Retail Food Price Vulnerability to Extreme Weather Events

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 binarized heatwave, coldwave, flood, drought, and storm events using gridded data for the study period of 2000 – 2020. The sample included 1,346,513 monthly price observations in 2,321 markets in 71 countries. We observe mixed results by food group and type of extreme weather event. Moisture-related extreme events such as Storms, Floods, and Droughts differentially impact perishable food groups, whereas extreme temperatures have greater impact on non-perishable food groups. Relative price increases of 23-42% are observed for Fruits and Vegetables after Storms and Droughts, and approximately 22% for Dairy and Eggs after Floods. A 35% relative price decrease is observed for the Dairy and Eggs food group after Storms, indicating lowered demand due to regional income losses. These findings can inform policies and programs to make healthy diets affordable for all under climate change.

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

1. INTRODUCTION

Anthropogenic climate change has led to increased climate variability and greater frequency of extreme weather events such as heatwaves, wildfires, floods, droughts, and tropical cyclones (IPCC, 2021). The economic damage caused by such events averaged USD 170 billion per year in the last decade (FAO, 2021c). Climate shocks directly impact the food system through disrupted food production and consumption, livelihood losses, and diminished health and nutrition (Hallegatte et al., 2016). The impacts of extreme weather events on food prices are particularly relevant for provisioning healthy and affordable diets for all.

Reduced yields and supply constriction provides a critical pathway from extreme events to food price impacts. Adverse climate effects on global yields (Cottrell et al., 2019; Lesk, Rowhani, & Ramankutty, 2016; Lobell & Gourdji, 2012; Vogel et al., 2019) and prices (Algieri, 2014; D'Agostino & Schlenker, 2016; Haile, Kalkuhl, & Braun, 2015; Peri, 2017) of staple grains and cereals have been particularly well-studied. These climate-driven production shifts and resulting commodity price adjustments can potentially increase extreme poverty rates for nonagricultural households in Africa and Asia by 20-50% (Hertel, Burke, & Lobell, 2010). Commodity prices of cereal grains have also received particular attention during periods of global food price crises (Headey & Fan, 2008; Webb, 2010) and most recently during the Covid-19 pandemic (Dietrich, Giuffrida, Martorano, & Schmerzeck, 2021; Narayanan & Saha, 2021).

Consumption shifts in response to extreme weather events provide another pathway for climate to potentially affect local food prices. Precipitation shocks such as floods and storms can accelerate the spread of waterborne illnesses (Hashim & Hashim, 2016; Smith et al., 2014), and heatwaves can cause physical exhaustion limiting labor (Kjellstrom, Kovats, Lloyd, Holt, & Tol, 2009). Health effects from extreme weather events thus depress wages and may add to household healthcare costs, forcing households to absorb livelihood and asset losses, and/or engage in coping strategies to smooth consumption (Dercon, Hoddinott, & Woldehanna, 2005; Dercon & Krishnan, 2000; Hirvonen & Hoddinott, 2016). Since poorer households spend a larger fraction of their budget on foods, they are more acutely affected by both production losses and labor impacts caused by shocks (Green et al., 2013; Ivanic & Martin, 2014). Low-income households rapidly respond to high prices or low incomes by adjusting consumption through reduced intake and substitution of expensive nutrient-rich foods with staple foods (Dercon et al., 2005; Gibson & Kim, 2019). Disease and undernutrition in-utero are associated with reduced immunity, lower educational attainment, lower developmental levels, and lower incomes later in life (Ampaabeng & Tan, 2013; Black et al., 2013; Dewey & Begum, 2011; Hoddinott et al., 2013; Maccini & Yang, 2009; Solomons et al., 2015). The provisioning of diverse, nutritious, and affordable food items at all markets is therefore a global nutrition priority.

Global evidence regarding the impact of extreme weather events on food prices requires robust analysis of retail food prices around the world. Retail food prices better represent the additional cost paid by the consumer for transportation and storage of bulky, perishable food items (Takayama, 1971). Differential price impacts across food groups can thus provide critical insights into the heterogenous supply and demand effects of extreme weather events. 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). Recent literature on has further utilized retail food prices to investigate price impacts of the Covid-19 pandemic due to spatially heterogenous policy responses such as lockdowns and travel and mobility restrictions (Akter, 2020; Imai, Kaicker, & Gaiha, 2021; Narayanan & Saha, 2021). Data availability is a key limiting factor in such investigations as databases to enable global multi-market, multi-commodity retail price monitoring are relatively recent. Early warning systems and food price monitoring systems 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) provide valuable data on retail food prices and can enable such analysis. Price observations from these sources are often used in localized predictive 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 events.

In this paper, we aim to describe retail price changes by food group 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). Approximately 3 billion people were unable to afford the minimum cost of a healthy diet in 2017 (Herforth et al., 2020). As the food system intensifies to feed 9.7 billion people in a rapidly warming world, 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. Quantification of these heterogenous impacts can inform long-term climate adaptation as well as rapid interventions to mitigate immediate damage to livelihoods in the aftermath of various extreme weather events.

2. DATA

2.1 Early Warning System retail food price data

Monthly retail food item prices for this analysis 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 – 2020 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 (LCU) 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).

2.2 Food Item Classification

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).

2.3 Food Composition

To allow for comparison across food groups, each food item in the EWS retail price dataset was 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 two outcomes as purchased: 2017 USD/kg and 2017 USD/kcal of item.

