Impacts of extreme weather and COVID-19 shocks on retail food prices in LMICs

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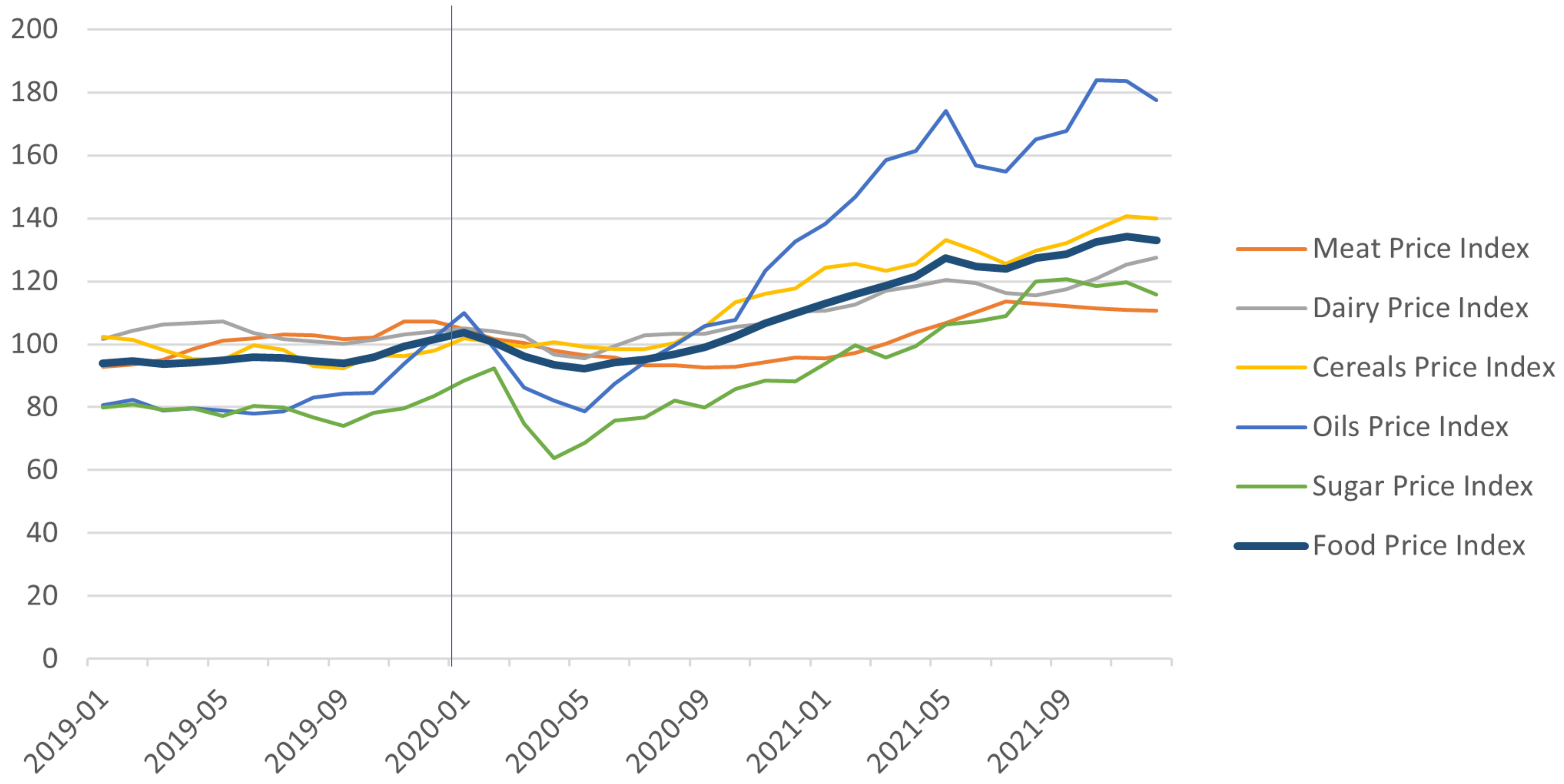
How resilient are retail food prices?

- This paper addresses
  - resilience to shocks
    -- first climate (extreme weather), and then Covid (illness and lockdowns)
  - in retail food prices
    -- affecting real income and welfare, at the consumer end of food supply chains
  - for all food groups
    -- with different nutritional attributes, as well as different market structures
- Shocks have an ambiguous effect:
  - lower supply and higher costs, but also
  - lower demand that would reduce price
- We test for the net effect of climate and COVID shocks
  - using the largest possible set of food items and market locations around the world

Our work complements previous studies that focus on farm commodities

- Following initial declines early in the pandemic due to lower demand, the FAO food price index has generally risen, due partly to supply concerns

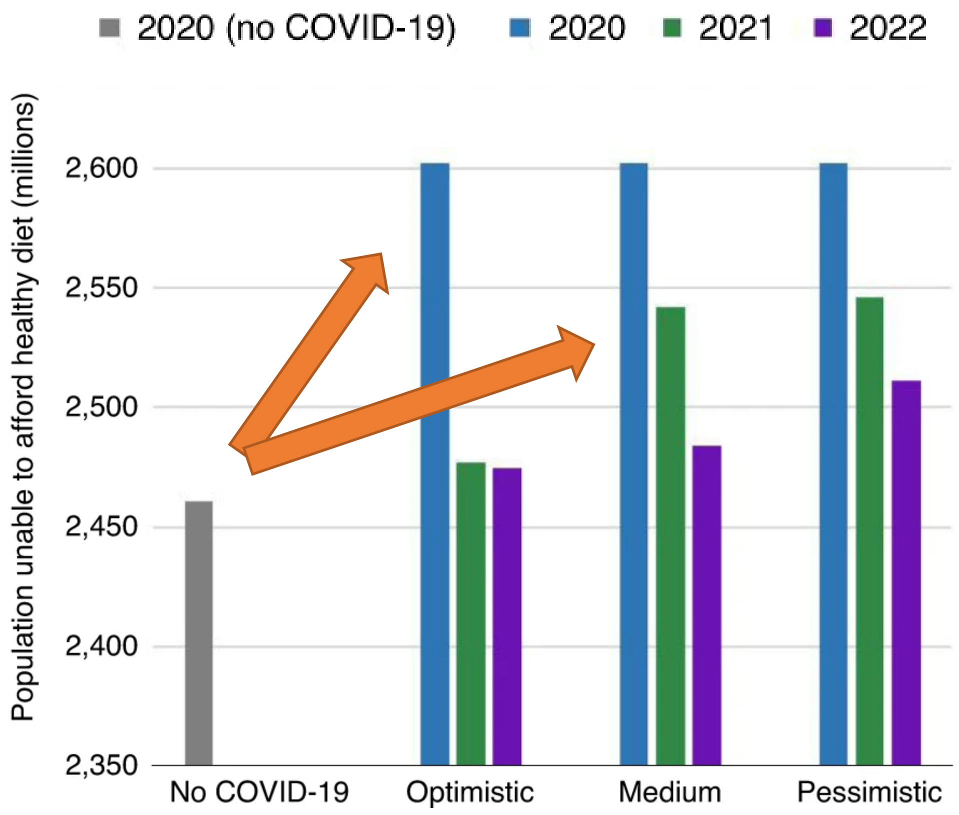
FAO Food Price Index (real, 2014-16=100), January 2019 - December 2021



Source: FAO, accessed January 5, 2022

Previous work on COVID shocks focused on income loss and on a few retail food prices

Number of people in 63 LMICs who would not be able to afford a healthy diet



Source: Figure 1 in Laborde, D., A. Herforth, D. Headey, and S. de Pee, 2021. [COVID-19 pandemic leads to greater depth of unaffordability of healthy and nutrient-adequate diets in low- and middle-income countries](). (2021). *Nature Food* 2(7): 473–75..

