Staff Discussion Paper/Document d’analyse du personnel—2023-24

Last updated: October 13, 2023

Variations in Pass-Through from Global Agricultural Commodity Prices to Domestic Food Inflation

by Daniel Hyun and Jacky Lee

International Economic Analysis Department
Bank of Canada
dhyun@bankofcanada.ca

DOI: https://doi.org/10.34989/sdp-2023-24 | **ISSN** 1914-0568

Acknowledgements

We thank Kun Mo, Subrata Sarker, Reinhard Ellwanger and participants at an internal Bank of Canada seminar for their feedback and suggestions.

Abstract

This paper examines factors that affect the transmission of fluctuations in global agricultural commodity prices to domestic food inflation. Using panel regressions on data from 53 advanced and emerging-market countries, we investigate how factors such as local crop production conditions, the extent of food industry development and the net agricultural trade status interact with global agricultural prices to affect pass-through to local food prices. Results show that pass-through varies significantly based on these factors. Pass-through decreases during better-than-normal crop conditions, highlighting the importance of local production. Countries with less-developed food industries experience higher pass-through, likely due to the greater importance of raw commodities in diets and less-complex supply chains. Interestingly, net exporters of agricultural commodities exhibit greater pass-through, potentially due to strategic trade adjustments that take advantage of global supply and demand dynamics. These variations in pass-through suggest potential avenues for managing food price inflation in response to shocks to global food prices under different scenarios.

Topics: Inflation and prices; International topics
JEL codes: E31, Q02, Q11, Q17, Q18

Résumé

Cette étude examine des facteurs qui influent sur la transmission des fluctuations des prix mondiaux des produits agricoles aux hausses de prix des aliments au pays. À l'aide de régressions sur données de panel pour 53 économies avancées et émergentes, nous étudions l'incidence de facteurs comme les conditions locales de culture, le niveau de développement de l'industrie alimentaire et la balance commerciale nette de l'industrie agricole – conjugués aux prix mondiaux des produits agricoles – sur les prix des aliments à l'échelle locale. Les résultats montrent que la transmission des fluctuations des prix mondiaux varie considérablement en fonction de ces facteurs. Elle diminue lorsque les conditions de culture sont anormalement favorables, ce qui souligne l'importance de la production locale. La transmission est plus forte dans les pays ayant une industrie agricole moins développée, probablement en raison de la plus grande importance des produits de base non transformés dans la diète des populations et des chaînes d'approvisionnement moins complexes. Il est intéressant de noter que le niveau de transmission est plus élevé dans les pays qui sont des exportateurs nets de produits agricoles en raison, possiblement, d'ajustements stratégiques des échanges qui tirent parti des dynamiques mondiales d'offre et de demande. Ces variations de la transmission laissent entrevoir des avenues possibles pour la gestion de l'inflation dans l'alimentation qui est attribuable aux chocs des prix mondiaux, dans divers scénarios.

Sujets : : Inflation et prix; Questions internationales
Codes JEL : E31, Q02, Q11, Q17, Q18

1. Introduction

For many countries, major spikes in the prices of global agricultural commodities are often followed by episodes of elevated domestic food inflation. Pass-through from global prices to domestic markets has been cited as a key contributor to the food price crises of the 21st century, including in 2010–11 and 2020–23 (Helbling and Roache 2011; International Monetary Fund [IMF] 2022; Glauber et al. 2022). Price transmission primarily occurs through trade and arbitrage because global and domestic agricultural markets are partially integrated in most countries. The law of one price suggests that prices for similar goods that are traded should be equal after accounting for transaction and transport costs. Trade dependency exposes countries to movements in world agricultural prices, and arbitrage between global and domestic markets keeps long-term prices linked.

While spillovers from world agricultural prices are a common issue, the extent of pass-through to domestic prices can vary significantly across countries. Understanding variations in pass-through can help policy-makers identify which countries are likely to experience more-severe food inflation after global food price shocks. Higher pass-through can increase fears of food insecurity during major market disruptions and threaten to de-anchor general inflation expectations if rapid price increases are sustained over a longer period.

In this paper, we explore a number of factors that could affect pass-through from global agricultural commodity prices to domestic food inflation. Using a panel model with monthly data from March 2000 to January 2020, where available, for 53 countries, we test empirically whether factors that impact local food supply could affect the degree of pass-through. We then estimate how long-term pass-through to domestic food inflation can vary under different scenarios.

Notably, we examine the effect of local food production shocks on the magnitude of pass-through—a variable often overlooked in existing literature. Intuitively, local food prices could depend directly on local food production since most countries produce a significant portion of their domestic food requirements (IMF 2011; Furceri et al. 2016). While studies have quantified the relationship between local production shocks and domestic food inflation, the idea that these shocks could impact the degree of pass-through from global agricultural prices is underexplored. We test whether local food production shocks could affect domestic food inflation indirectly by altering the degree of pass-through from global to domestic food prices. To capture local food production shocks, we use high-frequency satellite data on vegetation density following Brown and Kshirsagar (2015). In the process, we demonstrate that using satellite data as a proxy for shocks to local crops could contribute to global inflation monitoring.

We also test whether the size of pass-through differs based on local food industry structure. How developed a country's food industry is determines the types of firms and sub-industries involved in the transmission of international price movements. A more complex supply chain implies that price signals need to be transmitted through a greater number of firms, potentially dampening pass-through to domestic prices (Cachia 2014). Furthermore, we test if pass-through estimates vary across net exporters and importers of agricultural commodities. Incentives for net exporters to sell more of their agricultural commodities abroad and resistance by local producers to government-imposed export restrictions when global prices are rising could facilitate greater price transmission.

Our results suggest that substantial variations in pass-through exist after 12 months under different circumstances. For a 1% increase in world agricultural prices, long-term pass-through is estimated to be 0.14% when local crop conditions are normal or below average. Pass-through decreases by about 35% when crop conditions are better than normal. In addition, countries with less-developed local food industries have a pass-through coefficient of 0.15, which is around 65% higher than in countries with more-developed food industries. We also find that net exporters of agricultural commodities have an average pass-through coefficient of 0.15 and experience about 65% more pass-through than net importers.

The rest of the paper proceeds as follows. Section 2 provides a review of the literature. Section 3 discusses the data and methodology. Section 4 presents the results, and section 5 provides details on our robustness checks. Finally, section 6 concludes.

