COMMODITY SPECIAL FEATURE: ONLINE ANNEX 1.1

Commodity Prices and Monetary Policy: High Frequency Analysis

Data

Regressions in the high-frequency analysis use disaggregated daily data on nominal commodity prices, denominated in USD, for 39 different commodities (see Online Annex 1.1 Table 1.SF.1).

Online Annex 1.1 Table 1.SF.1. List of USD Denominated Commodity Prices

Commodity Name	Exchange	Quote Unit	Average Daily Trading Volume in 2019
Gold	Commodity Exchange, Inc.	USD/t oz.	177,464,234
Nickel	London Metal Exchange	USD/MT	138,216,764
Copper	London Metal Exchange	USD/MT	104,462,976
Primary Aluminum	London Metal Exchange	USD/MT	53,664,049
Cocoa	ICE Futures US Softs	USD/MT	34,864,965
WTI Crude Oil	New York Mercantile Exchange	USD/bbl.	33,448,184
Low Sulphur Gas Oil	ICE Futures Europe Commodities	USD/MT	32,409,243
Zinc	London Metal Exchange	USD/MT	27,017,217
Brent Crude Oil	ICE Futures Europe Commodities	USD/bbl.	16,004,134
Platinum	New York Mercantile Exchange	USD/t oz.	13,081,480
Tin	London Metal Exchange	USD/MT	10,664,502
Soybean Meal	Chicago Board of Trade	USD/T.	10,028,620
Lead	London Metal Exchange	USD/MT	8,151,304
Robusta Coffee	ICE Futures Europe Commodities	USD/MT	6,955,321
Palladium	New York Mercantile Exchange	USD/t oz.	4,963,332
Silver	Commodity Exchange, Inc.	USD/t oz.	806,660
Soybean	Chicago Board of Trade	USd/bu.	656,923
Corn	Chicago Board of Trade	USd/bu.	576,671
Henry Hub Natural Gas	New York Mercantile Exchange	USD/MMBtu	357,420
Wheat	Chicago Board of Trade	USd/bu.	233,634
Copper	Commodity Exchange, Inc.	USd/lb.	111,662
Hard Red Winter Wheat	Chicago Board of Trade	USd/bu.	102,467
Gasoline	New York Mercantile Exchange	USd/gal.	96,112
Heating Oil	New York Mercantile Exchange	USd/gal.	91,004
Arabica Coffee	ICE Futures US Softs	USd/lb.	17,706
Live Cattle	Chicago Mercantile Exchange	USd/lb.	16,154
Soybean Oil	Chicago Board of Trade	USd/lb.	10,151
Lean Hogs	Chicago Mercantile Exchange	USd/lb.	9,166
Sugar No.11	ICE Futures US Softs	USd/lb.	8,084
Cotton	ICE Futures US Softs	USd/lb.	7,361
Rough Rice	Chicago Board of Trade	USD/cwt	6,322
Feeder Cattle	Chicago Mercantile Exchange	USd/lb.	4,297
Rotterdam Coal	ICE Futures Europe Commodities	USD/MT	4,130
Newcastle Coal	ICE Futures Europe Commodities	USD/MT	3,551
Class III Milk	Chicago Mercantile Exchange	USD/cwt	3,171
Richards Bay Coal	ICE Futures Europe Commodities	USD/MT	2,820
Oats	Chicago Board of Trade	USd/bu.	1,028
Frozen Concentrate Orange Juic	ICE Futures US Softs	USd/lb.	907
Sugar No.16	ICE Futures US Softs	USd/lb.	41

Sources: Bloomberg L.P.; and IMF staff calculations.
Note: Trading volume unit is US dollar. bbl. = Barrel of Crude Oil; bu. = Bushel; cwt. = Hundredweight; gal. = Gallon; lb. = Pound; MMBtu = Million Birtish Thermal Units; MT = Metric Ton; t oz. = Troy Ounce.