The impact of COVID-19 related 'stay-at-home' restrictions on food prices in Europe: findings from a preliminary analysis

Sonia Akter

The impact of COVID-19 on food prices in China: evidence of four major food products from Beijing, Shandong and Hubei Provinces

Xiaohua Yu
Chang Liu

Urban food markets and the COVID-19 lockdown in India

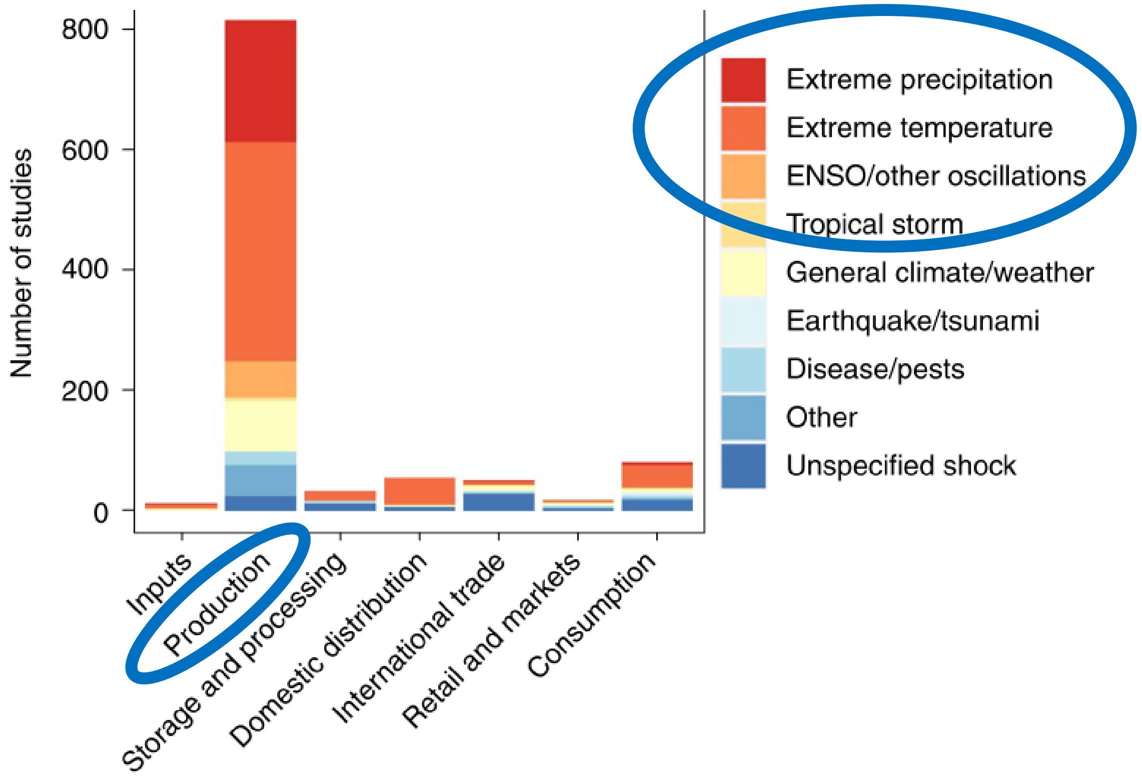
Sudha Narayanan [a], Shree Saha [b]

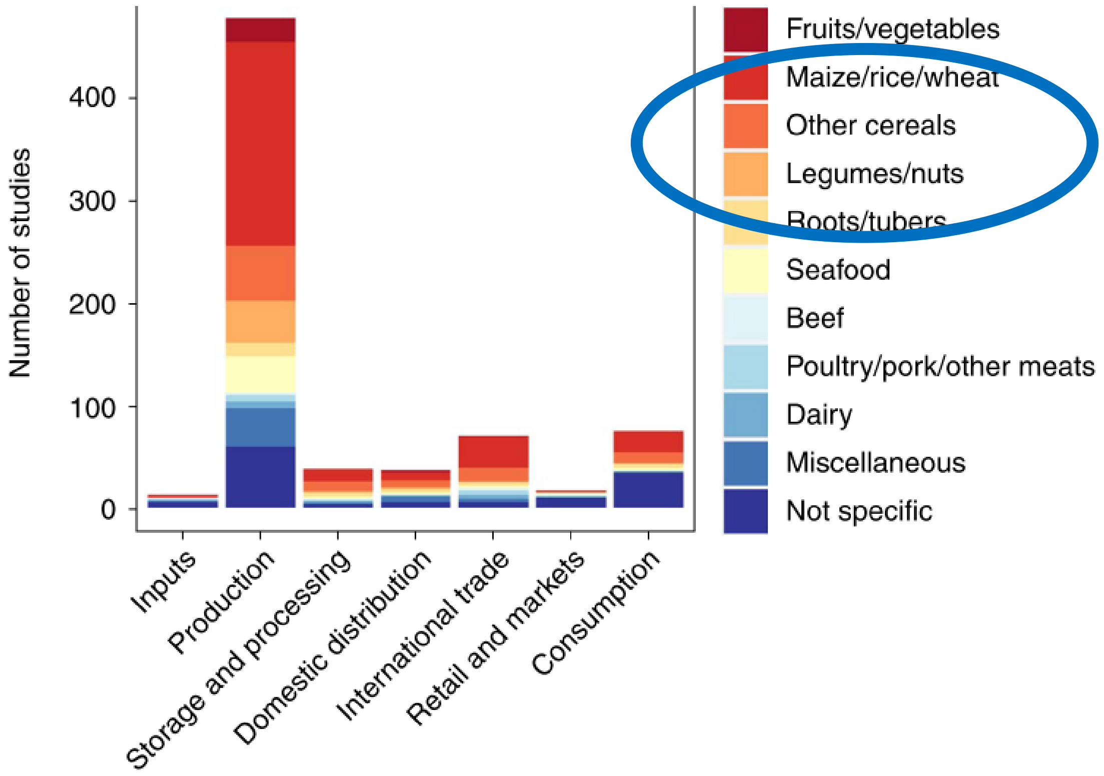
Food prices, processing, and shocks: Evidence from rice and COVID-19

(in Myanmar)

Joseph Goeb[1] | Phoo Pye Zone[2] | Nang Lun Kham Synt[2] | A. Myint Zu[2] | Yulu Tang[3] | Bart Minten[2]

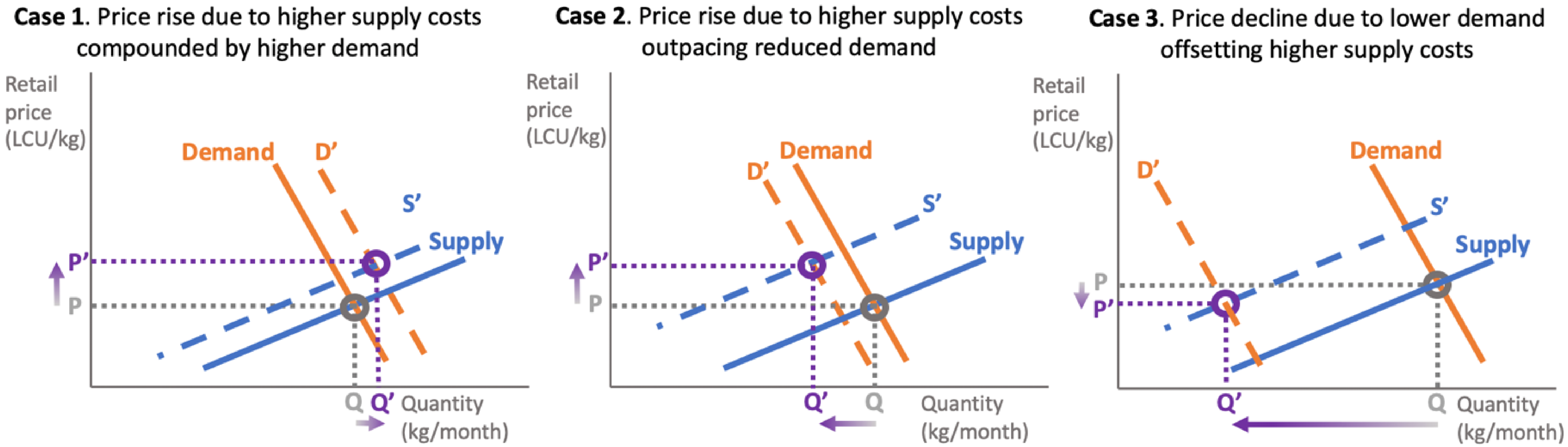
We also expand on previous studies of climate shocks that focus on farm production and on staple foods





Source: Figure 2 in Davis, K. F., Downs, S., & Gephart, J. A. (2021). Towards food supply chain resilience to environmental shocks. *Nature Food*, *2*(1), 54-65.