2.3 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 Evapotranspiration Index (SPEI) (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 SPEI values greater than or equal to 1.5 (corresponding to Severe or Extreme conditions) were classified as having experienced Flood conditions (Bischiniotis et al., 2018).

2.4 Trade

The role of trade was captured through the FAO monthly food price index for the commodity group corresponding to each food item (FAO, 2021a). These FAO commodity groups include: Cereals, Vegetable Oils, Dairy, Meat, and Sugar.

3. METHODS

R 4.1.2, RStudio Build 372, and Stata 16.1 were used for all statistical analysis and visualization. All item price series were plotted and order of magnitude errors were corrected based on the complete time series for each item in each market. We then used the winsor2 Stata package to trim the top and bottom 0.5 percent of price observations within each food group category to remove extreme values most likely due to data entry errors. After trimming, a total of 1,346,513 prices were available from 2,321 markets in 71 countries.

We then used OLS regression models with fixed effects to examine the correlation between retail food prices and each extreme event. For each food item (*i*) at each market location (*j*), month (*m*), and year (*y*), our baseline specification is the following:

$$\ln(\mathrm{P_{ijmy}}) = \beta_0 + \beta_1 Extreme\ Event_{\mathrm{jmy}} + \beta_2 FG_{\mathrm{i}} + \beta_3\ (Food\ Group_{\mathrm{i}} * \mathrm{Extreme\ Event_{jmy}}) + \beta_4 E_{jmy} + \beta_5 \mathrm{F}_{jmy} + \gamma_{\mathrm{jy}} + \lambda_{\mathrm{my}} + \theta_{jy} + \tau_i + \varepsilon \qquad (1)$$

Where *i* refers to food item, *j* refers to market location, *m* refers to month, and *y* refers to year of price observation. P_{ijmy} indicates one of two price outcomes: 2017 USD/1000 kCal or 2017 USD/kg. $Extreme\ Event_{jmy}$ is a dummy variable which represents one of Flood, Drought, Storm, Heatwave, or Coldwave. FG_i represents a categorical variable that assigns each food item to one of eight food groups, using Breads and Cereals as the reference category. β_3 represents the effect of the extreme event on month-to-month variation in retail food prices for a given group compared to the reference change in price level for Breads and Cereals. E_{jmy} represents a vector of time-varying factors including average temperature, precipitation, and the contemporaneous interaction of these variables at each market. F_{jmy} represents the FAO commodity group price index for the FAO food group corresponding to *i*. We also include market location fixed effects γ_j to account for unobserved heterogeneity over space, market-month fixed effects λ_m 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. In alternate specifications we examine the robustness of our results to inclusion of lagged extreme events and differentially lagged retail food prices to further account for spatial and temporal heterogeneity.

4. RESULTS

4.1 Data Summary

Figure 1 shows market locations, number of price observations, and price trends by food group across all 2,321 markets between January 2000 and December 2021. As indicated by Figure 1 Panel A, the distribution of market locations across the source datasets is quite varied. Majority of EWS market locations are in the global south and in low and middle-income countries. Differences across datasets are also evident; FEWS market locations are concentrated in Sub-Saharan Africa, whereas GIEWS and WFP provide broader coverage across Africa and Asia. Market coverage in the Americas remains very sparse. Figure 1 Panel B presents the number of price observations for each month in the dataset. WFP VAM comprises majority of the EWS retail price dataset (85%), whereas GIEWS and FEWS contribute approximately 7% each. Food price monitoring has also improved significantly during the study period, particularly in the WFP VAM dataset after 2010.

Figure 1 Panel C provides a time series of average global retail prices in 2017 USD/1000 kCal for each of the eight food groups. Breads and Cereals and Sugars and Confectionery are consistently the cheapest food groups, whereas Fish and Seafood and Meats are the most expensive across all datasets. The number of markets tracking each of the eight food groups are also highly variable. Prices for Breads and Cereals are tracked in 98% of markets, whereas Meat prices (in USD) are only available in 2% of markets. Positive slopes are observed across all time series. Price spikes visualized herein are often artefactual anomalies due to poorly measured inflation, and are most frequently observed in the FEWS dataset due to the low number of countries tracked in the dataset. The increase in prices of staple foods in 2008 – 2010 are also seen as a brief increase in the price of Breads and Cereals across all datasets.

Figure 1: (A) Market locations, (B) number of price observations, and (C) price trends by food group, across FEWS, GIEWS, and VAM datasets for 2000-2021

Figure 2 presents the frequency of extreme event occurrence by month and year in the study period. Extreme events are determined by climatology, and the spatial heterogeneity of market locations considered in this analysis necessitates that the timing of each extreme event within a calendar year not be compared. However, event frequencies provide critical information about the occurrence of extreme weather events. Heatwaves are the most frequently occurring hazard during the study period (69% of observed months), followed by floods (54%), droughts (49%), coldwaves (28%), and storms (14%). Markets in this dataset observed major heatwaves in 2015, 2019, and 2020; record droughts in 2015 and 2017; and record floods in 2010, 2015, and 2018. Extremely destructive storms appear regularly after 2012, and coldwaves appear more frequently after 2007. However, this increased frequency is not attributable to significant change in climate during the study period; rather, it likely reflects the addition of more markets and more routine price monitoring after 2010 (Figure 1 Panel B).