2. Literature review

Since the world food price crisis of 2010–11, empirical studies have investigated pass-through to domestic food prices. One branch of the literature uses cointegration to focus on pass-through to individual commodities such as wheat, corn and rice (Minot 2011; Ghoshray 2011; Greb et al. 2012; Conforti 2004). Some of these studies find that a significant portion of global and domestic commodity price pairs do not have long-term relationships. Greb et al. (2012) find that only 43% of price pairs are linked but suggest the lack of cointegration may be due to the failure to control for regime changes such as policy interventions, the use of generalized models that are not tailored to domestic circumstances and data limitations. Minot (2011) also shows that only about 20% of the studied price pairs in Sub-Saharan Africa are linked. However, clear pass-through was observed in 2008, which Minot (2011) attributes to the exceptionally large magnitude of the increases in world agricultural prices and the rise in oil prices.

Greb et al. (2012) find that for pairs exhibiting cointegrating relationships, long-term pass-through is about 0.75% on average for a 1% increase in world prices for wheat, corn and rice. Nonetheless, pass-through is found to vary significantly across crops and countries. The speed of transmission is generally slower if the crop is more politically sensitive, as measured by the size of net imports relative to domestic consumption. For instance, Minot (2011) shows that African rice prices are more integrated with world prices than African corn prices because many countries depend on rice imports but are nearly self-sufficient when it comes to corn. While analyzing volatility pass-through, Ceballos et al. (2017) find similar results across Latin America, Africa and Asia, with wheat and rice markets more affected by international price volatility than the corn market due to trade dependency. Consequently, pass-through depends on which global prices spike because different countries rely on different staples.

While the above studies focused on individual commodity prices, another branch of literature examines pass-through to aggregated domestic food prices. Estimated pass-through is similarly incomplete and varied across countries, but the magnitude is smaller than that for raw commodities. The literature finds that pass-through for a 1% increase in world agricultural prices is about 0.3% on average globally, and emerging-market economies (EMEs) tend to have greater pass-through than advanced economies (AEs) (Ianchovichina, Loening and Wood 2012; IMF 2011; Furceri et al. 2016; IMF 2022; Bekkers et al. 2017). This does not mean that pass-through within these income-based groupings is uniform: Sahoo, Kumar and Gupta (2020) show that long-term pass-through for a sample of six EMEs ranges from 0.25 to 1.97.

The higher pass-through in EMEs can be partly attributed to the fact that raw agricultural commodities account for a higher share of costs in EME food consumption relative to that of AEs. Bekkers et al. (2017) argue that AEs consume fewer low-quality, unprocessed staples than EMEs do, and their food consumption includes a larger share of margin services such as transport, processing and retailing. For example, Cowley and Scott (2022) show that for every dollar spent on food at home in the United States, the production of farm commodities contributes to only a little more than 10 cents on average. However, food processing and wholesale and retail trade account for almost 65 cents of each food dollar. Since most world food price indexes usually track relatively unprocessed agricultural products (Furceri et al. 2016), the cost share of raw commodities in food consumption can affect pass-through.

Other studies find that the local food industry drives pass-through. Cachia (2014) argues that smaller and slower price transmission in developed regions is due to extended value chains, which limit pass-through since price signals need to be transmitted through a greater number of actors at different stages in the chain. Despite similar trade and sectoral policies, Lloyd, McCorriston and Zvogu (2015) identify significant variation in the impact of a common shock from global wheat prices across 11 European Union member states. Their results suggest that country differences are driven by variations in the functioning of the local food industry. For example, lower barriers to competition for retail in general are associated with higher pass-through, but at the same time, greater vertical control by retailers is also weakly correlated with higher pass-through. The importance of the local food industry on domestic food inflation is clear: Lloyd et al. (2015) estimate that 50% of the total variation in bread prices in their sample was driven by the domestic food chain compared with 36% from world wheat prices.

Government policies, particularly related to trade, also contribute to differences in pass-through. Flachsbarth and Garrido (2014) and IMF (2022) provide evidence that greater openness in agricultural and general trade leads to larger pass-through. However, trade openness can change during crises. Policies aimed at insulating domestic markets from world food price shocks can cause global and domestic prices to diverge in the short run (Laborde, Lakatos and Martin 2019). Net exporters of agricultural commodities often implement export restrictions, while net importers reduce import tariffs and increase food subsidies (Laborde, Lakatos and Martin 2019; Martin and Minot 2022). The effectiveness of these policies at limiting domestic volatility does, however, depend on the ability of states to enforce and fund them for sustained periods (Baltzer 2013). Ianchovichina, Loening and Wood (2012) show that despite the use of food subsidies and other policies to protect domestic markets, there was significant pass-through to countries in the Middle East and North Africa. Nevertheless, most wealthier Gulf Cooperation Council countries that could afford to maintain insulative policies generally had smaller and slower pass-through.

Although the literature on pass-through variation is abundant, one rarely explored area is the role of shocks to local food production. The effect of changes in domestic crop production on local food inflation has been tested on a cross-country level, but the results are mixed. On one hand, using annual data, Kohlscheen (2022) finds that a 10% increase in domestic crop growth reduces the following year's food inflation by 0.47% for member countries in the Organisation for Economic Co-operation and Development (OECD). Potential explanations for this relationship could be the presence of significant domestic food production and imperfect integration with global agricultural markets (IMF 2011; Furceri et al. 2016; Brown and Kshirsagar 2015). On the other hand, an earlier study by Lee and Park (2013) using a broader sample of countries with annual data did not find any significance.

To our knowledge, however, few studies have analyzed how local food production shocks could alter the degree of pass-through from global agricultural prices. Brown and Kshirsagar (2015) use high-frequency satellite data on local crop conditions to provide a solution to limitations imposed by infrequent annual agricultural production data, but this approach has yet to be widely applied to the study of pass-through from global agricultural prices. Brown and Kshirsagar (2015) show that local weather disturbances could have a significant and direct effect on individual local food commodity prices in the short run. We:

- extend their approach to the level of aggregated national food markets
- incorporate AEs into the analysis
- test whether the amount of pass-through from global prices depends on local production conditions, affecting domestic food inflation indirectly

3. Methodology

3.1 Data

Domestic food prices used in this paper are mainly from consumer price indexes for food and beverages (FCPI) from the OECD, national statistical agencies and central banks via Haver Analytics. For countries with significant amounts of missing data from these sources, we use prices that were interpolated by the Food and Agriculture Organization of the United Nations (FAO) instead.

World agricultural prices, the main variable that allows us to measure pass-through, are proxied using the Agriculture and Livestock subindex of the S&P Goldman Sachs Commodity Index (GSCI), which tracks primarily raw agricultural commodity futures in US dollars. We chose the GSCI because it excludes processed foods and beverages that are present in other world food price indexes. This ensures a closer match with our independent variables that impact local food supply, while capturing the extent of the pass-through coming specifically from raw commodities.