Online Annex 1.1 Table 1.SF.2. Trade Weights in the Construction of Subindexes
(Percent)

Commodity	All	Agriculture	Energy	Metal	Food	Base Metal	Beverage	Precious Metal	Agricultural Raw Material	Cereal	Meat	Vegatable Oil
Aluminum	3.15	--	--	8.86	--	23.92	--	--	--	--	--	--
Beef	3.97	14.40	--	--	18.17	--	--	--	--	--	57.57	--
Brent Crude	18.43	--	50.00	--	--	--	--	--	--	--	--	--
Cocoa	1.23	4.47	--	--	--	--	46.13	--	--	--	--	--
Coffee Arabica	1.44	5.22	--	--	--	--	53.87	--	--	--	--	--
Copper	6.53	--	--	18.38	--	49.61	--	--	--	--	--	--
Corn	2.10	7.63	--	--	9.63	--	--	--	--	34.78	--	--
Cotton	1.58	5.72	--	--	--	--	--	--	51.67	--	--	--
Gold	19.68	--	--	55.36	--	--	--	87.93	--	--	--	--
Lead	0.70	--	--	1.98	--	5.35	--	--	--	--	--	--
Nickel	1.33	--	--	3.74	--	10.11	--	--	--	--	--	--
Oats	0.11	0.38	--	--	0.48	--	--	--	--	1.75	--	--
Orange	2.07	7.52	--	--	9.49	--	--	--	--	--	--	--
Palladium	0.57	--	--	1.61	--	--	--	2.56	--	--	--	--
Platinum	0.85	--	--	2.38	--	--	--	3.78	--	--	--	--
Rice	1.16	4.19	--	--	5.29	--	--	--	--	19.12	--	--
Rubber	1.48	5.35	--	--	--	--	--	--	48.33	--	--	--
Silver	1.28	--	--	3.61	--	--	--	5.73	--	--	--	--
Soybean	3.58	12.96	--	--	16.36	--	--	--	--	--	--	85.82
Soybean Oil	0.59	2.14	--	--	2.70	--	--	--	--	--	--	14.18
Sugar No. 11	2.67	9.68	--	--	12.21	--	--	--	--	--	--	--
Swine	2.93	10.61	--	--	13.39	--	--	--	--	--	42.43	--
Tin	0.32	--	--	0.90	--	2.42	--	--	--	--	--	--
Wheat	2.68	9.73	--	--	12.27	--	--	--	--	44.35	--	--
WTI Crude	18.43	--	50.00	--	--	--	--	--	--	--	--	--
Zinc	1.13	--	--	3.18	--	8.59	--	--	--	--	--	--

Sources: IMF Primary Commodity Price System database; UN Comtrade; and IMF staff calculations.

Nine sub-indexes (base metals, crude oil, precious metals, food, beverages, cereals, cotton and rubber, meat, and oilseed) are constructed using commodities prices that are available at daily frequency for the whole sample period 1990-2019 (Online Annex 1.1 Table 1.SF.2). Trade weights are from the IMF Primary Commodity Price System (PCPS) database.

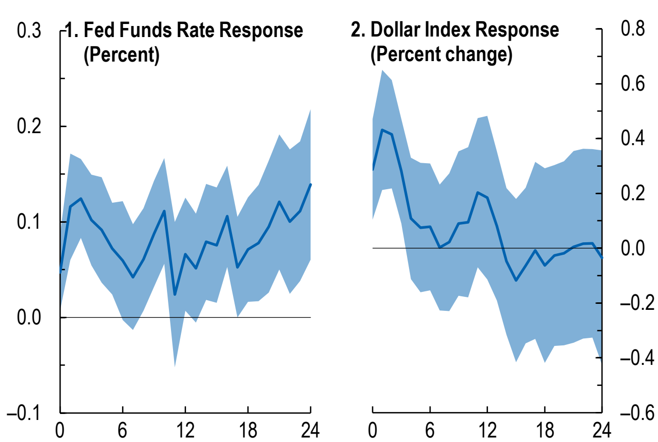
High-Frequency Local Projections

Local Projection (LP) regressions (Jordà, 2005) are used to study the effects of monetary policy shocks on commodity prices

$$\ln y_{i,t+h} - \ln y_{i,t-1} = \alpha_{i,t} + \beta_{i,h} MPS_t^{US} + \sum_{l=1}^{L} \phi_{x,l}\, x_{t-l} + \mu_{i,t+h} \quad (1)$$