Figure 2: Frequency of extreme events (flood, drought, storm, heatwave, and coldwave) by month and year, 2000 - 2021

4.2 Estimated Effect of Contemporaneous Extreme Events

Regression results from a minimal specification with only the extreme event and sequential inclusion of market-month, market-year, and item fixed effects, is presented in Table 1. Differential impacts on retail prices in units of 2017 USD/kg are readily observed across extreme events. During Heatwaves, Coldwaves, and Floods, a negative association is observed between extreme events and change in standardized prices. In contrast, a positive association is observed during Storms and Droughts. The overall magnitude of price impacts is quite small;

Heatwaves, Coldwaves, and Floods are all associated with a price decrease of less than 2.5%, whereas Storms are associated with a 3.6% increase and Droughts are associated with a 0.5% increase in 2017 USD/kg respectively. Sequential inclusion of market-month, market-year, and item-level fixed effects demonstrably improves Adjusted R2 both between and across markets.

Table 1: Coefficients from OLS regression of exclusively contemporaneous extreme weather events on price variation

This minimal specification was augmented per Equation (1) to estimate the effect of contemporaneous extreme events on retail food price. Detailed model output from our preferred specifications with market, market-month, market-year, and item fixed effects is presented in Table 2 for the outcome of 2017 USD/kg, and in Table 3 for the outcome of 2017 USD/kCal. The inclusion of food groups highlights critical differences across different food items compared to a reference category of Breads and Cereals. All food groups are more expensive than Breads and Cereals in terms of weight and kilocalories. Perishable food groups including Dairy and Eggs, Fish and Seafoods, and Meats are approximately 1.15-1.84x more expensive than breads and cereals in weight units, and 2.1-3.0x more expensive in calorie units. Fruits and Vegetables are comparable to Breads and Cereals in terms of weight, but are 2.94x more expensive than Breads and Cereals in kilocalorie terms, underlining the need for studying both outcomes. Non-Perishable food groups are comparatively cheaper; calorie-dense food groups including Sugar and Confectionery and Fats and Oils are approximately 0.5x more expensive than Breads and Cereals, whereas Pulses, Nuts, and Seeds are 1.4x as expensive in kilocalorie terms.

Food groups also respond differentially to extreme events. Perishable food groups most notably respond to moisture-related stressors as observed during Storms, Floods, and Droughts. Price per kilocalorie of Fruits and Vegetables are observed to increase by 26% during Storms (β

coefficient = 0.235; 95% CI:[0.212 – 0.258]) and by 20% during Droughts (β coefficient = 0.183; 95% CI:[0.1289 – 0.237]) relative to Breads and Cereals. Meat prices also increase by approximately 11% during droughts lasting at least six months (β coefficient = 0.107; 95% CI:[0.0798 – 0.1342]). The Dairy and Eggs category displays a slightly different pattern; prices in this category are observed to fall by 42% during Storms (β coefficient = -0.549; 95% CI:[-0.6063]– [-0.4917]) but increase by 20% during Floods (β coefficient = 0.182; 95% CI:[0.1368 – 0.2272]). Less perishable food groups are particularly responsive to temperature-related stressors including Heatwaves and Coldwaves. Prices of Oils and Fats increases by 11% following Coldwaves (β coefficient = 0.101; 95% CI:[0.0784 – 0.1236]) relative to Breads and Cereals. Drought also impacts non-perishables; price per kilocalorie of Sugars and Confectionery increased by over 50% (β coefficient = 0.412; 95% CI:[0.294 – 0.530]), and Pulses, Nuts, and Seeds by approximately 14% (β coefficient = 0.129; 95% CI:[0.1074 – 0.1506]) after a Drought.

Table 2 and Table 3 also allow for a comparison of the two price outcomes in terms of weight and kilocalories. Unit-level differences are absorbed into the food group (β_2 in Equation (1)), leaving similar interaction effects between extreme weather events and food groups. Therefore, the simpler outcome of 2017 USD/kg is presented in the remainder of this paper.

Table 2: Coefficients from OLS regression of contemporaneous extreme weather events on price variation in 2017 USD/KCal

Table 3: Coefficients from OLS regression of contemporaneous extreme weather events on price variation in 2017 USD/kg

4.3 Effect of Trade

Detailed regression output including the effect FAO Commodity Price Index for each commodity group in the EWS dataset are shown in Table S1, and a comparison between model coefficients is presented in Figure 1. The direct effect of trade on retail food prices is very small but statistically significant across all extreme events (β coefficient $\approx$ 0.0028; 95% CI:[0.0025 – 0.0.003]). Controlling for trade improves model fit and sharpens the observed effect of contemporaneous shocks on retail food prices. The largest impact is to the Perishable food groups; the effect of Floods on Dairy and Eggs prices after controlling for trade is approximately 28% (β coefficient = 0.248; 95% CI:[0.198 – 0.298]). The additional variability captured by the FAO commodity group index moderates the effects of Storms on Meats and Dairy and Eggs.

Figure 1: Coefficient plot of contemporaneous shocks and price variation by food group in 2017 USD/kg in models including (A) precipitation and temperature; and (B) additionally including FAO commodity group index.

4.4 Estimated Effect of Lagged Extreme Events

Regression output from additional specifications including lagged extreme events and differentially lagged prices to investigate persistence are provided in Table S2-5. Interaction coefficients from these specifications are shown in Fig 2. We conclude that longer-term effects may be present for particular combinations of extreme events and food groups. Specifically, price per kg of Dairy and Eggs remains lowered by approximately 50%, up to 3 months after Storms relative to Breads and Cereals. On the other hand, Fruits and Vegetable prices remain approximately 42% higher than Breads and Cereals three months after a storm. These effects may indicate seasonal availability of food groups in particular regions, preferential substitution in the aftermath of extreme events, and/or seasonally disrupted trade.