To incorporate timely local crop conditions and weather disturbances, we use normalized difference vegetation index (NDVI) data as in Brown and Kshirsagar (2015). The NDVI measures the amount of vegetation density over land areas based on satellite imagery and is available in near real time for almost all political jurisdictions.[1] The United States Department of Agriculture (USDA) uses the data to monitor crop conditions around the globe and develop forecasts on crop yields (Becker-Reshef et al. 2010). To make the data comparable over different time periods, NDVI values can be subtracted from their historical mean to produce NDVI anomalies. Anomaly values greater (less) than zero represent above-(below-)average crop conditions.

We use the Moderate Resolution Imaging Spectroradiometer NDVI eight-day anomaly data collected at the country level and aggregated to a monthly frequency.[2] A dummy variable, which is equal to one when NDVI anomaly values are greater than zero, is used to track above-average crop conditions.

As a proxy to measure how developed a local food industry is, we use the weight of food and beverages in national consumer price indexes (CPIs). Although the share of raw agricultural commodities in the food and beverage portion of CPI would be more informative, a higher share of food in CPI is generally associated with less-developed food industries, which have

[1] The NDVI is based on remotely sensed data from satellites. According to the USDA, it compares the red portion of light reflected off land surfaces with the amount of near-infrared light being reflected. The index ranges from -1 to 1, where -1 indicates water or flooding, 0 bare soil and 1 the most vegetation. See "Normalized Difference Vegetation Index (NDVI)" on the USDA website for more details.

[2] We use general NDVI anomaly data at the country-level, which do not filter out land mass or target growing areas for specific crops. The historical average used to calculate anomaly values is based on the 2001–21 period. The data were retrieved from the GIMMS Global Agricultural Monitoring System.

less-extensive value chains. Smaller value chains can lead to greater pass-through, as price signals are transmitted through fewer actors (Cachia 2014). The data are taken from the International Labour Organization, as well as national statistical agencies and the OECD via Haver Analytics. We calculate country averages from 2011–19 (if available) and use them to construct a dummy variable, where countries with above-average food weight in their CPI relative to others in the sample have a value of one.

Similarly, we classify countries as net exporters or net importers of agricultural commodities based on total import and export quantities for major grains and oilseeds over 2000–19. The data are taken primarily from the FAO food balance sheets, but data for a few countries are from the USDA Production, Supply and Distribution database.

Our dataset consists of monthly data for 53 countries.[3] See **Table A-1** in the appendix for a full list of countries. Depending on data availability, our sample runs from March 2000 to January 2020. Any variables that incorporate lags, however, may also reference data from 1999.

See **Table A-2** in the appendix for a list full list of variables and sources.

3.2 Models

To assess the impact of local conditions on the degree of global agricultural price pass-through, we apply the framework used by the IMF (2011) and Furceri et al. (2016), with three distinct variations. First, we use a panel regression framework rather than country-by-country regressions. This allows us to estimate a global pass-through coefficient, while capturing country-specific variations by country fixed effects. Second, we include local factors such as the NDVI as interaction terms with world agricultural prices in order to test the significance of their impact on pass-through. Lastly, we introduce a number of control variables to better target the effect of raw commodity price shocks on domestic food prices.

The estimated monthly panel regression on domestic food price inflation includes current and 12 lags of international agricultural price inflation as well as 12 lags of domestic food price inflation. The regression is specified as follows:

$$\pi_{i,t}^{dom} = \alpha_i + \sum_{j=0}^{12} \beta_{1+j}^{int} \pi_{t-j}^{\mathrm{int}} + \sum_{j=0}^{12} \beta_{1+j}^{LF} LF_{dum} + \sum_{j=0}^{12} \beta_{1+j}^{int,LF} (\pi_{t-j}^{\mathrm{int}} * LF_{dum}) + \sum_{j=1}^{12} \beta_j^{dom} \pi_{i,t-j}^{\mathrm{dom}} + controls + \varepsilon_{i,t}, \quad (1)$$

where, for each country i and month t, $\pi_{i,t}^{\mathrm{dom}}$ is domestic food CPI inflation, π_t^{int} is global agricultural price inflation proxied by the log difference of the GSCI in US dollars, α_i is country fixed effects, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

Separate regressions are estimated for each local factor dummy, LF_{dum}, proxied by variables described in the previous section. These include dummy variables for positive NDVI anomalies,

[3] Major economies from most regions except Oceania are represented. Country coverage for the Middle East and Africa is also limited.

countries with less-developed food industries and net exporters of grains and oilseeds. The first dummy variable has both time and cross-sectional variations. While the latter two cross-sectional dummies are interacted with global agricultural price inflation to examine their impacts on pass-through, they are omitted from the regressions as standalone regressors because cross-sectional characteristics are already accounted for through country fixed effects.

A broad range of control variables are included. We use the log level of exchange rates, log differences of core CPI, short-term interest rates, annualized CPI inflation volatility over the entire sample, the level of Brent prices, the log level of the Baltic Dry Index and a dummy variable capturing when the spread between changes in the FCPI and changes in the food manufacturing producer price index (FPPI) is positive. This dummy variable attempts to control for periods of potential margin expansion in the retail industry characterized by growth of consumer prices exceeding that of producer prices for similar goods.[4] In addition, the Southern Oscillation Index is included to control for El Niño and La Niña weather events, which could disrupt normal rainfall patterns, while harvest dummies are included to account for seasonality. Dummy variables for the 2007–08 and 2010–11 periods also control for idiosyncratic events such as the global financial crisis and the previous world food price crisis that could potentially bias global pass-through coefficients.

In this framework, long-term pass-through coefficients, which refer to total pass-through after 12 months, can be calculated under two scenarios for each of the three factors of interest. Pass-through coefficients differ based on whether the local factor dummy is equal to one or zero. With the NDVI anomaly dummy as an example, the pass-through coefficient in times of average or worse crop conditions (i.e., $LF_{dum} = 0$) would equal the following:

$$PT_{worse} = \frac{\sum_{j=0}^{12} \beta_{1+j}^{int}}{1-(\sum_{j=1}^{12} \beta_j^{dom})}. \qquad (2)$$

Conversely, the pass-through coefficient under better crop conditions (i.e., $LF_{dum} = 1$) would equal:

$$PT_{better} = \frac{\sum_{j=0}^{12} \beta_{1+j}^{int} + \sum_{j=0}^{12} \beta_{1+j}^{int,LF=NDVI}}{1-(\sum_{j=1}^{12} \beta_j^{dom})}. \qquad (3)$$

We repeat this exercise for other dummy variables of interest to compute differences in long-term pass-through coefficients for countries with more- or less-developed food industries and net exporters or importers of grains and oilseeds.

