Annex 1.SF.1.

Dynamic causal effects of energy, harvest, and monetary policy shocks on food commodity prices

We use Local Projection Instrumental Variables to obtain causal estimates of the spillover effects from fertilizer to cereal prices as well as dynamic causal effects of US monetary policy shocks and of cereal harvest shocks. To study how oil prices affect cereal prices we expand the framework introduced by Kilian (2009), which disentangles the effect of oil supply shocks, oil-specific demand shocks and aggregate demand shocks on oil prices.

The LP-IV can be expressed as:

$$y_{t+h} = a_h + \theta_h x_t + \lambda_h(L) z_{t-1} + u_{t+h} \qquad \text{for } h \in \{0,1,2,3,4\} \qquad (1)$$

where y_t is the delta log of real price of cereals, x_t is the regressor of interest representing each of the three channels, namely, delta log of fertilizers' price (average across urea, potash, and phosphates[1]) in real terms, absolute change of the interest rate on the three months treasury bill and (standardized) delta log of global cereal production[2]. The vector z_{t-1} contains predetermined controls like global GDP growth and the US dollar real effective exchange rate. Our specification of the right-hand side variables is standard in the literature (Gilbert, 2010, Baffes and Haniotis, 2016). Further, $\lambda_h(L)$ is a polynomial of order 4 in the lag operator and θ_h is the dynamic effect of the regressor of interest at horizon h.

Dynamic causal effects of each channel are represented under the form of Impulse Response Functions (h, θ_h). Each $\theta_{h,z}$ is estimated via classical instrumental variables (IV) $\frac{E(y_{t+h}z)}{E(y_t z_t)}$. To ease the interpretation of the IRF, the unit effect normalization is imposed automatically in the 2SLS approach, whereby a 1% increase in one of the shocks, say the monetary policy shock, leads to a 1% increase in the 3-months treasury bill rate. To give θ_h a causal interpretation we use instruments to induce exogenous variation in each of the three channels given respectively by: changes in real gas prices, US monetary policy shocks from Jarocinski and Keradi (2020)[3] and cereal harvest shocks from De Winne and Peersman (2016)[4].

[1] Nitrogen-based fertilizers like urea account for around two thirds of total fertilizer consumption, 60% of which is used to grow cereals.

[2] This variable was built by assigning FAO's annual production figures to a specific quarter based on each country's crop calendar and aggregating at the global level. The global series is then seasonally adjusted assuming a deterministic seasonal pattern.

[3] The authors identify monetary policy shocks and central bank information shocks using sign and zero restrictions in a VAR that includes the surprises in the three-month fed funds futures and the S&P 500 stock market index as well as five lower frequency macro variables.

[4] One instrument is the unexpected caloric shock from global cereal production, constructed as the residual from a regression of log cereal yields on country- and crop-specific time trends, which are then summed over all countries and crops using production weights and the caloric content of each crop. The second one is a "narrative" instrument given by a dummy equal to 1 for notorious global cereal shortcomings mostly from weather events and -1 for unexpected bumper harvests.

Due to data limitations on some of the variables, our final estimation sample covers from 1991Q1 to 2021Q1. All variables are deflated by the US GDP deflator.

Further, we estimate the following SVAR

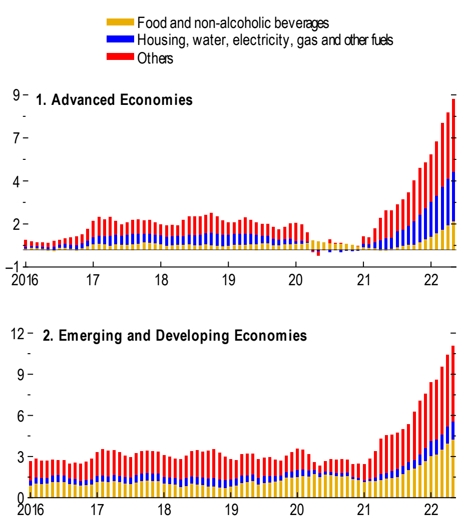
$$\boldsymbol{A y_t} = \boldsymbol{\alpha} + \textstyle\sum_{i=1}^{p} \boldsymbol{B_i y_{t-i}} + \boldsymbol{e_t} \qquad (2)$$

Where A and B are matrices of coefficients, y_t is a 6-dimentionsional vector that includes the original three variables in the same order as in Kilian (2009), i.e., delta log of global oil supply, global real economic activity indicator, and log oil prices, to which we add the log of gas prices, the log of fertilizer prices and the log of cereal prices. The vector of structural shocks is assumed to be mutually uncorrelated. Pre-multiplying both sides of equation (2) by A^{-1} it is easy to obtain the reduced form VAR as $\boldsymbol{y_t} = \boldsymbol{\omega} + \sum_{i=1}^{p} \boldsymbol{B_i^* y_{t-i}} + \boldsymbol{u_t}$ and the corresponding errors $\boldsymbol{u_t} = \boldsymbol{A^{-1} e_t}$.