Figure 2: Coefficient plot of interaction between extreme weather events and price variation by food group in 2017 USD/kg, in models including (A) 1-, 2-, and 3-month lagged extreme events; and (B) additionally including 1-, 2-, and 3-month lagged prices.

5. CONCLUSIONS

This observational study quantifies the effect of various extreme weather events and retail food price shifts. We discover heterogenous impacts of extreme weather events across nutritious 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 extreme events differentially affect retail food prices across low and middle income countries. Perishable food groups such as Fruits and Vegetables and Dairy and Eggs are most significantly impacted by moisture-related extreme events such as Storms, Floods, and Droughts. Non-perishable food groups are impacted by temperature-related extreme events such as Heatwaves and Coldwaves, as well as Droughts. Relative price increases of 23-42% are observed for Fruits and Vegetables after Storms and Droughts, and approximately 22% for Dairy and Eggs after Floods. Restricted supplies associated with these extreme events may cause higher prices retail prices of perishable foods. A 35% relative price decrease is observed for Dairy and Eggs food group after Storms, indicating lowered demand due to income losses at the regional scale. These findings can guide interventions to stabilize diets and support food security in the aftermath of extreme events, and potentially inform longer-term climate adaptation and mitigation programs.

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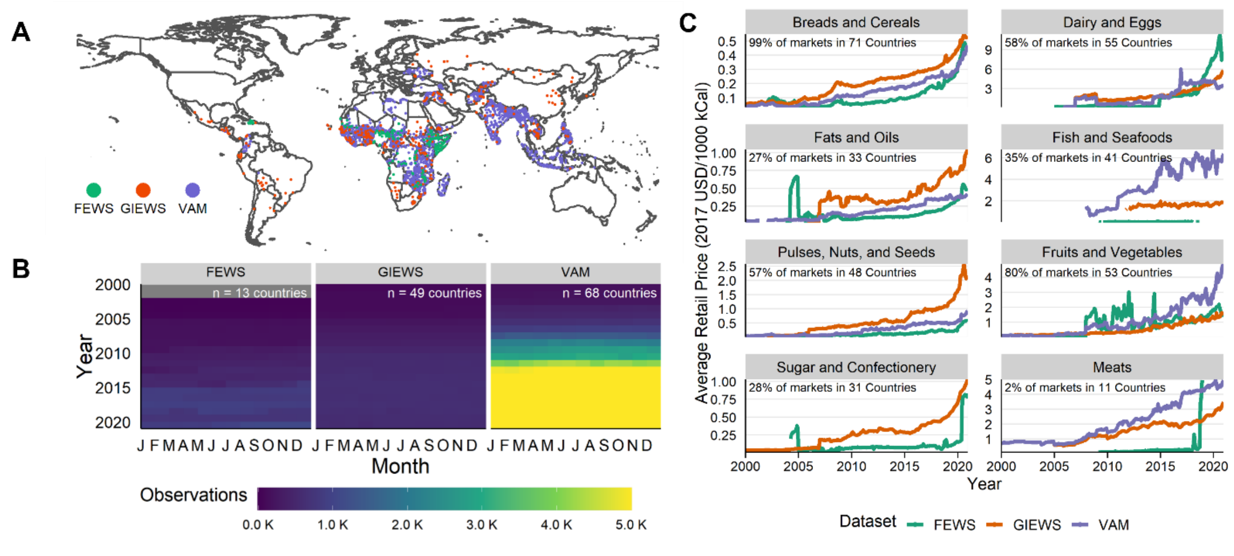
Figure 1: (A) Market locations, (B) number of price observations, and (C) price trends by food group, across FEWS, GIEWS, and VAM datasets for 2000-2021



Sources: Retail food prices are reported by the Food and Agriculture Organization (FAO) Global Information and Early Warning System (GIEWS) system (http://www.fao.org/giews/en/), the USAID Famine Early Warning System Network (FEWS) (https://fews.net/), and the World Food Programme (WFP) Vulnerability Analysis and Mapping (VAM) system (https://data.humdata.org/dataset/global-wfp-food-prices).

Notes: Data shown are from a total of 1,346,513 observations in 2,321 markets in 71 countries. Loess smoother with span of 0.50 was applied across all data points to generate Panel B.

Figure 2: Frequency of extreme events (flood, drought, storm, heatwave, and coldwave) by month and year, 2000 - 2021