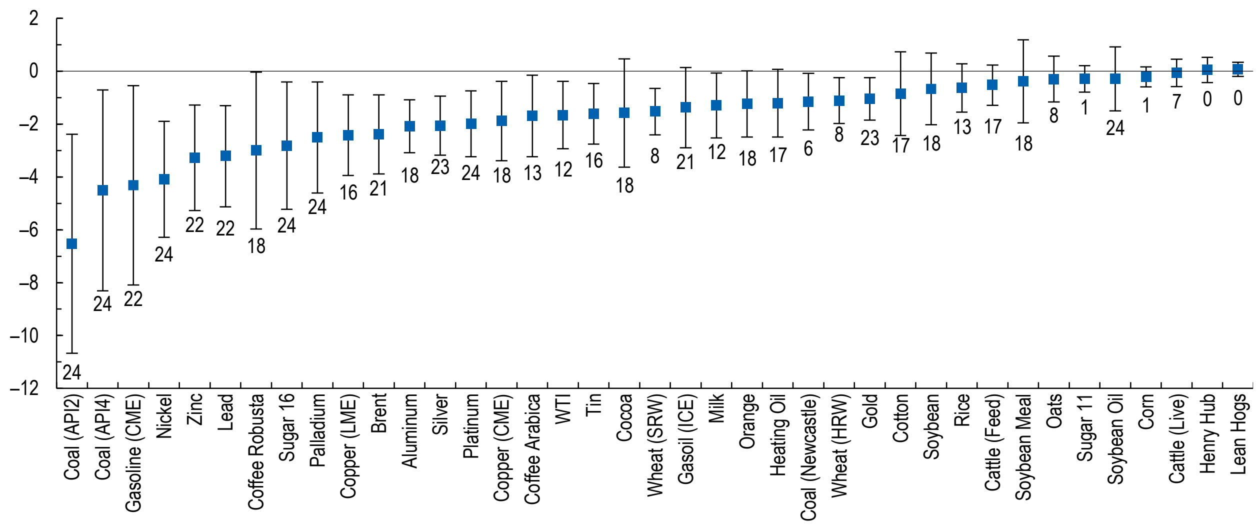
where $y_{i,t+h}$ is the price of commodity i at time (business day) $t+h$. The variable MPS_t^{US} is the "pure" monetary policy shock (measured in basis points), to the three-months-ahead federal funds futures, estimated by Jarociński and Karadi (2020) which eliminates the surprises that correlate positively with the stock market. x_{t-l} is a

Online Annex 1.1 Figure 1.SF.1. Fed Funds Rate and Dollar Index Response to a 10-Basis-Point Surprise in US Monetary Policy



Sources: Bloomberg L.P.; and IMF staff calculations.
Note: Shaded area is 90 percent confidence interval.

Online Annex 1.1 Figure 1.SF.2. Peak Commodity Price Responses to a 10-Basis-Point US Monetary Policy Shocks
(Percent change)

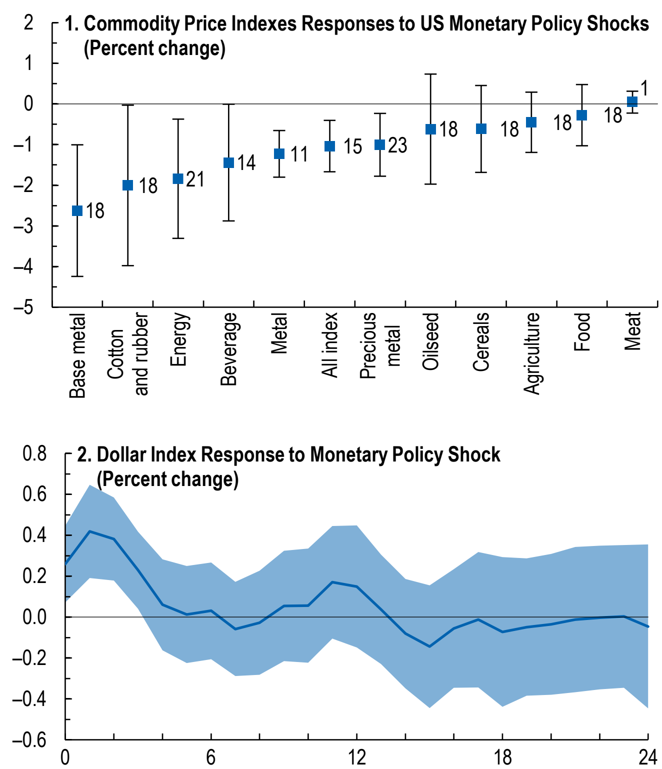


Sources: Bloomberg L.P.; IMF Primary Commodity Price System; UN Comtrade database; and IMF staff calculations.
Note: Numbers represent the horizon (day) of the maximum decline in commodity prices. 90 percent error bars are displayed.