[4] The spread between the food CPI and producer price index (PPI) is frequently used by grocery analysts and industry watchers to assess the state of retailers' gross margins. For example, see A. Bitter, "Food CPI, PPI spread narrows in February, signaling relief for grocers' profits," S&P Global Market Intelligence (March 16, 2018).

4. Results

We estimate the impact on domestic prices of a 1% increase in global agricultural commodity prices proxied by the GSCI index. **Table 1** presents the main estimation results, which suggest that the long-term pass-through of a 1% shock to world prices is roughly 0.12% on average globally.[5] Estimates of long-term pass-through coefficients conditioned on the state of the local factor of interest are also shown, following equations 2 and 3. Joint F-tests on regression coefficients of 13 interaction terms in **Table 2** show that the long-term pass-through estimates under all six scenarios are statistically significant.[6]

First, our results indicate that good conditions for local food production can lead to lower pass-through from global prices. Pass-through decreases to 0.09% when crop conditions are better than normal, but pass-through increases to 0.14% in times of bad or average crops. The reduced pass-through when crop conditions are above average can be attributed to less reliance on foreign trade associated with a surplus in local crop availability. Conversely, pass-through increases when local crop conditions deteriorate. One plausible explanation may be the price-taking behaviour exhibited by countries expecting reduced crop yields.

Table 1: Long-term pass-through for a 1% increase in global prices in US$ (GSCI)

Simple regression with only controls	0.12%
Interaction with NDVI	
Good crop conditions	0.09%
Average or bad crop conditions	0.14%
Interaction with food weight	
Above average	0.15%
Average or below	0.09%
Interaction with net exporter	
Net exporters	0.15%
Net importers	0.09%

Note: GSCI is Goldman Sachs Commodity Index; NDVI is normalized difference vegetation index.

Should such conditions materialize, these countries rely more on the global market to meet domestic food demand, leading to an increased pass-through. Nzuma (2013) and Baltzer (2013) highlight the case of Kenya in 2008, when several years of poor harvests increased the country's demand for large imports of corn. With poor domestic production unable to provide a buffer, crop failures likely contributed to increased pass-through from global corn prices. Local prices rose significantly in tandem with global corn prices and remained persistently high into 2009, consistent with a higher long-term pass-through in times of poor crop conditions.

[5] Estimates for long-term pass-through coefficients with only 12 lags of domestic food inflation and exchanges rates as controls are included in **Table A-3** in the appendix. In the absence of other control variables, the average global long-term pass-through coefficient rises to 0.19. Further, in unreported results we find that the coefficient rises to 0.28 when computed in local currencies, consistent with estimates from the literature.

[6] The full regression results are reported in **Table A-4** in the appendix.

Intuitively, our results suggest that domestic food prices react contemporaneously to changes in global agricultural and local production conditions. Local food prices rise in tandem with global prices (i.e., $\beta_1^{int} > 0$), while local prices fall when bumper harvests are expected (i.e., $\beta_1^{LF=NDVI} < 0$). In addition, however, we find that the contemporaneous NDVI interaction term with GSCI ($\beta_1^{int,LF=NDVI}$) is negative and highly statistically significant. This suggests that the anticipation of better crop yields due to favourable growing conditions can have an immediate impact on pass-through as well. Our results corroborate the theoretical framework presented by Kalkuhl (2014), in which intertemporal arbitrage in the presence of storage and trade instantaneously pushes domestic and global prices toward convergence. The storability of commodities allows for speculative storage demand shocks, whereby commodities traders can exert downward pressure on prices by drawing on more inventory than usual with the expectation of a bumper harvest locally.

Countries with less-developed food industries experience greater pass-through of 0.15% compared to 0.09% in more developed regions, proxied by the food weight in CPI. This can be partially attributed to the composition of input costs in economies with less-developed food industries. Raw commodity prices generally constitute a larger share of overall input costs in these economies, resulting in local food prices that are more sensitive to changes in global commodity prices. Further, the structure of supply chains can play a role in increased pass-through, as documented by Cachia (2014). Price transmission in countries with extensive value chains tends to be slower and less pronounced due to multiple market actors involved in processing, packaging, shipping and distributing that absorb and delay the impact of price shocks.

Table 2: Separate baseline long-term pass-through regressions

	NDVI	Food weight	Net exporter
Sum of 13 interaction terms with GSCI ($\sum_{j=0}^{12} \beta_{1+j}^{int,LF}$)	-0.04262***	0.05308***	0.05166***
Sum of 13 GSCI terms ($\sum_{j=0}^{12} \beta_{1+j}^{int}$)	0.11996***	0.08503***	0.08401***
Sum of 12 FCPI terms ($\sum_{j=1}^{12} \beta_{j}^{dom}$)	0.11392***	0.10265***	0.10411***
Contemporaneous interaction term with GSCI ($\beta_{1}^{int,LF}$)	-0.01699*** (0.00413)	0.00834* (0.00497)	0.00523 (0.00426)
Contemporaneous GSCI term (β_{1}^{int})	0.01775*** (0.00305)	0.00697*** (0.00245)	0.00793** (0.00304)
Contemporaneous dummy term (β_{1}^{LF})	-0.00035* (0.00018)		
Observations	10 708	10 708	10 708
Groups	53	53	53
Overall Adjusted R^2	0.417	0.418	0.417

Note: GSCI is Goldman Sachs Commodity Index; FCPI is the consumer price index for food and beverages. Standard errors are in parentheses. Asterisks for the sum of multiple coefficients refer to the results from joint F-tests. * p<0.1, ** p<0.05, *** p<0.01

Lastly, contrary to conventional wisdom, we find that net exporters of agricultural commodities experience greater pass-through than net importers. On average, domestic food prices in net exporting countries rise roughly 0.15% following a 1% increase in global prices, while prices in net importing countries rise by only 0.09%. Intuition suggests that net importers would have greater pass-through primarily due to their higher dependence on global trade to meet domestic food demand, while net exporters tend to have abundant production of crops at home. However, our findings raise the possibility of net exporters taking advantage of high global prices by selling down their inventories. In the process, local prices rise in tandem with global prices to encourage the sale of more supplies at home, effectively importing inflation from world agricultural markets.