We rely on zero restrictions on contemporaneous relations to recover the structural shocks and from them the cumulative orthogonalized IRF. Based on (Kilian, 20019)[5], the shocks corresponding to the first three equations are identified as the oil supply shock, the aggregate demand shock and the oil-specific demand shock. For the bottom three equations, our short-term restrictions imply that within the period (month) fertilizer prices don't affect gas prices and cereal prices don't affect fertilizer prices. While the first assumption seems plausible, since fertilizers are a small share of total gas usage, the second assumption may be less tenable, as fertilizer demand may react quickly to current or expected changes in cereal prices. However, the gas and fertilizer prices are included only as transmission channels from oil towards cereal prices, which is our only IRF of ultimate interest in this exercise. We do not attempt to label the corresponding shocks, as we don't include quantities in the last three equations.

Finally, we assume the top block of variable to be exogenous, within the month, to changes in any of the variables in the bottom block. Structural IRFs are shown in figure 1.SF.A.1. The top left chart shows that a 10% negative oil supply shock leads to an increase in oil prices of 0.4% after 9 months. The top right graph is the monthly frequency equivalent of the top-right IRF in figure 1.SF.7 Further, the effects of a 10% negative oil supply shock on fertilizer prices are mostly statistically insignificant, while for gas prices they peak at 10% after 8 months and stabilize afterwards.

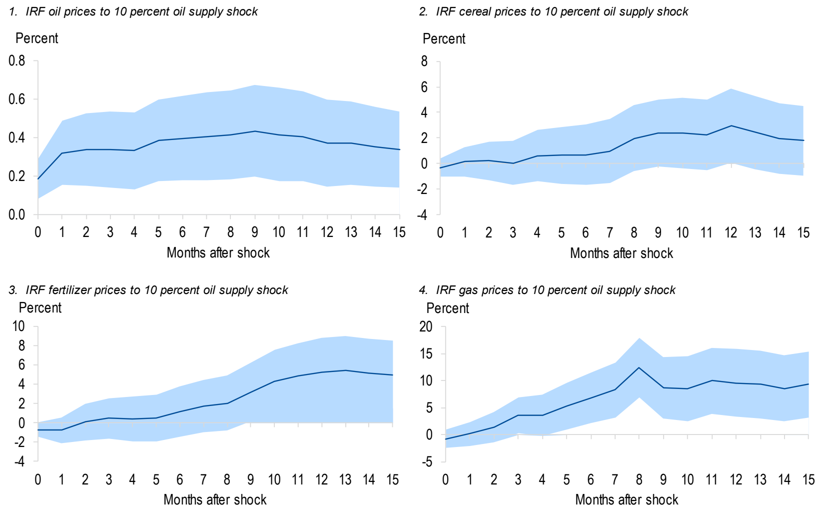
Figure 1.SF.4. Contribution of Food and Energy to Inflation
(Percent)



Sources: IMF Consumer Price Index database and IMF staff calculations.
Note: The inflation contribution is calculated based on OECD COICOP components methodology.

[5] Global oil supply is taken to be the "most exogenous" of all variables since its production is controlled by few large producers and elasticity of supply is low in the very short term (with the month) due the capital-intensive nature of the production. Second, global demand responds with the month to oil supply shock, but it will take more than one month for the global economy to respond to oil price changes.

Figure 1.SF.A 1. IRFs of oil supply shocks



Sources: Haver Analytics; World Bank; IMF CPI and PCPS database; and IMF staff estimates.
Note: 95-percent confidence bands. Orthogonalized impulse response function.

We also explore the influence of speculative demand and of the financialization of commodities markets on cereal prices. We define speculative periods as those during which cereal prices and net long positions of non-commercial traders (surplus of long positions over short positions for futures contracts with cereals as underlying held by non-commercial traders, typically, asset managers and other financial institutions) change in the same direction. We then build a dummy (S_t) that equals 1 for speculative periods and 0 otherwise. We estimate a triple "difference in difference"-type specification:

$$y_t = a + \beta_1 S_t + \beta_2 D_t + \beta_3 I_t + \beta_4 I_t S_t + \beta_5 D_t S_t + \beta_6 I_t D_t + \beta_7 D_t S_t I_t + e_t \qquad (2)$$

where y_t is the delta log of cereal prices and D_t is a dummy that equals 1 after 2003, which is the time identified in the literature when asset managers substantially increase involvement in commodities' futures and options, thus marking a stark intensification of financialization of commodities markets (Peersman, 2021). Further, I_t is the delta log of the S&P500 index. We empirically verify our hypothesis that the correlation between traditional financial asset prices (I_t) and cereal prices increased due to speculative demand after the start of the financialization process through a t-test on the interaction coefficient (H_0: $\beta_7 = 0$). We use monthly data covering the period 1980M1-2022M3. Results reported in Table A1 show that this is in fact the case. Financialization led the pass-through from the S&P500 to cereal price to be 56 percent higher in speculative periods than in non-speculative periods.