vector of controls, which in this case are 12 lags of the impact log-change of commodity prices ($\ln y_{it} - \ln y_{it-1}$) and 12 lags of the monetary policy shock. The sample covers the period from January 1990 to May 2019. After a 10 basis points monetary policy shock fed funds rate show a strong and persistent increase (Online Annex 1.1 Figure 1.SF.2 panel 1) while the dollar index show a temporary appreciation (Online Annex 1.1 Figure 1.SF.2 panel 2). The 90% confidence error bands are calculated as $\pm 1.645 \cdot SE_h$, where SE_h is the robust standard error at horizon h.

Statistically significant responses are found for coal prices, Nickel, Gasoline, Zinc, Lead, Coffee, Sugar, Palladium, Copper, Oil, Aluminum, Silver, Platinum, Tin, Wheat, Milk, and Gold (Figure 2). There is no effect on natural gas prices (Henry Hub price). However, for the more recent period 2015-2019, when US natural gas exports surged, there is strong evidence of a negative response of US natural gas prices to US monetary tightening shock.

Online Annex 1.1 Figure 1.SF.3. Commodity Prices and Exchange Rate Responses Sample 1990 to 2014



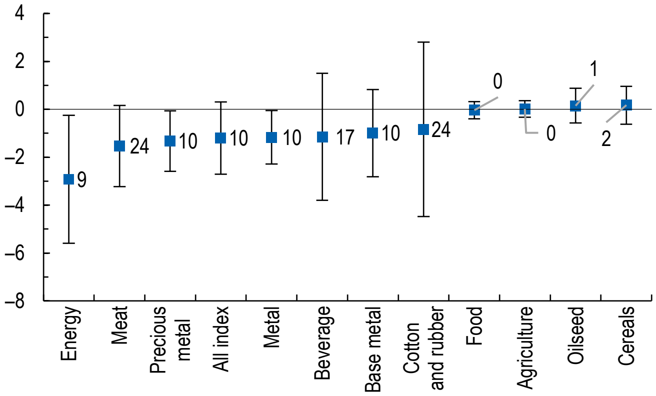
Sources: Bloomberg L.P.; IMF Primary Commodity Price System; UN Comtrade database; and IMF staff calculations.
Note: Numbers in the first panel represent the horizon (day) of the maximum decline in commodity prices. The x-axis unit is months after shock. 90 percent confidence intervals are displayed in both panels.

Is there a structural change in the relationship between commodity prices and US dollar?

The evidence in Hofmann, Igan and Rees (2023) suggests that the unconditional correlation between commodity prices and US dollar, which has been generally negative, has become positive in the last years. This evidence is corroborated by using rolling windows correlations on daily data. Since 2015, the correlation between commodity prices (oil or all commodities index) and US dollar changed sign and became positive.