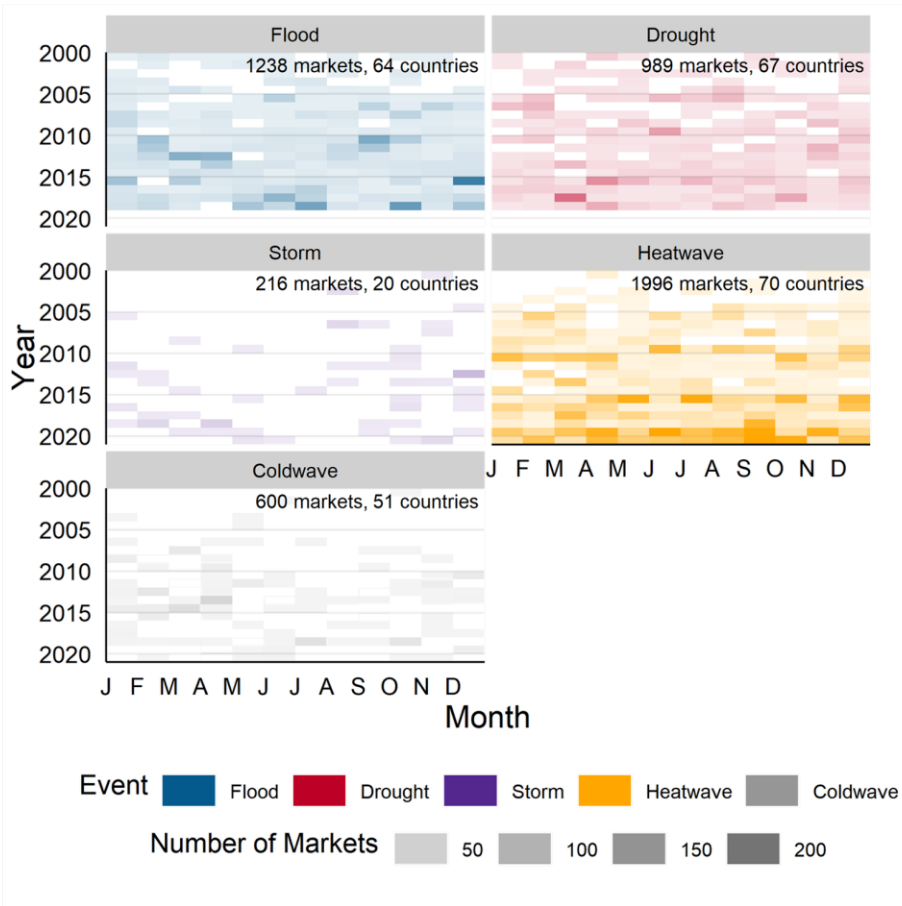


Table 1: Coefficients from OLS regression of exclusively contemporaneous extreme weather events on price variation

	Heatwave				Coldwave				Storm			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Extreme Event	-0.00947	-0.0299***	-0.0306***	-0.0244***	-0.0501*	-0.015	-0.00764	-0.0164*	0.00612	0.0552***	0.0441***	0.0354***
	-0.0104	-0.00477	-0.00477	-0.00423	-0.0218	-0.01	-0.00955	-0.00811	-0.0192	-0.0116	-0.011	-0.00947
Constant	0.468***	-1.339***	-1.406***	-0.778***	0.468***	-1.340***	-1.407***	-0.779***	0.468***	-1.341***	-1.407***	-0.779***
	-0.000544	-0.0722	-0.0723	-0.0777	-0.00011	-0.0721	-0.0723	-0.0776	-7.55E-05	-0.0721	-0.0722	-0.0776
Observations	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051	1,300,051
R2 Within	0	0.211	0.213	0.756	0	0.211	0.213	0.756	0	0.211	0.213	0.756
R2 Between	0.026	0.49	0.489	0.703	0.007	0.49	0.49	0.703	0.005	0.49	0.49	0.703
R2 Overall	0	0.279	0.28	0.717	0	0.279	0.28	0.717	0.001	0.279	0.28	0.717
Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Item FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

	Flood				Drought			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Extreme Event	-0.0478***	-0.0275***	-0.0282***	-0.00881	0.0677*	-0.000509	0.00254	0.00517
	-0.0135	-0.00754	-0.00742	-0.00656	-0.0298	-0.0158	-0.0155	-0.0146
Constant	0.208***	-1.435***	-1.498***	-1.138***	0.207***	-1.435***	-1.498***	-1.138***
	-	-0.0655	-0.0657	-0.0813	-	-0.0656	-0.0657	-0.0814

	0.000226				0.00033 7			
Observations	894,185	894,185	894,185	894,185	894,667	894,667	894,667	894,667
R2 Within	0	0.221	0.223	0.763	0	0.221	0.223	0.763
R2 Between	0.002	0.29	0.288	0.65	0.002	0.289	0.288	0.65
R2 Overall	0	0.245	0.246	0.695	0	0.245	0.246	0.695
Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	No	No	Yes	Yes
Item FE	No	No	No	Yes	No	No	No	Yes

Table 2: Coefficients from OLS regression of contemporaneous extreme weather events on price variation in 2017 USD/Kcal