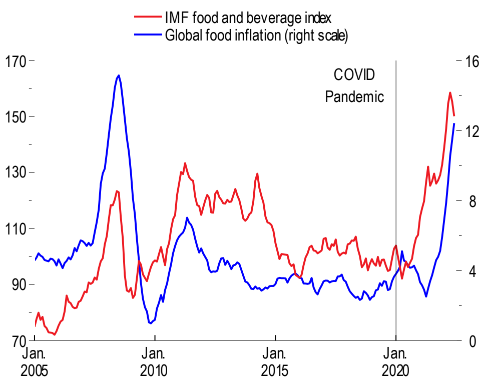
Table A1: Effect of financialization and speculative demand

I_t	0.114
	(0.0732)
S_t	0.00304
	(0.00460)
S_t*I_t	-0.188
	(0.133)
D_t	0.0110**
	(0.00510)
$D_t * S_t$	-0.0101
	(0.00775)
$D_t * I_t$	-0.142
	(0.127)
$D_t * S_t * I_t$	0.557**
	(0.239)
_cons	-0.00219
	(0.00273)
N	507

Note: * 0.10 ** 0.05 *** 0.01

Dynamic causal effects of food commodity price shocks on domestic food inflation and the role of country characteristics

Figure 1.SF.7. Food Inflation Follows Higher International Commodity Prices



Sources: Haver, IMF Consumer Price Index database and Primary Commodity Price System database, World Bank; and IMF staff calculations.
Note: Last observation is June 2022. 58.24 percent global population and 77 countries are covered at this time (based on 2018 world population).

To track the magnitude and trajectory of the pass-through from global food commodity prices to domestic food prices, we follow Jordà (2005), Montiel Olea and Plagborg-Møller (2021), De Winne and Peersman (2021), and others, and estimate impulse response functions (IRFs) from lag-augmented local projections with instrumental variables (LP-IV). For each horizon $h = 0,1,2,\ldots 18$, the following eq. is estimated using monthly data:

$$\begin{aligned} ln(\mathrm{P}_{i,t+h}) - ln(\mathrm{P}_{i,t-1}) &= \delta_h(L)\Delta \ln(\mathrm{P}_{i,t}) + \rho_h(L)\Delta ln(W_{i,t}) \\ &+ \vartheta_k^h char_{k,i} \\ +[\beta_0^h + \beta_k^h char_{k,i}]\Delta ln(X_t) &+ \alpha_i^h + \lambda^h t + \varepsilon_{i,t+h} \end{aligned}$$

Where $P_{i,t}$ is the food CPI in country i at time t, X_t is the vector of endogenous variables, i.e., the IMF's food price index and the Baltic Dry Index as our measures of food commodity prices and shipping costs respectively, and $W_{i,t}$ is a vector of controls determined before date *t*, i.e., the exchange rate (in LCU/USD), headline inflation, and real oil prices. The parameters α_i^h, $\lambda^h t$

and $\varepsilon_{i,t+h}$ represents country fixed effects, a year trend, and the error term respectively, while $\delta_h(L)$ and $\rho_h(L)$ are polynomials in the lag operator (L=18). The parameter $char_{k,i}$ reflects a set of country characteristics, specifically real income per capita (in 2010 USD) and trade openness (% of GDP), both of which are expressed in standard deviations from the global mean. Note that all regressors in *P*, *X* and *W* are incorporated on the right-hand side in monthly log-differences.

Dynamic causal effects of our two endogenous regressors are represented as impulse response functions (k, β_0^k). To isolate exogenous variation in our main predictor of interest and thus identify a causal effect through β_0^k, we follow De Winne and Peersman (2021) and employ harvest shocks as an instrumental variable for food commodity prices, and borrow the idea from Carriere-Swallow et al. (2022) to use closure events of the Suez Canal to instrument for the Baltic Dry Index. We thus depart from the existing literature by recognizing the potential for reverse causality between domestic food prices in large economies on the one hand and international food prices and shipping costs on the other hand.

To create the harvest shocks, we allocate annual production of the 4 most important staple foods (maize, rice, soybeans, and wheat) to a specific quarter by making use of crop and country-specific harvesting calendars. For each country, a rest-of-world harvest quantity is then obtained by taking the calorie-weighted average of all 4 crops across all countries minus harvests from countries in the same region. The harvest shocks are then obtained as the prediction errors from a regression of the harvest quantities on several lagged values and some control variables.