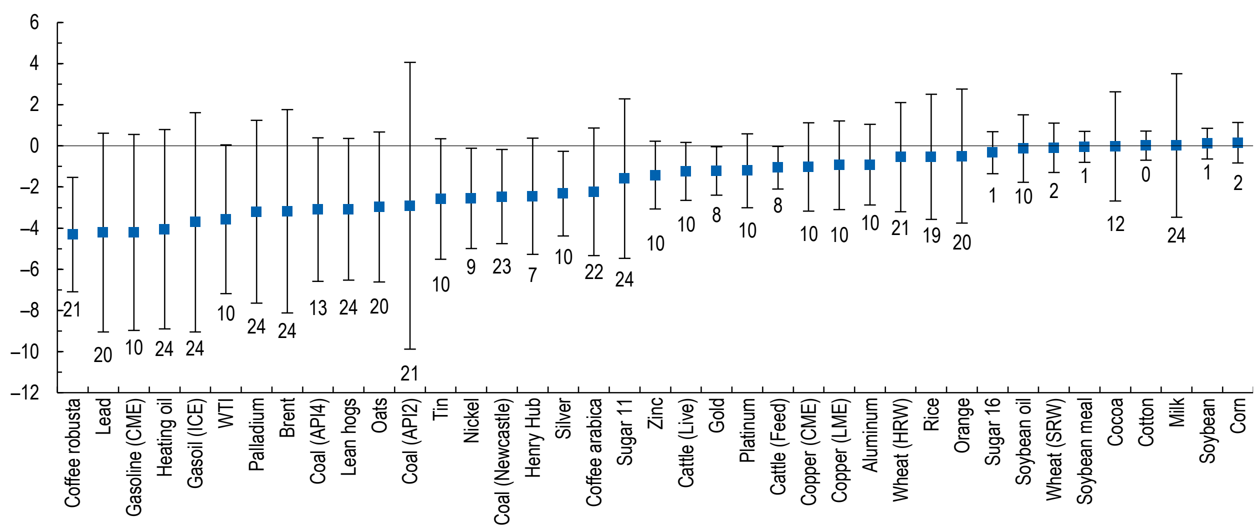
Conditional on monetary policy shock, however, the US dollar and commodity prices continue to present a negative correlation (Online Annex 1.1 Figure 1.SF.3). In fact, the responses of the US dollar and commodity prices to a monetary policy shock are robust to splitting the sample into before and after 2014.

Online Annex 1.1 Figure 1.SF.4. Commodity Price Indexes Responses to ECB Monetary Policy Shocks
(Percent change)



Sources: Bloomberg L.P.; IMF Primary Commodity Price System; UN Comtrade database; and IMF staff calculations.
Note: Numbers represent the horizon (day) of the maximum decline in commodity prices. 90 percent error bars are displayed. ECB = European Central Bank.

Online Annex 1.1 Figure 1.SF.5. Peak Commodity Price Responses to a 10-Basis-Point ECB Monetary Policy Shock
(Percent change)