There could also be differences with respect to government intervention. Typically, net exporters resort to export restrictions such as bans or taxes to mitigate elevated pass-through during periods of spikes in global food prices. It is plausible that local producers would resist such measures, possibly blunting the extent to which policy interventions shield increases in domestic prices. Conversely, net importers could be more proactive at protecting against global price shocks by using tools such as import subsidies, which may even be automatic in some cases. Greb et al. (2012) find that an increasing ratio of net imports to domestic consumption is associated with slower price transmission. They suggest this is likely caused by government intervention.

A lack of export capacity in countries that are traditionally net importers may be further dampening pass-through to local prices (Dawe 2010). Bangladesh in 2008, for instance, produced a bumper rice harvest just as a large supply was arriving from India. The government did impose an export ban, it but was ineffective in practice (Dawe 2010). Traders were unable to take advantage of arbitrage opportunities largely because the country, as a traditional importer, lacked the capacity (i.e., quality control and existing trade relationships) to export large quantities of rice in the short term. This insulated the country to an extent from significant price increases observed in international prices at the time (Dawe 2010; Baltzer 2013).

We also find that a number of control variables are highly statistically significant across all three scenarios (see **Table A-4** for details). First, local food prices rise when grocers widen their profit margins, as proxied by the spread between FCPI and FPPI. Core inflation also plays a substantial role in driving food inflation, corroborating findings by Cowley and Scott (2022). Higher costs of labour, transportation and rents, major components of core inflation, likely contribute significantly to rising local food prices. The appreciation of the local currency can dampen local food price inflation, given that global agricultural prices are primarily denominated in US dollars. The IMF (2011) finds real food prices had fallen since 2000 in select EMEs with exchange rates that appreciated against the US dollar, despite an 80% increase in the real US dollar world food price index. Thus, efforts to stabilize and manage currency fluctuations can be critical in mitigating the impact on local prices. Further, local food inflation tends to be higher in countries where overall inflation is less anchored, as indicated by the annualized volatility of CPI inflation over the entire sample. Lastly, the rise in Brent prices, reflecting increased input costs across the food value chain, contributes to local food price increases, albeit at small magnitudes.

5. Robustness checks

As part of our robustness checks, we test two additional hypotheses. Since EMEs tend to have a higher share of food in CPI, the variation in long-term pass-through due to food weight should be comparable with estimates for pass-through to EMEs versus AEs. Dietary preferences could also lead to differences across regions. We test whether pass-through for Asia is significantly different from other regions in the sample because the staple there is mainly rice, which the GSCI does not track. The absence of rice in the GSCI could lead to less pass-through to Asia.

Table 3: Other hypotheses

	EMEs	Asia
Long-term pass-through coefficient (LF_{dum}= 1)	0.14	0.08
Long-term pass-through coefficient (LF_{dum}= 0)	0.10	0.12
Sum of 13 interaction terms with GSCI ($\sum_{j=0}^{12} \beta_{1+j}^{int,LF}$)	0.04055**	-0.03590***
Observations	10 708	10 708
Groups	53	53
Overall Adjusted R^2	0.416	0.416

Note: Asterisks for the sum of multiple coefficients refer to the results from joint F-tests. EME is emerging-market economy; GSCI is Goldman Sachs Commodity Index. * p<0.1, ** p<0.05, *** p<0.01

The results in **Table 3** suggest that pass-through varies based on these characteristics. The joint F-test on all interaction terms is statistically significant for both EMEs and Asia. On average, long-term pass-through for EMEs is about 0.14% for a 1% increase in world agricultural prices but only 0.1% for AEs. These pass-through coefficients are in line with those estimated based on food weight. As for Asia, pass-through on average is about 0.08%, while pass-through for all regions excluding Asia is about 0.12%.

Although estimating separate models facilitates the calculation of individual pass-through coefficients, this approach cannot determine if the main independent variables (i.e., local factors) are simultaneously significant. To ensure orthogonality across these local factors, we run another model, which interacts the GSCI with the NDVI, food weight in CPI, net exporters of agricultural commodities and Asia variables at the same time. The results shown in **Table 4** reaffirm the main results: the joint F-test on each set of main variable interactions remains highly statistically significant. However, the significance on the joint F-test for the Asia variables falls to the 5% level.

As a final robustness check, we re-estimate the main models using the FAO food price index instead of the GSCI. The FAO index tracks a larger set of commodities that includes rice, contains some more processed products such as vegetable oils and incorporates a more diverse set of price quotations. The results are largely similar to those estimated with the GSCI, but pass-through is generally higher when using the FAO index.[7] The key difference is that the Asia variables are not jointly significant. A possible explanation is that the FAO index accounts for rice, which is not included in the GSCI.

Table 4: Main variables when included in the same model

	NDVI	Food weight	Net exporter	Asia
Sum of 13 interaction terms with GSCI ($\sum_{j=0}^{12} \beta_{1+j}^{int,LF}$)	-0.04161***	0.05335***	0.02584***	-0.04432**
Sum of 13 GSCI terms ($\sum_{j=0}^{12} \beta_{1+j}^{int}$)	0.09809***			
Sum of 12 FCPI terms ($\sum_{j=1}^{12} \beta_{j}^{dom}$)	0.09996***			
Contemporaneous interaction term with GSCI ($\beta_1^{int,LF}$)	-0.01630*** (0.00382)	0.00600 (0.00469)	0.00360 (0.00457)	0.00514 (0.00650)
Contemporaneous GSCI term (β_1^{int})	0.01322*** (0.00409)			
Contemporaneous dummy term ($\beta_1^{LF=NDVI}$)	-0.00035* (0.00018)			
Observations	10 708			
Groups	53			
Overall Adjusted R^2	0.421			

Note: NDVI is normalized difference vegetation index; GSCI is Goldman Sachs Commodity Index; FCPI is consumer price index for food and beverages. Standard errors are in parentheses. Asterisks for the sum of multiple coefficients refer to the results from joint F-tests. * p<0.1, ** p<0.05, *** p<0.01

[7] The results estimated with the FAO food price index are available upon request.

6. Concluding remarks

This paper examines whether factors that impact local food supply could lead to variations in long-term pass-through from global to domestic food prices and provides estimates of pass-through under different scenarios. Our results suggest that pass-through is relatively small and can vary significantly across time periods and countries.

On average, pass-through is about 35% lower when local crop conditions are better than normal. Since most countries produce a significant portion of their own food requirements, pass-through depends on local crop conditions. For countries with less-developed food industries, where the importance of raw agricultural commodities in diets is relatively greater and supply chains are less complex, pass-through is about 65% higher than for countries with more-developed food industries. Counterintuitively, net exporters of agricultural commodities also experience around 65% more pass-through than net importers. This may be due to incentives for exporters to offload more of their inventories abroad as global prices spike, forcing local prices to rise.