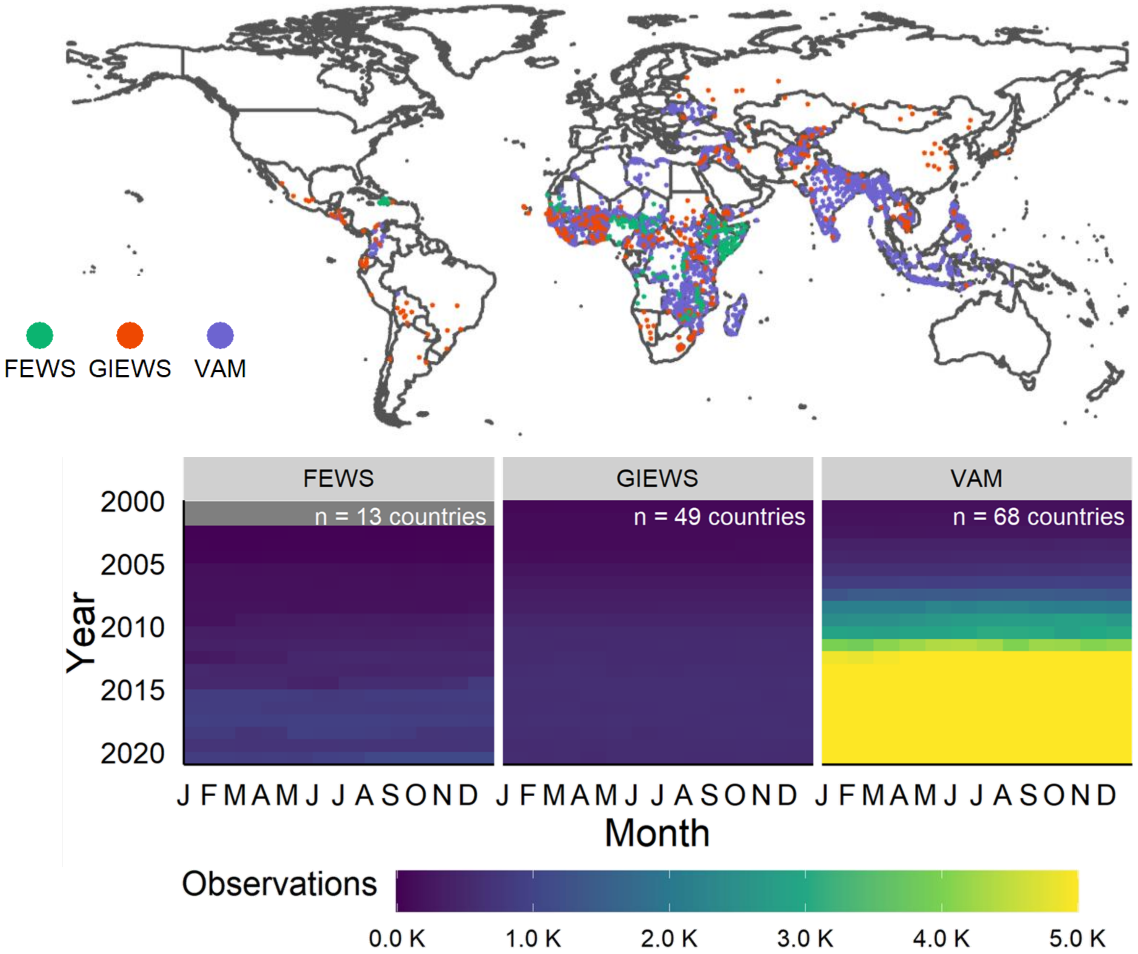
Consumer prices reflect nontradable costs as well as tradable commodities, with shocks in both supply & demand

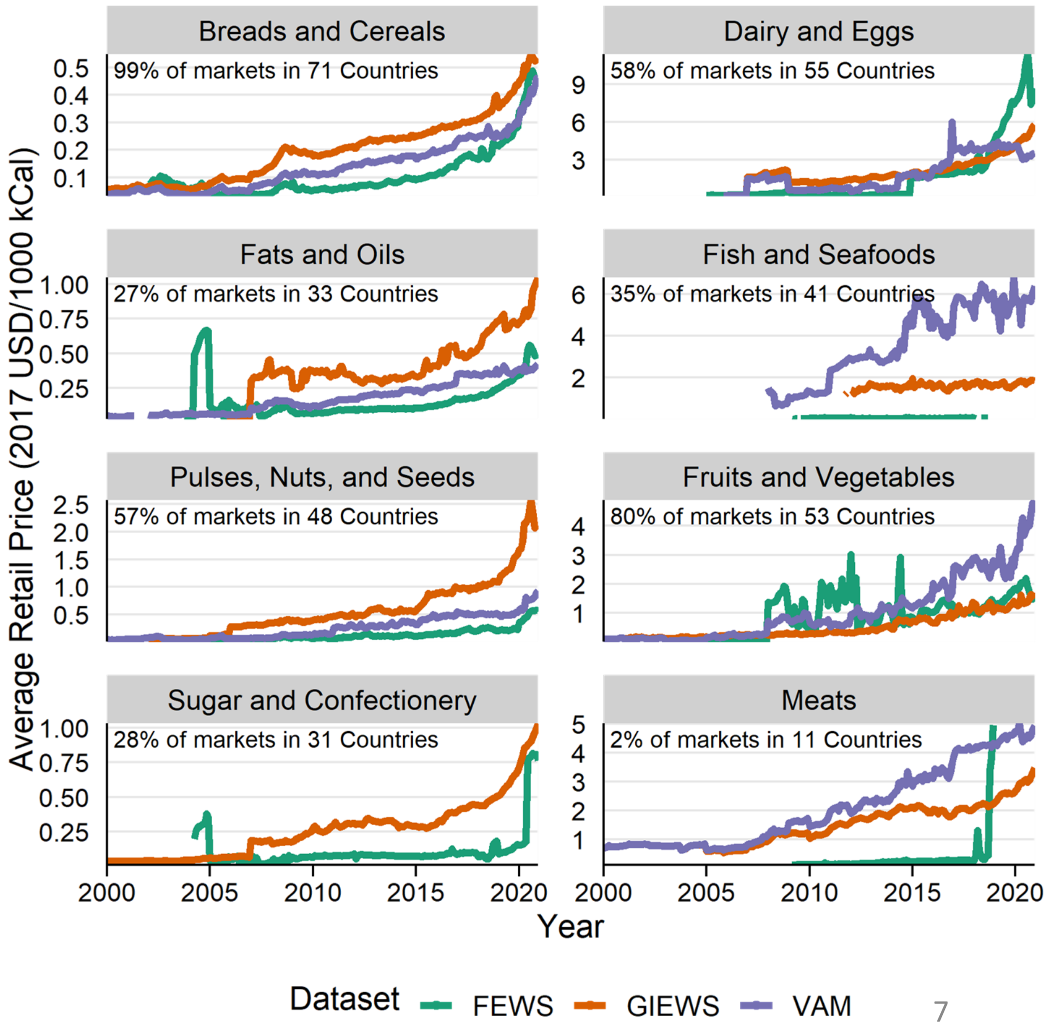


Notes: Solid blue and orange lines represent original supply and demand functions, and dashed blue and orange lines represent shifted supply and demand following a shock event. Grey circles represent the equilibrium between supply and demand prior to a shock event, while purple circles indicate the new equilibrium after a shock event.