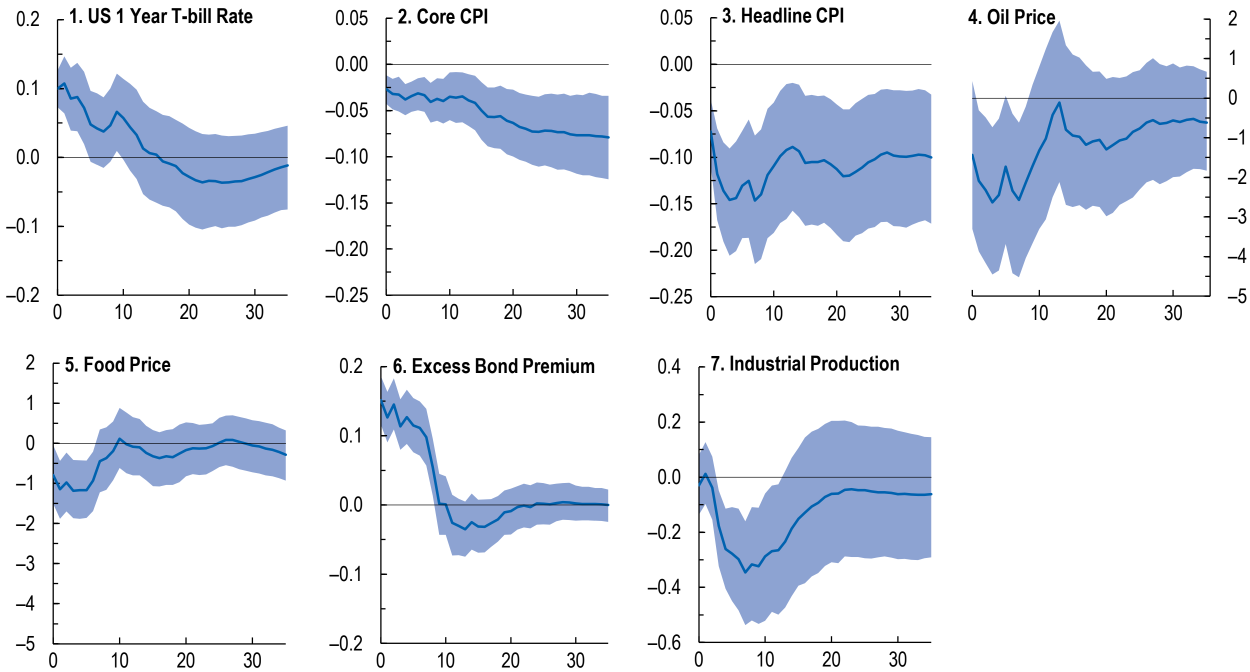


Sources: Bloomberg L.P.; IMF Primary Commodity Price System; UN Comtrade database; and IMF staff calculations.
Note: Numbers represent the horizon (day) of the maximum decline in commodity prices. 90 percent error bars are displayed. ECB = European Central Bank.

Commodity price responses to ECB monetary policy shocks

This section estimates of the impact of ECB monetary policy shocks, as in Jarociński and Karadi (2020), on commodity prices. This specification controls for US monetary policy stance by adding 24 business days lags of the one-year US bond yield. The effects on oil prices are analog to those documented for the US but less precisely estimated (Online Annex 1.1 Figure 1.SF.4). However,

Online Annex 1.1 Figure 1.SF.6. Impulse Response Functions Proxy-SVAR for the United States
(Percent)



Sources: Board of Governors of the Federal Reserve System; US Energy Information Administration; World Bank; and IMF staff calculations.
Note: 68 percent confidence intervals are displayed. CPI = Consumer Price Index.

there is no effect on base metals, raw materials and cereals. Online Annex 1.1 Figure 1.SF.5 shows the results for disaggregated commodity prices. In general, ECB shocks have negative effects on commodity prices, but again the responses are not precisely estimated, in part due to a shorter size of the sample, running from 1999 to 2019.

Proxy-SVAR Analysis

A Proxy Structural SVAR (Proxy SVAR) is used to study the spillover and spillbacks of the US monetary policy decisions. Consider the following structural SVAR:

$$y_t = \sum_{l=1}^{L} \Phi_l y_{t-l} + B\varepsilon_t \tag{2}$$

Where y_t is a vector containing n variables of interest, ε_t is a vector of unobservable zero mean white noise processes or structural shocks, Φ_l is the dynamic matrix, and B contains the coefficients with the impact effects of the structural shocks to the variables of interest.

The structural SVAR above admits the following reduced form representation:

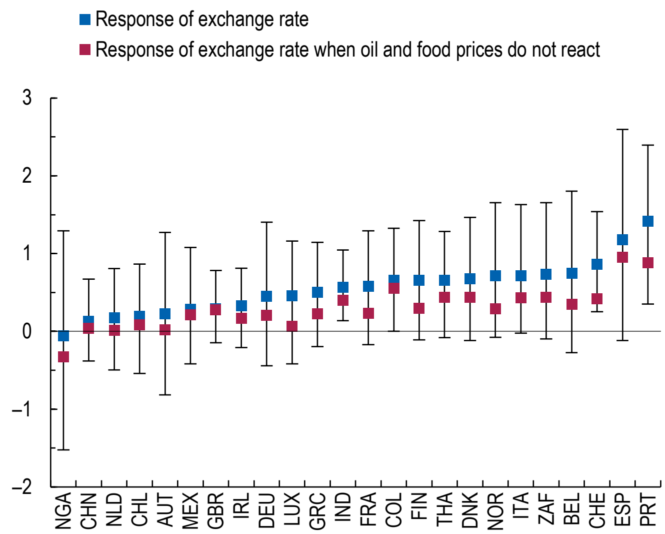
$$y_t = \sum_{l=1}^{L} \Phi_l y_{t-l} + u_t \tag{3}$$

Where u_t is a vector with the reduced-form residuals or innovations of the system. Following a vast part of the literature, the monetary policy shock is identified using an external instrument, z, which has to be correlated with the shock of interest and uncorrelated with other structural shocks

$$E[\varepsilon_t^{MonPol}, z_t'] \neq 0$$
$$E[\varepsilon_t^{others}, z_t'] = 0 \quad (4)$$

Consistently with the previous section, the Jarociński and Karadi (2020) pure monetary policy shock is used as instrument, which satisfies condition (4). A two-stage traditional procedure is employed to identify the impact effects of the monetary policy shock on all the macroeconomic variables. In the first stage, we regress the instrument on the reduced-form VAR innovation for the one-year treasury bill. This step allows us to identify the impact effect of the monetary policy shock on the interest rate. The second stage regresses the predicted value from the first stage regression on the remaining VAR innovations. The coefficients from these regressions identify, up to a scaling factor, the impact coefficients of the matrix B, that shapes the effects of a structural monetary policy shock (see Online Annex 1.1 Figure 1.SF.6).