Our analysis raises several policy implications. First, it may be prudent for policy-makers in countries heavily reliant on imports to improve the resilience of domestic food production through investment in agricultural infrastructure and technology. Favourable crop conditions leading to increased local production can help mitigate the impact of price fluctuations in international markets, potentially shielding the country from significant food price spikes. Countries with less-developed food industries that experience higher pass-through from global prices could opt to diversify import sources. Efforts at reducing concentrated exposure to a limited number of trading partners may enhance food security. Lastly, states that traditionally act as net importers could consider developing export capacities to take advantage of high global prices during periods of a glut in local supply. This may also increase local supply, which promotes stability in the domestic market.

Our results, however, do not account for nonlinearities found in the literature (Ferrucci, Jiménez-Rodríguez and Onorantea 2012; Ianchovichina, Loening and Wood 2012; Ghoshray 2011). For example, asymmetric price transmission, where pass-through is higher when world agricultural prices increase and lower when prices decrease, could limit the fall in domestic food prices caused by declines in global prices. Threshold effects also suggest that pass-through occurs only when fluctuations in world prices are sufficiently large or that pass-though is significantly amplified during major spikes in food prices. Under these scenarios, local variables that impact food supply would likely still lead to variations in pass-through. A question for further research is whether patterns of pass-through change when nonlinear effects are active.

Appendix

Table A-1: Countries in the sample

Region	Countries
North America	Canada, Costa Rica, Mexico, United States
South America	Argentina, Brazil, Chile, Colombia, Peru
Europe	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, Ukraine
Middle East	Israel, Türkiye
Africa	South Africa
Asia	China, India, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan (province of China), Thailand

Table A-2: Variables in the model

Variable	Description	Source
FCPI_ret	Log difference of national food and beverage consumer price index (CPI)	Organisation for Economic Co-operation and Development (OECD), national statistical agencies (or other government sources) and central banks via Haver Analytics, Food and Agriculture Organization of the United Nations (FAO)
GSCI_ret	Log difference of S&P GSCI Agricultural & Livestock Index	Standard and Poor's via Haver Analytics
NDVI_dum	Dummy that is equal to 1 when a country's normalized difference vegetation index anomaly (i.e., deviation from 2001–21 average) is greater than 0, signifying above-average crop conditions	GIMMS Global Agricultural Monitoring System by NASA Goddard Space Flight Center, GIMMS and USDA Foreign Agricultural Service

F_weight_dum	Dummy that is equal to 1 when a country's average weight of food expenditure in CPI from 2011 to 2019 (where data are available) is above the sample's cross-country average	International Labour Organization, national statistical agencies and OECD via Haver Analytics
N_exporter_dum	Dummy that is equal to 1 when a country is a cumulative net exporter of major grains and oilseeds over the period from 2000 to 2019. The classification is based on yearly import and export data from FAO and USDA.	FAO, USDA, authors' calculations
EME_dum	Dummy that is equal to 1 when a country is an emerging-market economy and equal to 0 when a country is an advanced economy	
Asia_dum	Dummy that is equal to 1 when a country is in Asia	
FCPI_FPPI_dum	Dummy that is equal to 1 when the spread between month-over-month food CPI growth is greater than month-over-month food producer price index growth	OECD, national statistical agencies (or other government sources) and central banks via Haver Analytics, authors' calculations
Core_ret	Log difference of national core CPI, which excludes energy and food	OECD, national statistical agencies (or other government sources) and central banks via Haver Analytics
Ln_FX	Log level of exchange rates with US$ as the base	Bank for International Settlements and central banks via Haver Analytics, Bloomberg L.P.
Interest_rate	Short-term interest rate or monetary policy rate	Central banks, government sources and OECD via Haver Analytics
CPI_vol_ann	Annualized headline CPI inflation volatility (i.e., annualized standard deviation) over the entire sample	OECD, national statistical agencies (or other government sources) and central banks via Haver Analytics, FAO, authors' calculations

Brent	Global oil price benchmark	Intercontinental Exchange, Inc. via Haver Analytics
Ln_BDIY_index	Log level of the Baltic Dry Index	Baltic Exchange via Bloomberg L.P.
SOI	Southern Oscillation Index, which captures episodes of El Niño and La Niña	National Oceanic and Atmospheric Administration
North_harvest	Dummy that is equal to 1 if the observation is between August and October, which roughly coincides with harvest season in the northern hemisphere	
South_harvest	Dummy that is equal to 1 if the observation is between February and April, which roughly coincides with harvest season in the southern hemisphere	
Shock_2007_2008	Dummy that is equal to 1 if the observation is in the 2007–08 period, which coincides with a major world food price crisis	
Shock_2010_2011	Dummy that is equal to 1 if the observation is in the 2010–11 period, which coincides with a major world food price crisis	

Table A-3: Long-term pass-through for a 1% increase in global prices in US$ with only ln_FX and 12 lags of domestic food inflation as controls (GSCI)

Simple regression with only ln_FX and FCPI lags as control	0.19%
Interaction with NDVI	
Good crop conditions	0.16%
Average or bad crop conditions	0.22%
Interaction with food weight	
Above average	0.23%
Average or below	0.17%
Interaction with net exporter	
Net exporters	0.23%
Net importers	0.16%

Note: FCPI is consumer price index for food and beverages; NDVI is normalized difference vegetation index.

Table A-4: Separate baseline long-term pass-through regressions (GSCI)

	NDVI	Food weight	Net exporter
Contemporaneous interaction term with GSCI ($\beta_1^{int,LF}$)	-0.01699*** (0.00413)	0.00834* (0.00497)	0.00523 (0.00426)
L1_interaction with GSCI ($\beta_2^{int,LF}$)	0.00518 (0.00368)	0.01482** (0.00696)	0.01342** (0.00524)
L2_interaction with GSCI ($\beta_3^{int,LF}$)	-0.00460 (0.00412)	0.01392*** (0.00377)	0.00825** (0.00386)
L3_interaction with GSCI ($\beta_4^{int,LF}$)	0.00577* (0.00317)	-0.00457 (0.00421)	0.00680** (0.00312)
L4_interaction with GSCI ($\beta_5^{int,LF}$)	0.00124 (0.00337)	0.01348** (0.00648)	0.00506 (0.00520)
L5_interaction with GSCI ($\beta_6^{int,LF}$)	-0.00575 (0.00375)	-0.00090 (0.00416)	0.00892** (0.00386)
L6_interaction with GSCI ($\beta_7^{int,LF}$)	0.00415 (0.00315)	-0.00099 (0.00370)	-0.00342 (0.00357)
L7_interaction with GSCI ($\beta_8^{int,LF}$)	-0.00793** (0.00366)	-0.00085 (0.00533)	0.00405 (0.00510)
L8_interaction with GSCI ($\beta_9^{int,LF}$)	-0.00243 (0.00467)	-0.00011 (0.00494)	-0.00622* (0.00368)
L9_interaction with GSCI ($\beta_{10}^{int,LF}$)	-0.00401 (0.00442)	0.00169 (0.00365)	-0.00232 (0.00391)

