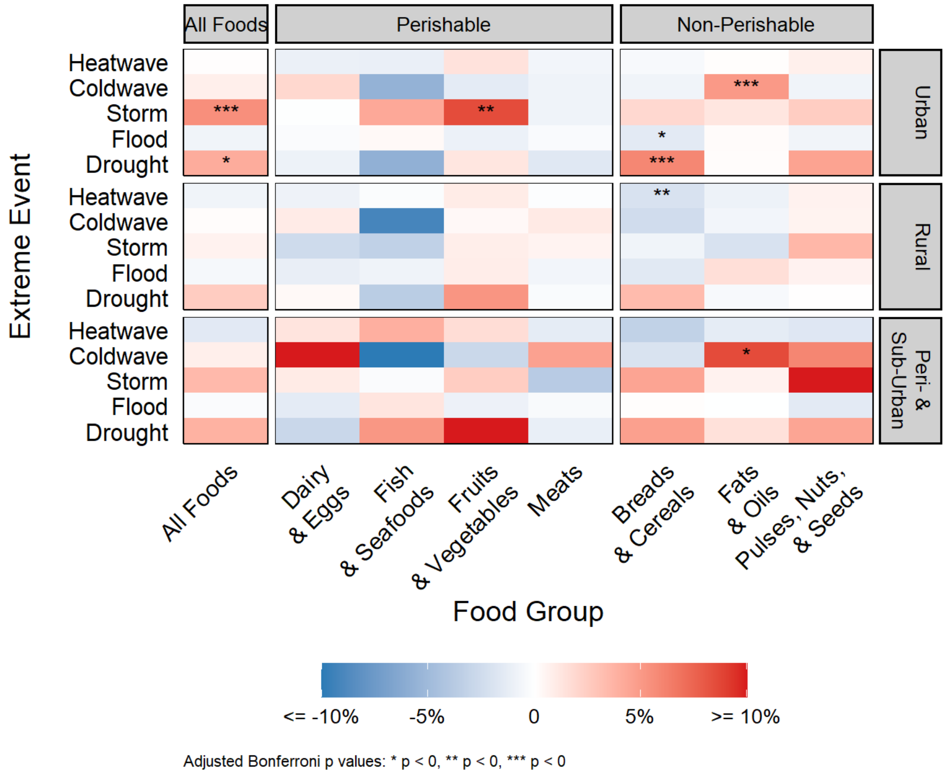

Figure 3 Change in retail price per 1000 kCal (%) by market typology (urban, rural, peri- & sub-urban) during extreme events (flood, drought, storm, heatwave, and coldwave). Note: Sugar and Confectionery food group is excluded from this graph due to data sparsity across Rural and Peri- and Sub-Urban partitions.

Differential impacts are observed across different types of markets for various food groups. Retail prices of most food groups in Rural and Peri- and Sub-Urban areas are not significantly perturbed across any of the five extreme events, indicating relative stability. The exception to this is the Breads and Cereals food group, for which demand reduction is observed in rural areas during heatwaves ($\beta_{breads\ and\ cereals,rural}$ = -1.9%, -0.019 ± 0.008). In Urban markets, supply constriction occurs more frequently in response to Storms ($\beta_{fruits\ \&\ vegetables,urban}$ = 14.2%, 0.133 ± 0.017) and seasonal droughts ($\beta_{breads\ and\ cereals,urban}$ = 2.1%, 0.02 ± 0.009). Minimal demand reduction is also observed in urban markets during floods, potentially due to physical barriers to market access during these months.

Effect of Covariates and Lagged Extreme Events

Detailed comparisons of coefficients across models including environmental covariates (temperature, precipitation, and interaction), lagged prices by 1, 2, and 3 months, and world prices per the FAO Food Price Commodity Group Index, are presented in Supplemental Materials. Presented coefficients are stable to the inclusion most covariates. One exception is observed in retail price changes to Fruits and Vegetables during Storm months. This regression specification is sensitive to lagged prices with potential persistence in the month following a storm. This deviation is interpreted as indicating potential unobserved variables or highly variable seasonal production cycles which mediate observed price changes. In general, coefficients observed in contemporaneous specifications do not change significantly in the following month, but the precision of estimated effects often improves in the latter specification. This observation provides preliminary evidence of limited persistence effects.

Regional Patterns

Figure 4 presents coefficients estimated for the baseline regression across event, food group, market type, and regions as defined by the World Bank. Widespread heterogeneity is observed across partitions and even among regions experiencing the same event. This finding underlines the limited generalizability of global results and the importance of local context while assessing localized effects. Some consistent effects are observed; for example, in Sub-Saharan Africa (SSF), both urban and rural markets indicate demand reduction of Breads and Cereals during months with concurrent flood, heatwave, and coldwave. The magnitude of demand reduction is less than 5%, but the persistence may indicate strained diets in response to environmental stressors. In contrast, significant supply constriction of Breads and Cereals and Pulses, Nuts, and Seeds is observed in SSF during heatwave months, consistent with expected calorie smoothing. Supply constriction of Breads and Cereals is also observed in Latin America and the Caribbean after floods and storms.