Online Annex 1.1 Figure 1.SF.7. Decomposition of the Bilateral Exchange Rate Response to US Monetary Policy
(Percent)



Sources: Board of Governors of the Federal Reserve System; US Energy Information Administration; World Bank; and IMF staff calculations.
Note: Blue and red squares are the average one year response of exchange rate after an increase of 10 basis points in the US interest rate. 68 percent confidence intervals are displayed. Data labels in the figure use International Organization for Standardization (ISO) country codes.

Once we have identified the impact effects of the monetary policy shock, we compute the impulse response functions, IR, in a traditional way, where:

$$IR_t = B \qquad \text{for } t = 0 \quad (5)$$
$$IR_t = \phi IR_{t-1} \qquad \text{for } t = 1, 2, \ldots, H$$

To understand the contribution of the oil prices in the pass-through of monetary policy shocks we perform a decomposition exercise where we shut down the effects of this structural shock to the oil prices, making its response equal to zero at all horizons by setting the coefficients of the oil price equation to zero.

Results Proxy-SVAR Analysis

Consistently with the high-frequency evidence, a 10-basis points shock to the Fed Funds Rate induces a 2 percent and a 1 percent decline in oil and food prices, respectively. The responses of headline CPI, core CPI, excess bond premium (EBP), and industrial production (IP) are in line with the results in Jarocinski and Karadi (2020). The one-standard deviation error bands are calculated using bootstrapping methods.[1]

Online Annex 1.1 Figure 1.SF.7 shows the results from our econometric exercise that also identifies the spillovers effects of monetary policy shocks on the (nominal) exchange rate between the US and a given country (blue diamonds). Evidence suggests that, after a US monetary policy shock that increased interest rate by 10 basis points, the local currencies of most of the countries tend to depreciate against the US dollar after a year of the shock (except for Nigeria, which is a major oil exporter, although the response is not statistically significant).

These reactions describe another channel through which the US monetary policy could have spillover effects on other countries' inflation: a depreciation of the local currencies increases prices locally, that might be dampening the direct response of inflation to the US monetary policy shock. Online Annex 1.1 Figure 1.SF.7 also shows the response of the nominal exchange rate of each country under our decomposition exercise, where we assume that neither oil nor food prices react to the US monetary shock (red diamonds). The local currencies would have had a smaller depreciation, under this hypothetical scenario. On average among the countries, a US monetary policy shock that increases the interest rate by 10 basis points would lead to an increase on the nominal exchange rate of 0.60% in the benchmark model and of 0.28% when considering the case in which neither oil nor food prices react to this shock.

Mediation Analysis

A mediation analysis (Dippel et al., 2017) is used as robustness to study the commodity-price channel of monetary policy. The methodology aims at unpacking the causal chain that arises when a treatment (i.e., interest rates), and its outcome (i.e., commodities prices), jointly cause a second outcome i.e., (consumer price inflation).

In the first step, we estimate the dynamic causal effect of a US monetary policy shock on commodities prices using a linear local projection specification for commodities prices, estimated via 2SLS (using monthly data between 1990m2 to 2019m6):

$$r_t = \beta_0^h z_t + \varphi^h(L)X_{t-l} + \varepsilon_t^r$$

$$c_{t+h} - c_{t-1} = \beta_1^h r_t + \varphi^h(L)X_{t-l} + \varepsilon_{t+h}^c \tag{6}$$

where c_t and r_t are a commodity price index and the US 12-months treasury bills rate, respectively, while X_t includes a constant and lags of the monthly industrial production, the nominal effective exchange rate and of the outcome variable itself. Finally, $\varphi^h(L)$ is a polynomial in the lag operator. The first equation in (6) represents the first stage, where the instrument (z_t) is given by US monetary policy shocks identified by Jarociński and Karadi (2020). Under the usual assumption of instrument

[1] Specifically, the draws are taken from wild cluster bootstrap samples using the Rademacher distribution with 500 replications.

relevance and exogeneity, β_1^h identifies the h-months ahead effect of a US monetary policy tightening on commodity prices.