For the climate study, we track *many* LMIC food prices, 2000 – 2021

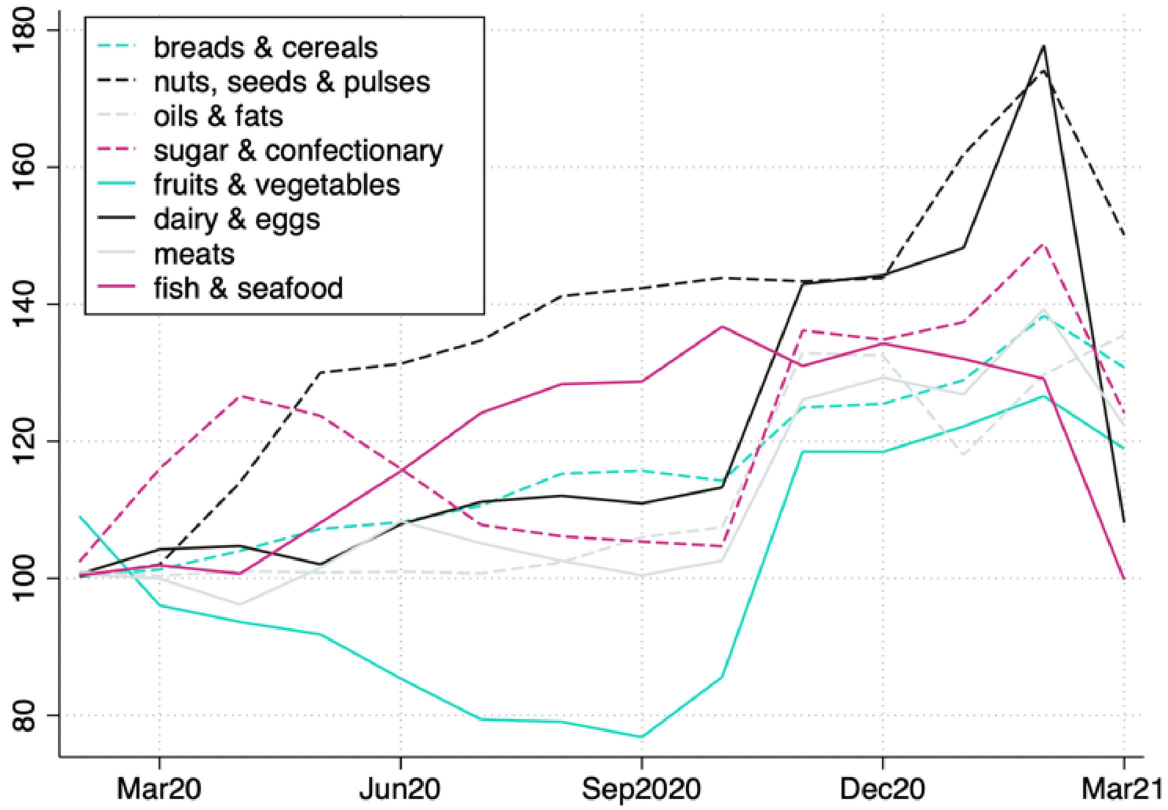
Total *n* = 1,346,513
in 2,321 markets in 71 countries



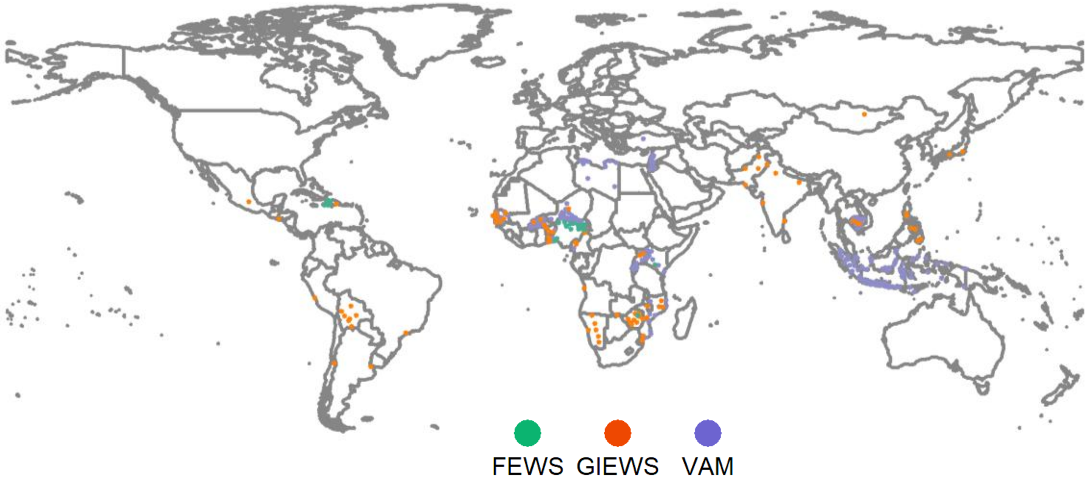


Sources: Retail prices are reported by FAO GIEWS, USAID FEWS, and WFP VAM

For COVID impacts, we zoom into 2020 – 2021



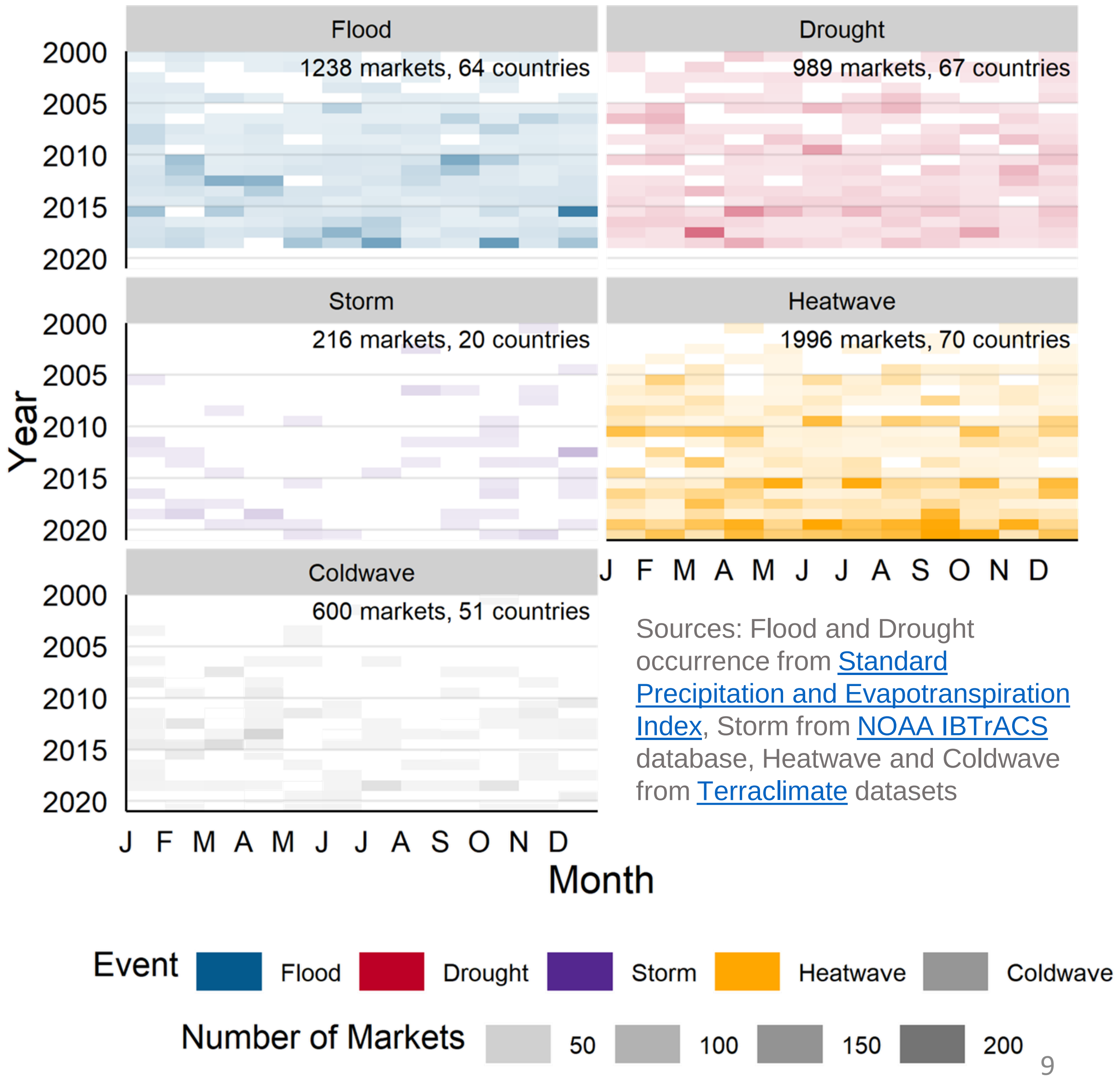
Total n = 73,424
in 436 markets in 36 countries