L10_interaction with GSCI ($\beta_{11}^{int,LF}$)	-0.00612 (0.00467)	0.00636 (0.00388)	0.00678** (0.00313)
L11_interaction with GSCI ($\beta_{12}^{int,LF}$)	-0.00219 (0.00352)	0.00645 (0.00428)	0.00167 (0.00393)
L12_interaction with GSCI ($\beta_{13}^{int,LF}$)	-0.00894*** (0.00329)	-0.00454 (0.00328)	0.00344 (0.00352)
GSCI_ret (β_{1}^{int})	0.01775*** (0.00305)	0.00697*** (0.00245)	0.00793** (0.00304)
L1_GSCI_ret (β_{2}^{int})	0.01883*** (0.00328)	0.01584*** (0.00333)	0.01594*** (0.00447)
L2_GSCI_ret (β_{3}^{int})	0.01596*** (0.00285)	0.00907*** (0.00183)	0.01080*** (0.00205)
L3_GSCI_ret (β_{4}^{int})	0.00274 (0.00250)	0.00739*** (0.00169)	0.00316 (0.00231)
L4_GSCI_ret (β_{5}^{int})	0.01497*** (0.00294)	0.01052*** (0.00197)	0.01333*** (0.00373)
L5_GSCI_ret (β_{6}^{int})	0.00318 (0.00230)	0.00140 (0.00192)	-0.00231 (0.00238)
L6_GSCI_ret (β_{7}^{int})	0.00186 (0.00247)	0.00422* (0.00224)	0.00520** (0.00235)
L7_GSCI_ret (β_{8}^{int})	0.00672** (0.00297)	0.00419* (0.00247)	0.00233 (0.00258)
L8_GSCI_ret (β_{9}^{int})	0.00894*** (0.00261)	0.00707*** (0.00177)	0.00942*** (0.00239)
L9_GSCI_ret (β_{10}^{int})	0.00291 (0.00249)	0.00138 (0.00240)	0.00285 (0.00237)
L10_GSCI_ret (β_{11}^{int})	0.00613** (0.00244)	0.00133 (0.00193)	0.00099 (0.00242)
L11_GSCI_ret (β_{12}^{int})	0.01334*** (0.00254)	0.01077*** (0.00189)	0.01238*** (0.00248)
L12_GSCI_ret (β_{13}^{int})	0.00662*** (0.00227)	0.00489** (0.00212)	0.00199 (0.00222)
Contemporaneous dummy term (β_{1}^{LF})	-0.00035* (0.00018)		
L1_dummy term (β_{2}^{LF})	-0.00002 (0.00019)		
L2_dummy term (β_{3}^{LF})	0.00004 (0.00015)		

L3_dummy term (β_4^{LF})	-0.00011 (0.00015)		
L4_dummy term (β_5^{LF})	0.00002 (0.00018)		
L5_dummy term (β_6^{LF})	-0.00022 (0.00015)		
L6_dummy term (β_7^{LF})	-0.00003 (0.00014)		
L7_dummy term (β_8^{LF})	0.00001 (0.00018)		
L8_dummy term (β_9^{LF})	0.00029* (0.00017)		
L9_dummy term (β_{10}^{LF})	0.00026* (0.00014)		
L10_dummy term (β_{11}^{LF})	0.00003 (0.00014)		
L11_dummy term (β_{12}^{LF})	-0.00004 (0.00014)		
L12_dummy term (β_{13}^{LF})	0.00003 (0.00018)		
L1_FCPI_ret (β_1^{dom})	0.13286*** (0.03187)	0.13158*** (0.03137)	0.13161*** (0.03145)
L2_FCPI_ret β_2^{dom}	-0.03592 (0.02271)	-0.03684 (0.02246)	-0.03683 (0.02280)
L3_FCPI_ret β_3^{dom}	-0.04280* (0.02179)	-0.04403** (0.02187)	-0.04405** (0.02181)
L4_FCPI_ret β_4^{dom}	-0.02189 (0.01423)	-0.02368* (0.01397)	-0.02351 (0.01445)
L5_FCPI_ret β_5^{dom}	-0.03191* (0.01896)	-0.03272* (0.01858)	-0.03235* (0.01926)
L6_FCPI_ret β_6^{dom}	-0.01107 (0.01179)	-0.01208 (0.01174)	-0.01213 (0.01191)
L7_FCPI_ret β_7^{dom}	-0.04370*** (0.01387)	-0.04342*** (0.01366)	-0.04288*** (0.01388)
L8_FCPI_ret β_8^{dom}	-0.00587 (0.02402)	-0.00680 (0.02348)	-0.00667 (0.02366)
L9_FCPI_ret β_9^{dom}	-0.03316** (0.01396)	-0.03567** (0.01391)	-0.03582** (0.01394)

L10_FCPI_ret β_{10}^{dom}	-0.01360 (0.01390)	-0.01392 (0.01401)	-0.01376 (0.01394)
L11_FCPI_ret β_{11}^{dom}	0.03733*** (0.01148)	0.03527*** (0.01153)	0.03594*** (0.01167)
L12_FCPI_ret β_{12}^{dom}	0.18365*** (0.02381)	0.18499*** (0.02393)	0.18458*** (0.02387)
FCPI_FPPI_dum	0.00882*** (0.00078)	0.00884*** (0.00078)	0.00883*** (0.00078)
Core_ret	0.22707*** (0.08238)	0.22474** (0.08354)	0.22538*** (0.08321)
ln_FX	0.00433*** (0.00114)	0.00440*** (0.00118)	0.00442*** (0.00115)
Interest_rate	0.00010** (0.00004)	0.00011** (0.00004)	0.00010** (0.00004)
CPI_vol_ann	2.43085*** (0.38430)	2.38662*** (0.38193)	2.39874*** (0.37739)
Brent	0.00002*** (0.00000)	0.00002*** (0.00000)	0.00002*** (0.00000)
ln_BDIY_index	-0.00029* (0.00015)	-0.00025* (0.00014)	-0.00025* (0.00013)
SOI	-0.00020** (0.00010)	-0.00016 (0.00010)	-0.00016 (0.00010)
north_harvest	-0.00024 (0.00040)	-0.00034 (0.00040)	-0.00034 (0.00040)
south_harvest	-0.00088** (0.00034)	-0.00088** (0.00033)	-0.00088** (0.00033)
shock_2007_2008	0.00293*** (0.00036)	0.00279*** (0.00035)	0.00279*** (0.00036)
shock_2010_2011	0.00070*** (0.00026)	0.00055** (0.00026)	0.00055** (0.00026)
Observations	10 708	10 708	10 708
Groups	53	53	53
Overall Adjusted R^2	0.417	0.418	0.417