Demand reduction of perishable food groups occurs frequently, with drastic decrease in prices of Dairy and Eggs and Fish and Seafood during flood and storm months. Rural-urban differences are particularly pronounced for these food groups, particularly in Latin America and Caribbean and East Asia and Pacific. Supply constriction of Fruits and Vegetables is observed in rural South Asia (28%, 0.247 ± 0.028) and urban East Asia and Pacific markets (6.8%, 0.065 ± 0.015) during storm months. Urban markets in South Asia also experience this supply construction during flood months (4.7%, 0.046 ± 0.013), indicating that this food group may be particularly sensitive to moisture-related extreme events in the Asia region. This finding contrasts with net demand reduction of Fruits and Vegetables in Middle East and North Africa and Europe and Central Asia during heatwave months, perhaps due to this food group being relatively expensive in these regions.

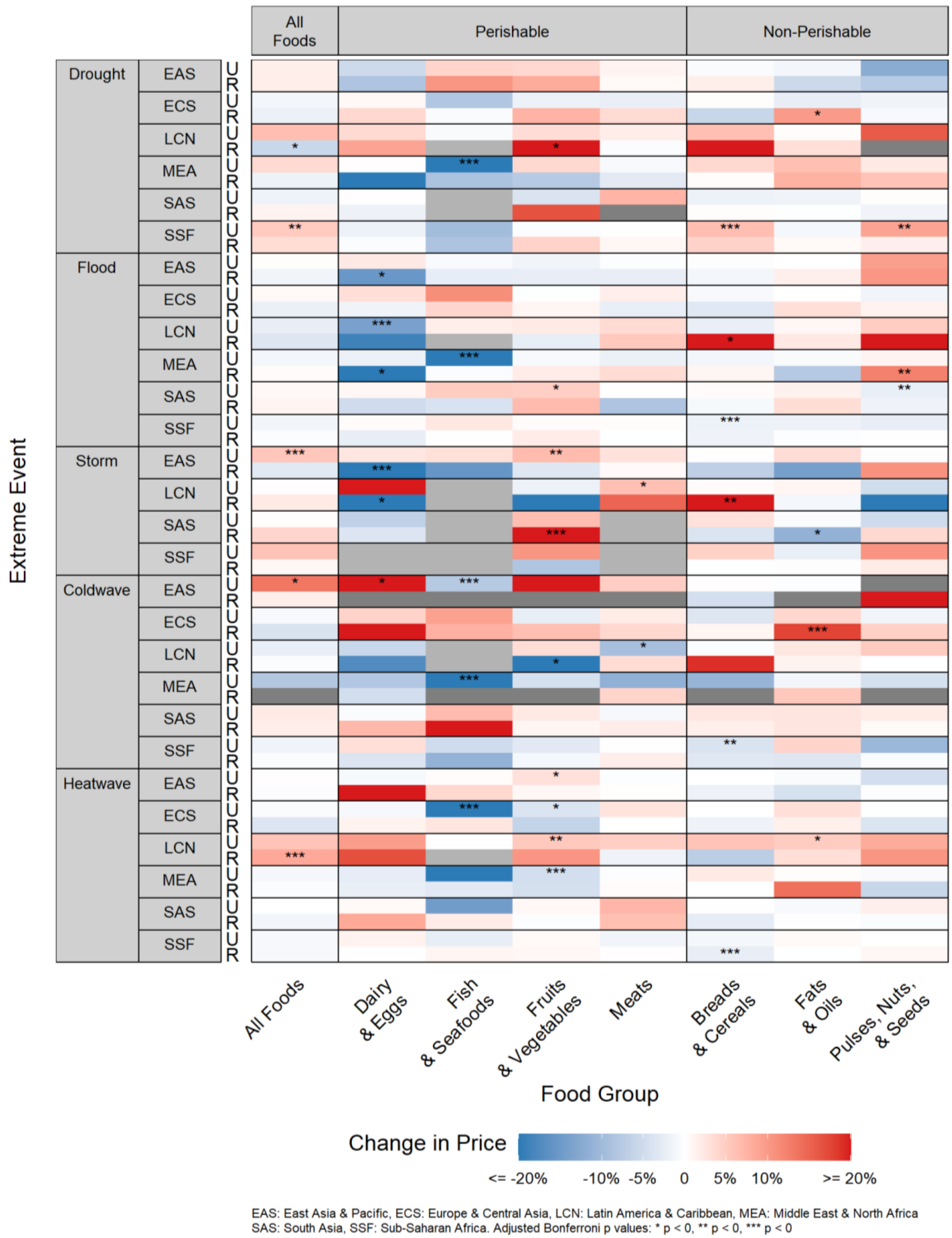

Figure 4 Changes in retail price per 1000 kCal (%) by extreme events in the contemporaneous month, World Bank regional unit, market type (urban, and rural), and food group. Note: Sugar and Confectionery food group and Peri- and Sub-Urban market type are excluded due to data sparsity across most partitions.