Sources: Retail prices are reported by FAO GIEWS, USAID FEWS, and WFP VAM

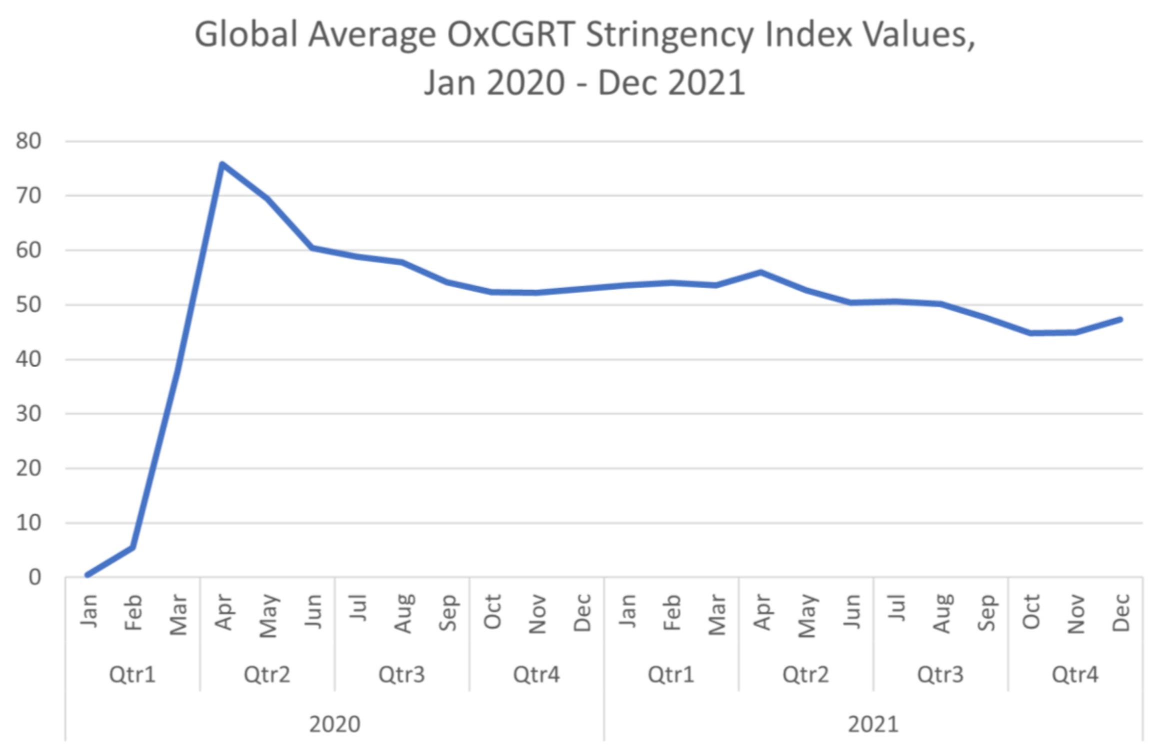
For the climate study, we consider five major extreme weather events

- Data Sources
  - Floods and Droughts: Standardized Precipitation and Evapotranspiration Index
  - Heatwaves and Coldwaves: Terraclimate
  - Storms (windspeeds): NOAA IBTraCS database
- Event definitions
  - Flood = 1 if SPEI > 1.5
  - Drought = 1 if SPEI <= -1.5
  - Heatwave if Tmax anomaly >= 2
  - Coldwave if Tmin anomaly <= -2
  - Storm = 1 if at least Category 2 (windspeeds of 43 m/s) was observed within 200 km vicinity of market
- Climate shocks are spatially and temporally heterogenous

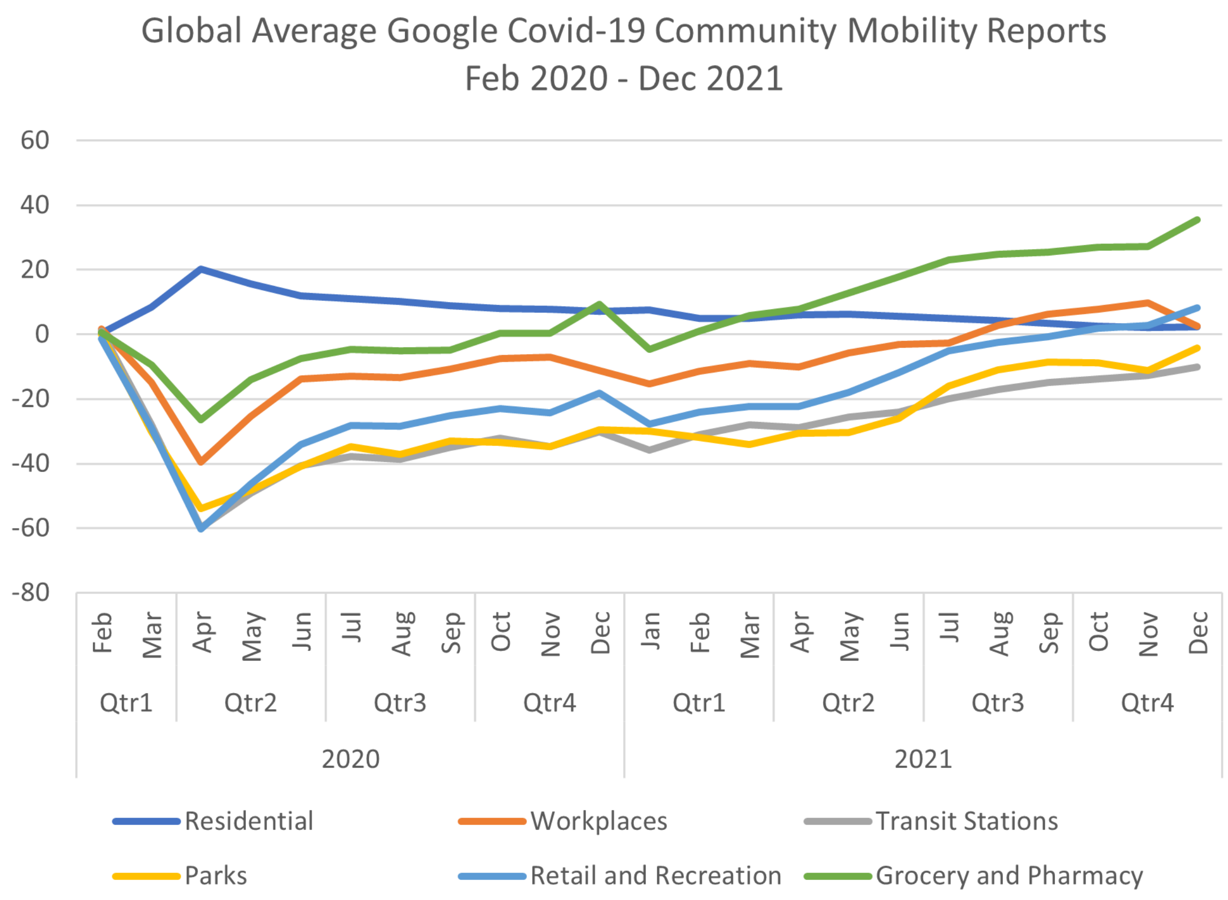


Sources: Flood and Drought occurrence from Standard Precipitation and Evapotranspiration Index, Storm from NOAA IBTrACS database, Heatwave and Coldwave from Terraclimate datasets