Note: NDVI is normalized difference vegetation index. Standard errors are in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

References

Baltzer, K. 2013. "International to Domestic Price Transmission in Fourteen Developing Countries During the 2007–08 Food Crisis." World Institute for Development Economic Research Working Paper No. 2013-031.

Becker-Reshef, I., C. Justice, M. Sullivan, E. Vermote, C. Tucker, A. Anyamba, J. Small, E. Park, E. Masuoka, J. Schmaltz, M. Hansen, K. Pittman, C. Birkett, D. Williams, C. Reynolds and B. Doorn. 2010. "Monitoring Global Croplands with Coarse Resolution Earth Observations: The Global Agriculture Monitoring (GLAM) Project." *Remote Sensing* 2 (6): 1589–1609.

Bekkers, E., M. Brockmeier, J. Francois and F. Yang. 2017. "Local Food Prices and International Price Transmission." *World Development* 96 (August): 216–230.

Brown, M. E. and V. Kshirsagar. 2015. "Weather and International Price Shocks on Food Prices in the Developing World." *Global Environmental Change* 35 (November): 31–40.

Cachia, F. 2014. "Regional Food Price Inflation Transmission." FAO Statistics Division ESS Working Paper No. 14-01.

Ceballos, F., M. A. Hernandez, N. Minot and M. Robles. 2017. "Grain Price and Volatility Transmission from International to Domestic Markets in Developing Countries." *World Development* 94 (June): 305–320.

Conforti, P. 2004. "Price Transmission in Selected Agricultural Markets." FAO Commodity and Trade Policy Research Working Paper No. 7.

Cowley, C. and F. Scott. 2022. "Commodity Prices Have Limited Influence on U.S. Food Inflation." *Economic Bulletin*. Federal Reserve Bank of Kansas City, September 23.

Dawe, D. 2010. "Can the Next Rice Crisis Be Prevented?" In *The Rice Crisis: Markets, Policies and Food Security*, 345–356. London and Washington, DC: FAO and Earthscan.

Ferrucci, G., R. Jiménez-Rodríguez and L. Onorantea. 2012. "Food Price Pass-Through in the Euro Area: Non-Linearities and the Role of the Common Agricultural Policy." *International Journal of Central Banking* 8 (1): 179–217.

Flachsbarth, I. and A. Garrido. 2014. "The Effects of Agricultural Trade Openness on Food Price Transmission in Latin American Countries." *Spanish Journal of Agricultural Research* 12 (4): 927–940.

Furceri, D., P. Loungani, J. Simon and S. M. Wachter. 2016. "Global Food Prices and Domestic Inflation: Some Cross-Country Evidence." *Oxford Economic Papers* 68 (3): 665–687.

Ghoshray, A. 2011. "Underlying Trends and International Price Transmission of Agricultural Commodities." Asian Development Bank Economics Working Paper Series No. 257.

Glauber, J., M. Hernández, D. Laborde, W. Martin, B. Rice and R. Vos. 2022. "No End in Sight Yet for the Global Food Price Crisis." IFPRI Blog Series: The Russia-Ukraine War and Global Food Security, September 27.

Greb, F., N. Jamora, C. Mengel, S. von Cramon-Taubadel and N. Würriehausen. 2012. "Price Transmission from International to Domestic Markets." Courant Research Centre Poverty, Equity and Growth in Developing and Transition Countries: Statistical Methods and Empirical Analysis. Discussion Paper No. 125.

Helbling, T. and S. K. Roache. 2011. "Rising Prices on the Menu: Higher Food Prices May Be Here to Stay." *Finance & Development* 48 (1): 24–27.

Ianchovichina, E., J. Loening and C. Wood. 2012. "How Vulnerable Are Arab Countries to Global Food Price Shocks?" World Bank Policy Research Working Paper No. 6018.

IMF. 2011. *World Economic Outlook: Slowing Growth, Rising Risks*. Washington DC: International Monetary Fund. September.

IMF. 2022. *World Economic Outlook: Countering the Cost-of-Living Crisis*. Washington DC: International Monetary Fund. October.

Kalkuhl, M. 2014. "How Strong Do Global Commodity Prices Influence Domestic Food Prices? A Global Price Transmission Analysis." 2014 Annual Meeting, July 27–29, Minneapolis, Minnesota. Agriculture and Applied Economics Association.

Kohlscheen, E. 2022. "Understanding the Food Component of Inflation." Bank for International Settlements Working Paper No. 1056.

Laborde, D., C. Lakatos and W. Martin. 2019. "Poverty Impact of Food Price Shocks and Policies." World Bank Policy Research Working Paper No. 8724.

Lee, H.-H. and C.-Y. Park. 2013. "International Transmission of Food Prices and Volatilities: A Panel Analysis." Asian Development Bank Economics Working Paper Series No. 373.

Lloyd, T., S. McCorriston and E. Zvogu. 2015. "Common Shocks, Uncommon Effects: Food Price Inflation across the EU." 2015 Conference, August 9–14. Milan, Italy: International Association of Agricultural Economists.

Martin, W. and N. Minot. 2022. "The Impacts of Price Insulation on World Wheat Markets During the 2022 Food Price Crisis." *Australian Journal of Agricultural and Resource Economics* 66 (4): 753–774.

Minot, N. 2011. "Transmission of World Food Price Changes to Markets in Sub-Saharan Africa." IFPRI Discussion Paper No. 01059.

Nzuma, J. M. 2013. "The Political Economy of Food Price Policy: The Case of Kenya." World Institute for Development Economics Research Working Paper No. 2013/026.

Sahoo, S., S. Kumar and B. Gupta. 2020. "Pass-through of International Food Prices to Emerging Market Economies: A Revisit." *Reserve Bank of India Occasional Papers* 41 (1): 47–76.