	No Event	*Heatwave*	*Coldwave*	*Storm*	*Flood*	*Drought*
Extreme Event		-0.0151**	-0.0325**	-0.0369*	-0.0202**	-0.0462***
		(0.00569)	(0.0116)	(0.0153)	(0.00750)	(0.0136)
Food Group						
Breads & Cereals	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Fruits & Vegetables	2.944***	2.944***	2.943***	2.943***	2.776***	2.776***
	(0.201)	(0.201)	(0.201)	(0.201)	(0.216)	(0.216)
Dairy & Eggs	2.988***	2.988***	2.988***	2.989***	2.666***	2.668***
	(0.204)	(0.204)	(0.204)	(0.204)	(0.214)	(0.214)
Fish & Seafood	2.102***	2.104***	2.103***	2.112***	2.954***	2.954***
	(0.192)	(0.192)	(0.192)	(0.192)	(0.210)	(0.210)
Meats	2.474***	2.478***	2.477***	2.477***	2.580***	2.580***
	(0.191)	(0.191)	(0.191)	(0.191)	(0.212)	(0.212)
Fats & Oils	0.511**	0.413*	0.408*	0.409*	0.38	0.38
	(0.198)	(0.190)	(0.190)	(0.190)	(0.211)	(0.211)
Pulses, Nuts, and Seeds	1.401***	1.400***	1.399***	1.399***	1.411***	1.411***
	(0.200)	(0.200)	(0.200)	(0.200)	(0.221)	(0.221)
Sugar & Confectionary	0.537*	0.534*	0.536*	0.537*	0.537*	0.513*
	(0.252)	(0.250)	(0.252)	(0.251)	(0.244)	(0.241)
Food Group * Extreme Event						
Breads & Cereals		Ref.	Ref.	Ref.	Ref.	Ref.
Fruits & Vegetables		-0.00262	0.0344	0.235***	0.0459**	0.183***
		(0.00935)	(0.0181)	(0.0230)	(0.0156)	(0.0541)
Dairy & Eggs		0.00449	0.000781	-0.549***	0.182***	-0.119*
		(0.0192)	(0.0315)	(0.0573)	(0.0452)	(0.0590)
Fish & Seafood		-0.000925	0.159**	-0.0398	-0.123**	0.00614
		(0.0162)	(0.0537)	(0.0303)	(0.0424)	(0.0414)
Meats		-0.00521	0.00686	-0.0145	-0.0225	0.107***
		(0.0105)	(0.0212)	(0.0230)	(0.0174)	(0.0272)
Oils & Fats		-0.0598***	0.101***	0.0242	0.0294*	0.0658**
		(0.0122)	(0.0226)	(0.0382)	(0.0147)	(0.0228)
Pulses, Nuts, and Seeds		-0.0207*	-0.0725**	0.0998***	-0.00724	0.129***
		(0.00906)	(0.0251)	(0.0254)	(0.0148)	(0.0216)
Sugar & Confectionary		0.0523	0.230*	-0.415*	0.103	0.412***
		(0.128)	(0.0995)	(0.203)	(0.0533)	(0.118)
Environment						
Precipitation		-0.000209**	-0.000214**	-0.000218**	-0.000368***	-0.000372***
		(0.0000790)	(0.0000796)	(0.0000794)	(0.0000829)	(0.0000829)
Temperature		-0.00187***	-0.00192***	-0.00191***	-0.00206***	-0.00207***

		(0.000225)	(0.000225)	(0.000225)	(0.000259)	(0.000259)
Precip * Temp		0.0000145***	0.0000147***	0.0000148***	0.0000210***	0.0000211***
		(0.00000281)	(0.00000283)	(0.00000283)	(0.00000296)	(0.00000295)
Constant	-3.845***	-3.804***	-3.802***	-3.803***	-3.857***	-3.857***
	(0.199)	(0.199)	(0.199)	(0.199)	(0.217)	(0.217)
N	1300051	1,293,730	1,293,730	1,293,730	889,092	889,574
R2 Within	0.842	0.842	0.842	0.842	0.838	0.838
R2 Between	0.858	0.860	0.859	0.860	0.799	0.799
R2 Overall	0.837	0.838	0.838	0.838	0.814	0.814

Table 3: Coefficients from OLS regression of contemporaneous extreme weather events on price variation in 2017 USD/kg

	No Event	*Heatwave*	*Coldwave*	*Storm*	*Flood*	*Drought*
Extreme Event		-0.0150**	-0.0321**	-0.0367*	-0.0201**	-0.0467***
		(0.00569)	(0.0116)	(0.0153)	(0.00751)	(0.0136)
Food Group						
Breads & Cereals	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Fruits & Vegetables	0.0941	0.0943	0.0933	0.0934	0.848***	0.847***
	(0.201)	(0.201)	(0.201)	(0.201)	(0.217)	(0.217)
Dairy & Eggs	1.274***	1.274***	1.274***	1.274***	0.952***	0.954***
	(0.204)	(0.204)	(0.204)	(0.204)	(0.215)	(0.215)
Fish & Seafood	1.150***	1.152***	1.151***	1.160***	2.415***	2.416***
	(0.192)	(0.192)	(0.192)	(0.192)	(0.210)	(0.210)
Meats	1.842***	1.846***	1.845***	1.846***	1.948***	1.948***
	(0.191)	(0.191)	(0.191)	(0.191)	(0.212)	(0.212)
Fats & Oils	1.465***	1.366***	1.360***	1.362***	1.333***	1.333***
	(0.198)	(0.190)	(0.190)	(0.190)	(0.211)	(0.211)
Pulses, Nuts, and Seeds	1.734***	1.733***	1.732***	1.732***	1.744***	1.745***
	(0.200)	(0.200)	(0.200)	(0.200)	(0.221)	(0.222)
Sugar & Confectionary	0.683**	0.680**	0.681**	0.683**	0.683**	0.659**
	(0.248)	(0.247)	(0.249)	(0.248)	(0.242)	(0.238)
Food Group * Extreme Event						
Breads & Cereals		Ref.	Ref.	Ref.	Ref.	Ref.
Fruits & Vegetables		-0.00293	0.0338	0.234***	0.0454**	0.185***
		(0.00938)	(0.0181)	(0.0230)	(0.0156)	(0.0544)
Dairy & Eggs		0.00436	0.000342	-0.550***	0.182***	-0.119*
		(0.0191)	(0.0315)	(0.0574)	(0.0452)	(0.0588)
Fish & Seafood		-0.000919	0.158**	-0.0394	-0.124**	0.00862
		(0.0162)	(0.0536)	(0.0302)	(0.0423)	(0.0408)
Meats		-0.00502	0.00715	-0.0147	-0.0217	0.105***
		(0.0105)	(0.0211)	(0.0230)	(0.0174)	(0.0272)
Oils & Fats		-0.0596***	0.100***	0.0235	0.0294*	0.0670**
		(0.0121)	(0.0226)	(0.0382)	(0.0147)	(0.0228)
Pulses, Nuts, and Seeds		-0.0205*	-0.0728**	0.0992***	-0.00741	0.129***
		(0.00906)	(0.0251)	(0.0254)	(0.0148)	(0.0216)
Sugar & Confectionary		0.0528	0.230*	-0.416*	0.102	0.411***
		(0.128)	(0.0997)	(0.203)	(0.0532)	(0.118)
Environment						
Precipitation		-0.000209**	-0.000214**	-0.000218**	-0.000368***	-0.000372***
		(0.0000790)	(0.0000796)	(0.0000794)	(0.0000829)	(0.0000829)
Temperature		-0.00187***	-0.00192***	-0.00191***	-0.00206***	-0.00207***