For COVID shocks, we consider both policy and behavior (as well as case counts and mortality)



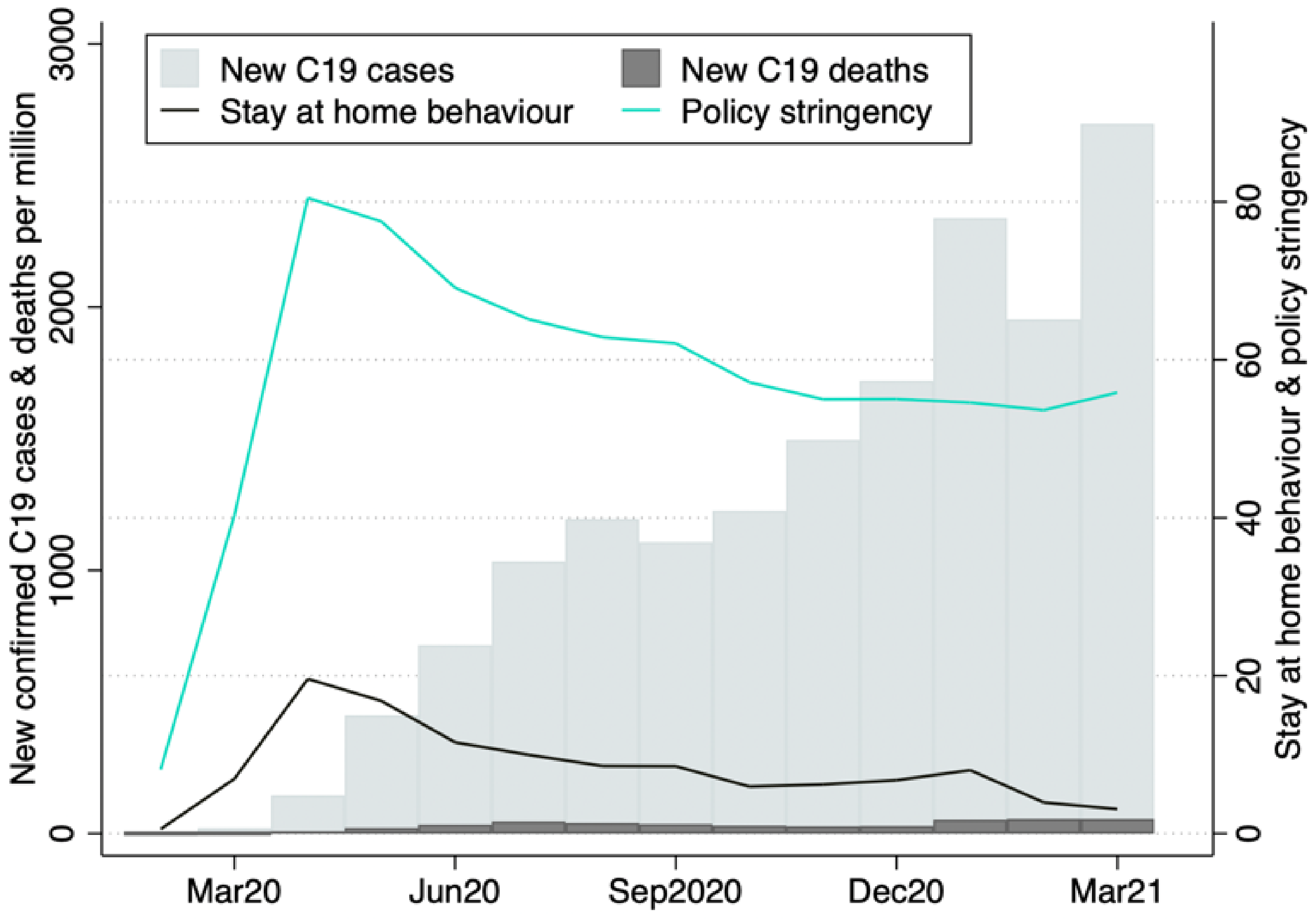
Note: The Oxford Covid-19 Government Response Tracker Stringency Index is a composite of 7 indicators measuring national policies related to closure of various institutions as well as movement restrictions.



Source: OxCGRT, accessed January 5, 2022

Source: Google Covid-19 Community Mobility Reports, accessed January 5, 2022

Our study matches waves of COVID cases, deaths, stay-at-home behavior and policy to local food prices



Sources: Stay at home behaviour data from Google's COVID-19 Community Mobility Trends, policy stringency data from the Oxford COVID-19 Government Response Tracker Stringency Index, COVID-19 case and death count data were downloaded from Our World in Data's COVID-19 Data Explorer.

We convert all food prices to standard units

Climate shocks

- Data compilation from three early warning systems (FAO GIEWS, USAID FEWSNET, WFP VAM)
- Inflation adjustment to June 2017 using IMF and FAO monthly consumer price indices for food items
- 2017 local currencies converted to 2017 USD using WB purchasing power parity for private consumption
- Each food item matched to USDA Standard Reference 28 or West Africa Food Composition Table to derive **2017 USD/1000 kCal**

COVID shocks

- Data compilation from three early warning systems (FAO GIEWS, USAID FEWSNET, WFP VAM)
- Item prices normalized to baseline period of January 2020
- Data transformed from local currencies to unitless price levels
- Normalized price level values were first differenced to obtain the **month-to-month percentage point change in price level** for each food item in each market

We use fixed effects for items, markets, and time periods

Climate shocks

$$P_{ijmy} = \beta_0 + \beta_1 Extreme\ Event_{jmy} + \beta_2 FG_i + \boldsymbol{\beta_3}(FG_i * Extreme\ Event_{jmy}) + \beta_4 E'_{jmy} + \gamma_{jy} + \lambda_{my} + \theta_{jy} + \tau_i + \varepsilon$$

- P_{ijmy} : Price level (2017 USD/1000 kCal)
- *Extreme Event*: occurrence of flood, drought, heatwave, coldwave, or storm during month of observation
- FG_i : one of eight food groups with breads and cereals as reference category
- E_{mt} : vector of time-varying factors
  - Mean temperature (deg C), precipitation (mm), and interaction of temperature and precipitation
- Fixed Effects: market location (γ_j), market-month (δ_{jm}), market-year (θ_{jy}), item (τ_i)