Discussion and Limitations

This paper presents a novel database of retail prices from early waring systems (EWS) to test the relationship between extreme events and food group costs. We find significant heterogeneity in price changes across food groups, market types, and geographic regions. Due to relatively small magnitudes of fluctuations, we conclude that retail price are very resilient to extreme weather. Notable findings include a significant supply reductions of Fruits and Vegetables in urban markets during storm months, primarily observed in East Asia and Pacific and South Asian markets. We also find that floods and droughts of at least six months are associated with a significant demand reduction of Breads and Cereals in Sub-Saharan African markets, whereas droughts are associated with a supply constriction of 4.4-6.4%. These dynamics provide preliminary insight into retail food price behavior during and immediately following extreme weather events, and provide a starting point for nutrition-sensitive interventions to adapt to a changing climate.

Several limitations affect presented results. Firstly, spatial resolution of both markets and source weather data influence our results. High resolution datasets were chosen to derive covariates, but pixel-level inconsistencies may have been abstracted into this analysis. Source earth observation datasets are also subject to error from variables such as cloud cover and smoke. The remote sensing datasets utilized in this analyses are already corrected for common issues, but available percent accuracy fields for each source raster were not examined. This may be particularly challenging during periods of greater storm activity or flooding when cloud cover is more likely to introduce error in earth observation. The accuracy of market GPS locations may also contribute to spatial error. GPS points were validated to ensure points are located on land, but no further corrections were correct provided coordinates from the EWS databases.

Temporal resolution is another key limitation. The GIEWS and FEWS databases provide weekly time series of retail price data from a subset of markets which were not utilized here; instead, we use monthly average retail prices to match the temporal scale of chosen earth observation data. This decision is associated with loss of precision (Alarcon Falconi, Estrella, Sempertegui, & Naumova, 2020) and limited ability to support early warning. Analysis of earth observation data at the weekly scale is also computationally intensive, and more readily realized at smaller spatial scales. However, the monthly time scale provides a more representative time interval to measure net outcomes of complex supply and demand forcings on retail prices. The monthly time scale is more commonly used in literature as well (Brown & Kshirsagar, 2015; Cedrez et al., 2020; Letta, Montalbano, & Pierre, 2021). However, as computational capacities improve, future work can study weekly time series to generate more precise estimates of extreme weather and its effects on retail prices.

The constructed market categories (urban, rural, peri- and sub-urban) utilized in this analysis can also bias effect estimates. The DEGURBA classification from which our typology was derived, faces several limitations including discrepancies in official population statistics, distinctions between adjacent conurbations, and somewhat arbitrary population thresholds to distinguish between categories (Dijkstra, Brandmüller, Kemper, Khan, & Veneri, 2020; Dijkstra, Poelman, & Veneri, 2019) An inverse source of error is also identified, whereby destruction of built-up area from natural disasters may affect input datasets used to derive the DEGURBA classification. Despite these limitations, this dataset was developed specifically for the purpose of facilitating international comparisons, and is thus extremely pertinent to the scope of our analysis. Despite the small sample size of Peri- and Sub-Urban markets (12.4%), we retain this category to demonstrate the gradient of climate impacts across our analysis. Future work can utilize more detailed DEGURBA classifications which can be used for identifying particular trends among subsamples of urban areas such as intensifying suburbs, urbanizing rural areas, and de-urbanizing cities (Table 1). The latter category is particularly relevant for investigations on the feedback loops between violence and retail prices of food and fuel as leading indicators of food insecurity (Raleigh, Choi, & Kniveton, 2015).

Human error in price data collection also impacts our analysis. All EWS databases collect retail prices from various national agencies and institutions and are thus subject to errors in the process of recording, reporting, and curating price data. We utilize a simple order of magnitude correction to identify and correct obviously egregious outliers; however, limited means are available to validate each data point. We further recognize that many critical data points may be collected during periods of social distress such as hyperinflationary periods, extreme food insecurity, and/or prolonged violent conflict. Given this context, we advocate for robust post-processing methods to help identify and resolve these errors. Sufficiently long time series data can allow for reasonable imputation of values, which further facilitates scenario development and forecasting of extreme weather impacts. Further standardization of ambiguous unit measures can help reduce human error and allow analysts to retain more data for downstream analysis and early warning.

Conclusions

This observational study quantifies the association between various extreme weather events and anomalies and retail food price changes. We discover heterogenous impacts across food groups, underscoring the importance of monitoring retail prices of a diverse range of foods to sustain healthy and affordable diets. Our results suggest that retail food prices in rural and peri-and sub-urban areas are comparatively resilient to extreme weather. Retail prices of Fruits and Vegetables appear somewhat vulnerable to Storm events in Asia, and retail prices of Breads and Cereals in Sub-Saharan Africa indicate significant responses to four of the five extreme events studied. These findings can be used to inform targeted policies and programs to support diets in the aftermath of extreme weather events.

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