		(0.000225)	(0.000224)	(0.000224)	(0.000259)	(0.000258)
Precip * Temp		0.0000145***	0.0000147***	0.0000148***	0.0000210***	0.0000211***
		(0.00000281)	(0.00000283)	(0.00000283)	(0.00000296)	(0.00000295)
Constant	-1.930***	-1.889***	-1.887***	-1.888***	-1.942***	-1.942***
	(0.199)	(0.199)	(0.199)	(0.199)	(0.217)	(0.217)
N	1300051	1,293,730	1,293,730	1,293,730	889,092	889,574
R2 Within	0.756	0.756	0.756	0.756	0.763	0.763
R2 Between	0.704	0.707	0.707	0.708	0.649	0.649
R2 Overall	0.717	0.718	0.718	0.718	0.695	0.695

Figure 1: Coefficient plot of contemporaneous shocks and their effect on food groups relative to Breads and Cereals in models including (A) precipitation and temperature; and (B) additionally including FAO commodity group index.

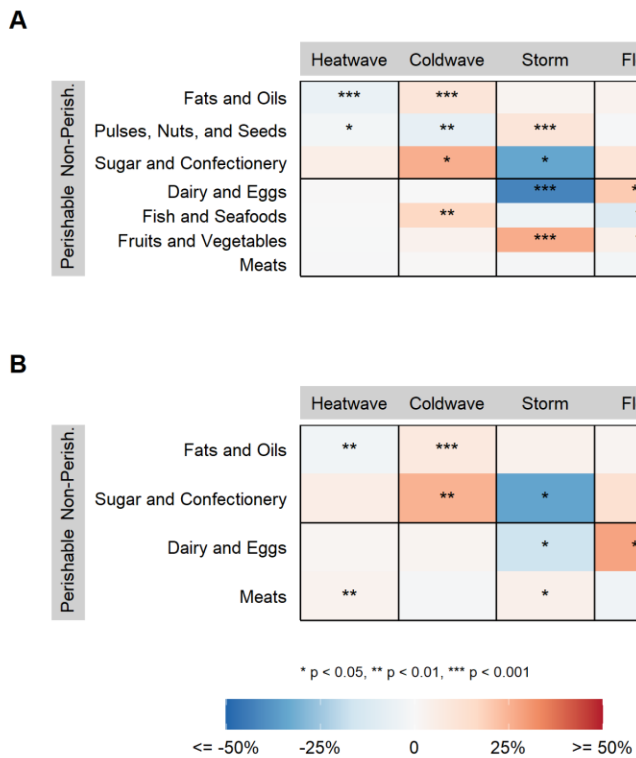
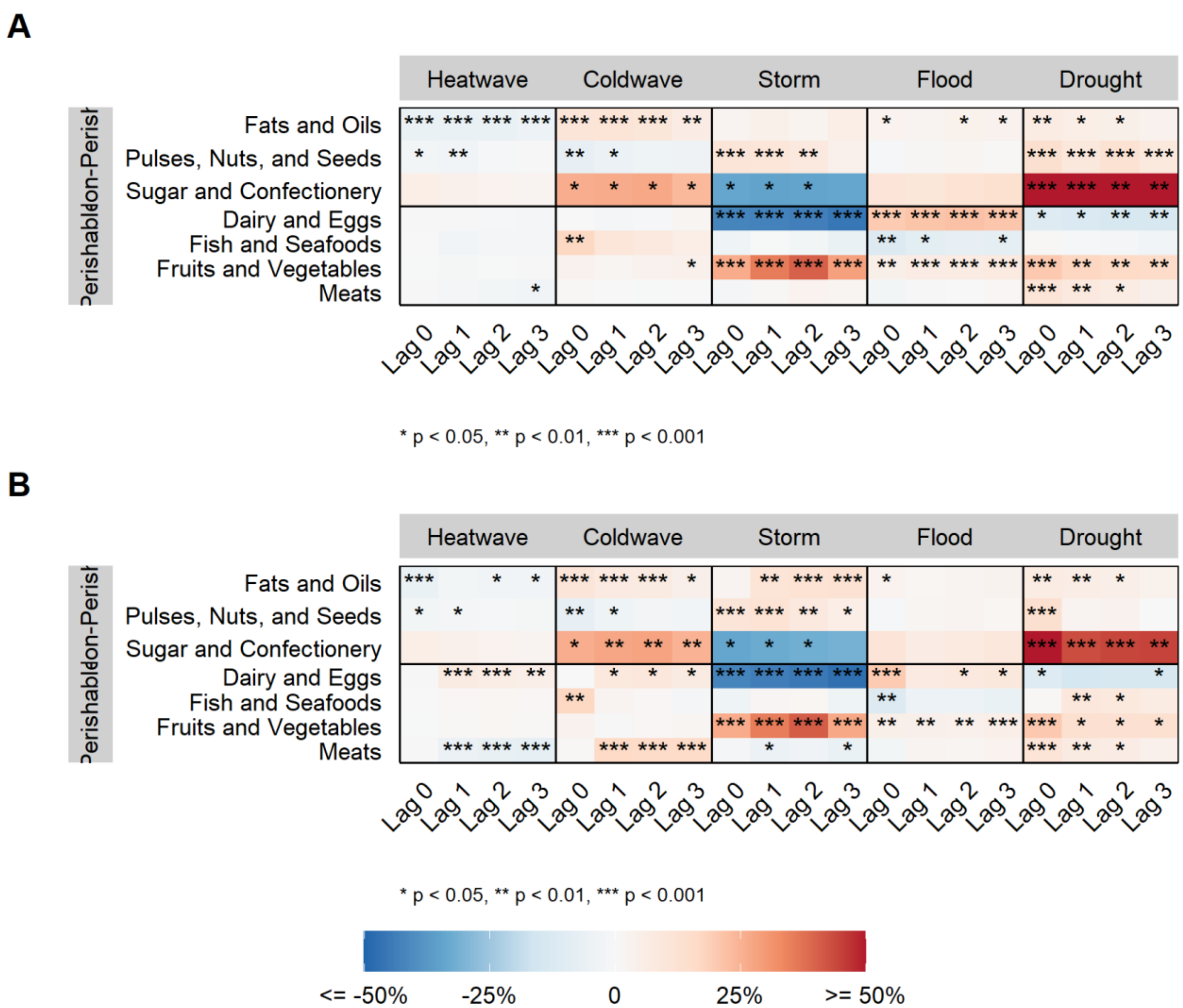