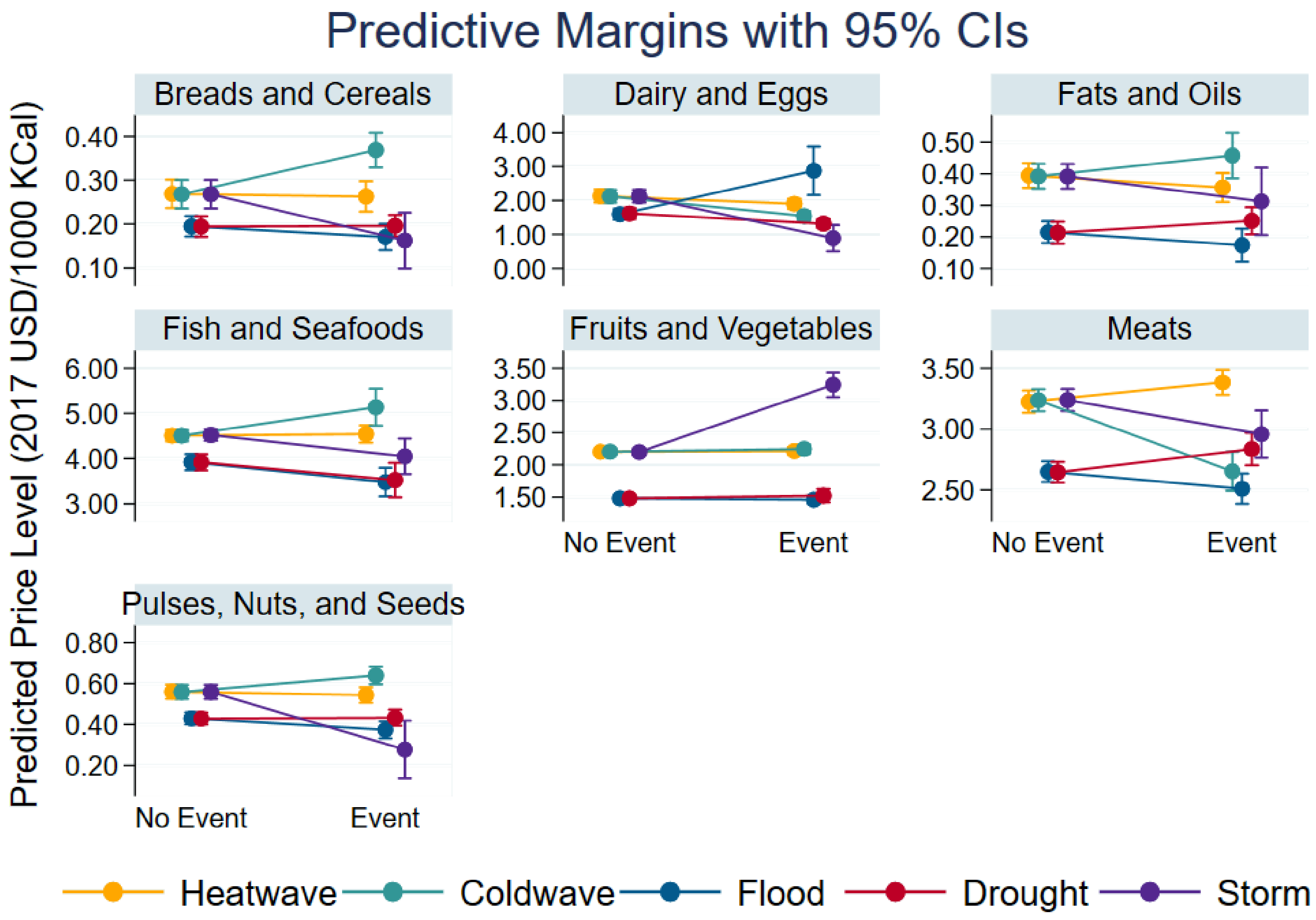
COVID shocks

$$P_{ijmy} = \beta_0 + \beta_1 Mobility\ Indicator_{jmy} + \beta_2 FG_i + \boldsymbol{\beta_3}(FG_i * Mobility\ Indicator_{jmy}) + \beta_4 X'_{jmy} + \gamma_j + \delta_{jm} + \theta_{jy} + \varepsilon_{ijmy}$$

- P_{ijmy} : percentage point change in retail price level
- *Mobility Indicator*$_{jmy}$: percentage point change in stay-at-home behavior or policy stringency
- FG_i : one of eight food groups with breads and cereals as reference category
- X_{mt} : vector of time-varying factors
  - Confirmed new COVID-19 cases and deaths per month per million, log(x + 1)-transformed
- Fixed Effects: market location (γ_j), region-month (δ_{jm}), region-year (θ_{jy})

The subscript *i* refers to food item, *j* refers to market location, *m* refers to month, and *y* refers to year of price observation

Results: Climate shocks

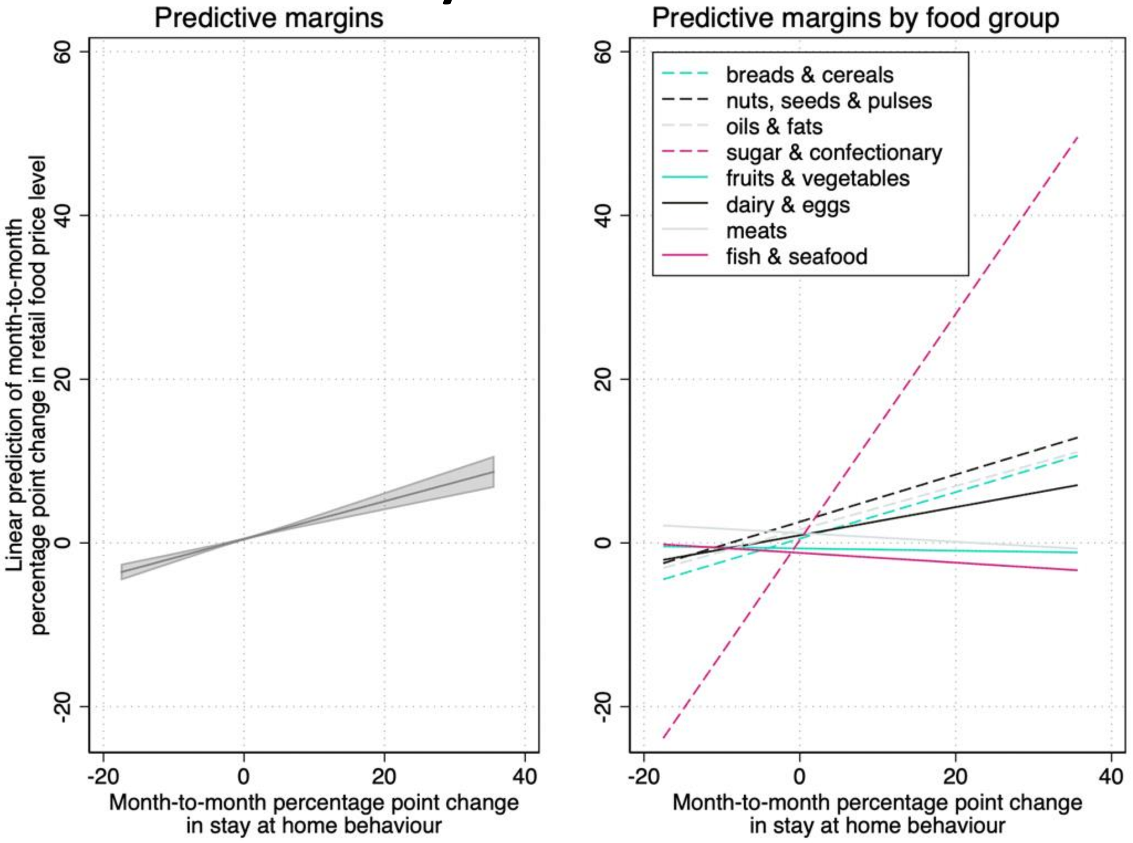


We find mixed results by food group and event type:

- **Heatwaves** are associated with higher prices for meats, little change for other food groups
- **Coldwaves** are associated with higher prices for several food groups, but lower for meats
- **Floods** associated with higher prices for dairy and eggs, small change for others
- **Droughts** associated with higher prices for meats, small increase for fats and oils
- **Storms** associated with lower prices of all food groups except fruits and vegetables