The sample covers more than 100 countries for the period 1991-2020 and spans two episodes of high international food prices (2007-2008 and 2010-2012). Our main results are reported in Table A2, where, by column, we display the regression coefficient estimates for various horizons. The pass-through from a 1pp food commodity price shock to domestic food prices is about 0.30pp after 12 months. The exchange rate pass-through is, as expected, very similar, as it shouldn't matter to food importers whether the source of the increase in commodity prices (in local currency units) is an exchange rate depreciation or an increase in the US dollar price of a food commodity. Over the same 12 month horizon, a 1pp increase in shipping costs translates into a 0.09pp increase in domestic food prices.

Finally, as our trade openness and income per capita variables are expressed in deviations from their global means, we can infer immediately from Table A2 that a country whose income per capita is 1 standard deviation below average will feature a food commodity price pass-through that is about 35 percent rather than 29 percent 9 months after the shock. Similarly, for a country with a degree of trade openness that is 1 standard deviation above average, the pass-through increases from 29 to 37 percent.

Table A2: Food commodity price pass-through and role of income per capita and trade openness.

	cumulative food inflation					
	h=1	h=3	h=6	h=9	h=12	h=18
food price index (mom log-diff)	0.009+	0.104***	0.207***	0.288***	0.302***	0.326***
	0.005	0.015	0.032	0.042	0.046	0.057
exchange rate (in LCU/USD) (mom log-diff)	-0.040***	0.080	0.197**	0.268***	0.341***	0.354***
	0.006	0.049	0.071	0.077	0.086	0.091
Baltic Dry Index (BDI) (mom log-diff)	-0.003	-0.019+	0.002	0.040	0.088**	0.075*
	0.003	0.011	0.020	0.027	0.030	0.037
headline CPI (mom log-diff)	1.234***	1.624***	1.722**	1.739*	1.712*	1.922*
	0.056	0.419	0.615	0.700	0.754	0.895
real oil price (in USD) (mom log-diff)	-0.006**	-0.000	-0.013	-0.024+	-0.032*	-0.037+
	0.002	0.006	0.010	0.013	0.015	0.019
income per capita X food price index	-0.010*	-0.025*	-0.045**	-0.060**	-0.047*	0.016
	0.004	0.011	0.016	0.020	0.023	0.028
trade openness X food price index	-0.002	0.004	0.049+	0.069+	0.049	-0.003
	0.005	0.016	0.029	0.037	0.044	0.059
trade openness	0.188***	0.683***	1.121***	1.462***	1.651***	1.336**
	0.041	0.131	0.231	0.297	0.364	0.481
income per capita	0.207	-0.002	0.474	1.132	1.526	1.917
	0.137	0.473	0.772	0.954	1.097	1.410
Observations	13788	13788	13788	13788	13788	13788
# of countries	97	97	97	97	97	97
R-sq	0.793	0.496	0.394	0.348	0.304	0.262
model	iv	iv	iv	iv	iv	iv

Sources: Food and Agriculture Organization; Haver Analytics; World Bank, World Bank Development Indicators database; IMF; and IMF staff calculations.
Robust standard errors clustered at the country level in parentheses. Country fe included but not reported
iv = instrumental variables. fe=fixed effects. Mom = month-on-month. LCU=local currency units.
+ p<0.10; * p<0.05; ** p<0.01; *** p<0.001.

References

Carriere-Swallow, M. Y., Deb, M. P., Furceri, D., Jimenez, D., & Ostry, M. J. D. (2022). *Shipping Costs and Inflation* (No. 17259). International Monetary Fund.

De Winne, J., & Peersman, G. (2016). Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States. *Brookings Papers on Economic Activity*, 183–263.

De Winne, J., & Peersman, G. (2021). The adverse consequences of global harvest and weather disruptions on economic activity. *Nature Climate Change*, *11*(8), 665-672.

Baffes, J. and Haniotis, T. (2016). What Explains Agricultural Price Movements?. *Journal of Agricultural Economics*, 67: 706-721.

Gilbert, C.L. (2010). How to Understand High Food Prices. *Journal of Agricultural Economics*, 61: 398-425.

Jarociński, M, and Karadi, P. 2020. Deconstructing Monetary Policy Surprises—The Role of Information Shocks. *American Economic Journal: Macroeconomics*, 12 (2): 1-43.

Kilian, Lutz. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *American Economic Review*, 99 (3): 1053-69.

Montiel Olea, José Luis, and Mikkel Plagborg-Møller (2021). Local projection inference is simpler and more robust than you think." *Econometrica* 89.4 (2021): 1789-1823.

Peersman, G., Rüth, S., K. and Van der Veken, W. (2021). The interplay between oil and food commodity prices: Has it changed over time? *Journal of International Economics*, Volume 133: (103540).