Figure 2: Coefficient plot of interaction between extreme weather events and price variation by food group in 2017 USD/kg, in models including (A) 1-, 2-, and 3-month lagged extreme events; and (B) additionally including 1-, 2-, and 3-month lagged prices.



APPENDICES

Table S1: Coefficients from OLS regression of contemporaneous extreme weather events and trade on price variation

	Heatwave	*Coldwave*	*Storm*	*Flood*	*Drought*
Extreme Event	-0.0267***	-0.0480***	-0.00357	-0.0210**	0.00438
	(0.00557)	(0.0106)	(0.0151)	(0.00736)	(0.0157)
Food Group					
Breads & Cereals	Ref.	Ref.	Ref.	Ref.	Ref.
Dairy & Eggs	0.844***	0.844***	0.844***	0.651***	0.664***
	(0.118)	(0.118)	(0.118)	(0.113)	(0.115)
Meats	1.256***	1.256***	1.256***	1.425***	1.434***
	(0.102)	(0.102)	(0.102)	(0.112)	(0.114)
Fats & Oils	0.796***	0.793***	0.793***	0.881***	0.891***
	(0.0979)	(0.0979)	(0.0980)	(0.109)	(0.112)
Sugar & Confectionary	0.367	0.369	0.37	0.457	0.439
	(0.359)	(0.361)	(0.361)	(0.292)	(0.282)
Food Group * Extreme Event					
Breads & Cereals	Ref.	Ref.	Ref.	Ref.	Ref.
Dairy & Eggs	0.0166	0.023	-0.186*	0.248***	-0.0617
	(0.0190)	(0.0343)	(0.0886)	(0.0500)	(0.0526)
Meats	0.0302**	-0.0149	0.0452*	-0.0346	0.0415
	(0.0104)	(0.0203)	(0.0193)	(0.0191)	(0.0262)
Oils & Fats	-0.0301**	0.0799***	0.0373	0.0209	0.0389
	(0.0108)	(0.0207)	(0.0309)	(0.0144)	(0.0248)
Sugar & Confectionary	0.0583	0.225**	-0.423*	0.122*	0.421***
	(0.117)	(0.0741)	(0.195)	(0.0609)	(0.127)
Environment					
Precipitation	-0.000433***	-0.000439***	-0.000442***	-0.000480***	-0.000484***
	(0.0000867)	(0.0000870)	(0.0000872)	(0.0000947)	(0.0000947)
Temperature	-0.00137***	-0.00142***	-0.00141***	-0.00157***	-0.00159***
	(0.000206)	(0.000204)	(0.000205)	(0.000246)	(0.000245)
Precip * Temp	0.0000232***	0.0000234***	0.0000235***	0.0000253***	0.0000254***
	(0.00000312)	(0.00000313)	(0.00000314)	(0.00000342)	(0.00000341)
FAO Commodity Price Index	0.00284***	0.00285***	0.00285***	0.00295***	0.00295***
	(0.000333)	(0.000333)	(0.000333)	(0.000373)	(0.000372)
Constant	-1.465***	-1.464***	-1.464***	-1.632***	-1.642***

	(0.116)	(0.116)	(0.116)	(0.119)	(0.121)
N	724415	724415	724415	532139	532543
R2 Within	0.767	0.767	0.767	0.767	0.767
R2 Between	0.803	0.803	0.803	0.741	0.741
R2 Overall	0.761	0.761	0.761	0.718	0.718

Table S2: Coefficients from OLS regression of 1-month lagged extreme weather events on price variation

Table S3: Coefficients from OLS regression of 2-month lagged extreme weather events on price variation

Table S4: Coefficients from OLS regression of 3-month lagged extreme weather events on price variation

Table S5: Coefficients from OLS regression of lagged extreme weather events and differentially lagged prices on price variation