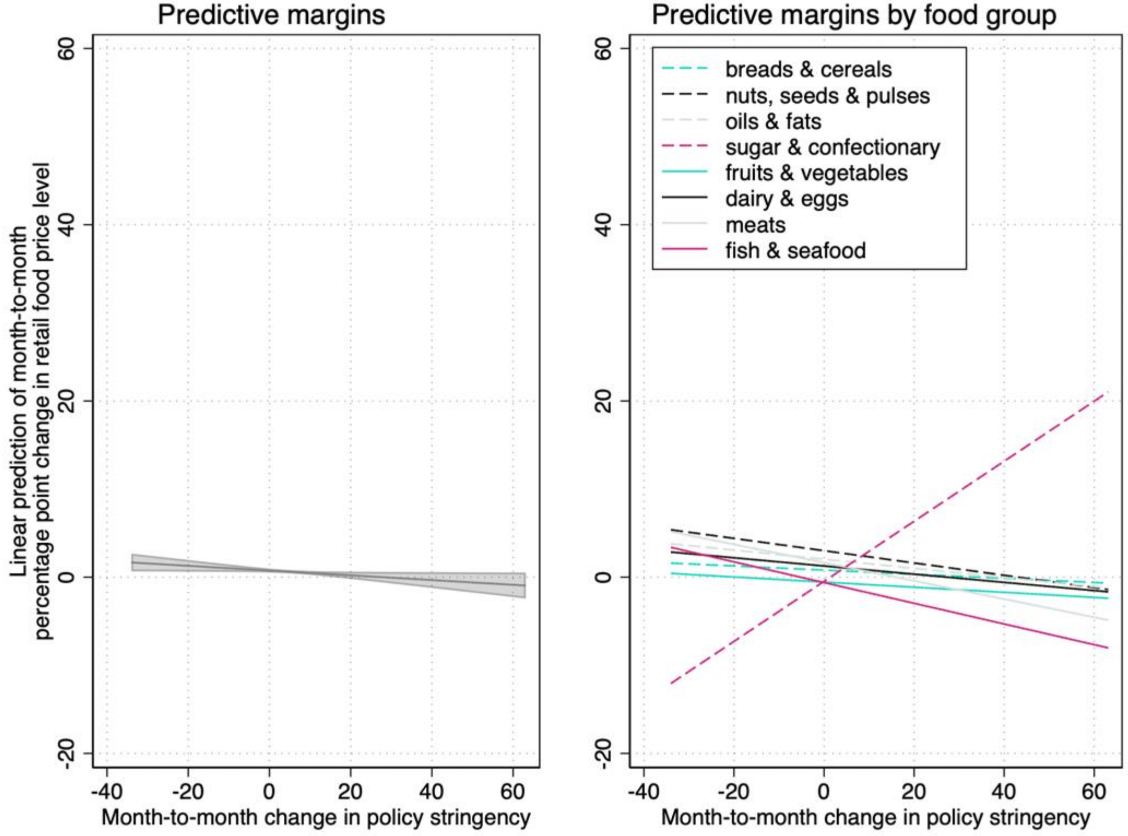
Results: COVID shocks

Stay-at-home behavior



More **stay-at-home behavior** is associated with higher prices for nonperishables and comfort foods (especially sugar and confectionery)

Policy stringency



More **policy stringency** is associated with higher prices for sugar and confectionery, but lower prices for all other food groups

Conclusions

- Retail food prices have mixed and usually small global average associations with climate and COVID shocks
  - Climate shocks of each type differ in their association with prices for each food group
  - COVID shocks have more systematic patterns worldwide
    - Higher prices for sugar and confectionery, suggesting higher demand and limited elasticity of supply
    - Higher prices for other non-perishables as well, but only in response to stay-at-home behavior
    - Lower prices for all food groups except sugar and confectionery in response to policy stringency
  - COVID findings suggest that policy stringency is more strongly associated with lower demand, while stay-at-home behavior is more often associated with cuts in supply and demand shift to non-perishables

- Data and methods could be driving results, for example regarding two-way fixed effects and differences in spatial resolution (e.g. stay-at-home behavior at each market, vs. national policy stringency)

- Next steps include more refined econometrics to address heterogeneity in space and time, and other outcomes such as price dispersion and market integration, as well as month-to-month price volatility

Thank you!

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Food Prices for Nutrition

BILL & MELINDA GATES foundation

Tufts UNIVERSITY | Gerald J. and Dorothy R. Friedman School of Nutrition Science and Policy

Conclusions

- Improvements to the monitoring and reporting of retail food price data will be key to better understanding the mechanisms that influence retail food price level fluctuations, and to informing government responses to the ongoing COVID-19 crisis.

Food Prices for Nutrition
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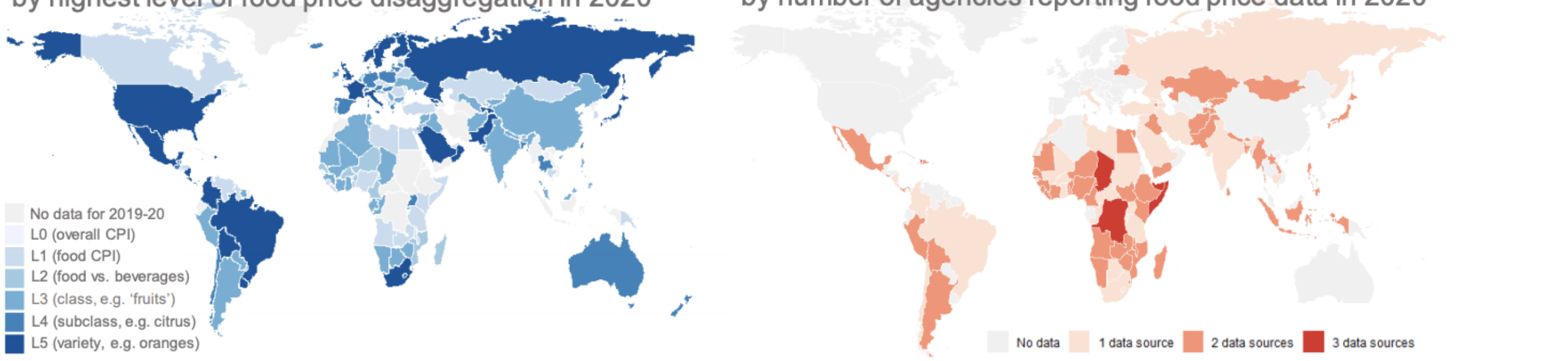
Review of global retail consumer food price data sources reveals gaps and ways to improve monitoring of global food systems

Improved data collection and reporting could show prices for nutritional food groups and healthy diet baskets, to guide policies and programs towards global development goals

National governments' consumer price indexes (CPI) by highest level of food price disaggregation in 2020

International market information and early warning systems (EWS) by number of agencies reporting food price data in 2020



Note: Data shown are from the websites of 170 national statistical organizations around the world. Levels of disaggregation correspond to the COICOP system which does not always reflect nutritional values (e.g. 'fruits' includes tree nuts).

Note: Data shown are from the Famine Early Warning Systems Network (FEWS NET), the FAO's Global Information and Early Warning System (GIEWS), and the WFP's Vulnerability Analysis and Mapping (VAM), covering 94 countries as of Nov. 2020.

Source: Bai, Y. et al. (2021), "Review: Retail consumer price data reveal gaps and opportunities to monitor food systems for nutrition", in *Food Policy*.

Next steps…

Food and Agriculture Organization of the United Nations

Cost and affordability of healthy diets across and within countries

Background paper for *The State of Food Security and Nutrition in the World 2020*

- Implications for least cost diets
  - ~3 billion people (38% of the world population) could not afford a healthy diet in 2017 (SOFI 2020).
  - Elevated retail food prices after shocks further threatens affordability of healthy diets.
  - Responses to limit the spread and severity of the pandemic are critical. Combinations of policies (including food assistance measures) may be important to mitigate unwanted spill-over effects from movement restriction policies into other domains, such as food security and nutrition.
- Improved analysis of magnitude and severity for climate shocks
- Urban protective effects