In a second step, we estimate the passthrough of commodity prices into headline inflation for a sample of countries:

$$P_{i,t+h} - P_{i,t-1} = \beta_2^h r_t + \beta_3^h c_t + \varphi^h(L)X_{i,t-l} + \mu_i + \varepsilon_{t+h}^{\pi} \tag{7}$$

where $P_{i,t}$ denotes the CPI index of country *i* at time *t, so* that the left-hand side variable is the cumulative price change between time *t-1* and *t+h*. μ_i are country fixed effects and $X_{i,t}$ includes lags of a country's industrial production, bilateral exchange rate with the dollar and of headline inflation. Equation (7) is estimated via 2SLS using the same instrument as before for c_t, while conditioning on r_t. For this part we use an unbalanced panel of 58 countries including both advanced economies as well as emerging and developing economies. The identification challenge comes from the fact that inflation is caused by interest rates both indirectly through commodity prices and "residually" through everything else. In this equation, both the interest rate and commodity prices are allowed to be endogenous, but only one instrument is available given by the monetary policy shock. Hence, an extra identifying assumption – beyond relevance and exogeneity of the instrument ($z_t \not\perp\!\!\!\perp c_t | r_t$; $z_t \perp \varepsilon^{\pi} | r_t$) – is that unobserved drivers of interest rates are unconditionally orthogonal with unobserved drivers of inflation, and they can affect inflation only through commodities prices ($\varepsilon^r \perp \varepsilon^{\pi}$ and $\varepsilon^r \not\perp\!\!\!\perp \varepsilon^{\pi} \mid c_t$). In our linear model, orthogonality of ε^r and ε^{π} simplifies to uncorrelatedness—tests on the estimated residuals, for ε^r and ε^{π} , show that orthogonality cannot be rejected.

Under these conditions, the commodities-mediated effect of monetary policy on inflation is given by the product of the effect of monetary policy on commodities and the passthrough of commodities on inflation ($\beta_1^h \beta_3^h$).

We compute the share of the mediated effect on the total effect of monetary policy on headline inflation. The latter is estimated *via* 2SLS with the same approach as in equation (6):

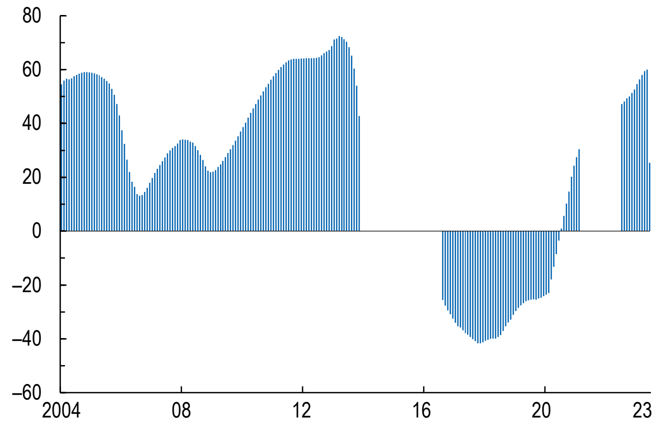
$$P_{i,t+h} - P_{i,t-1} = \beta_4^h r_t + \gamma^h(L)X_{i,t-l} + \eta_{t+h}^{\pi} \tag{8}$$

where β_4^h identifies the total effect of monetary policy on headline inflation of country *i* and $X_{i,t}$ is the same as in equation (7).

US Monetary Policy Spillovers to other Central Banks

The literature has documented the spillovers of US monetary policy on other central banks (see, for example, Kearns, Schrimpf, and Xia, 2023). Online Annex 1.1 Figure 1.SF.8 complements this evidence by showing that the monetary policy rates of G-20 Central Banks comoves strongly with the US monetary policy rate, especially during periods when common global shocks are dominant (e.g., Global financial crisis and COVID-19). The average 60 months rolling-window correlation among US monetary policy rate and G-20 rates fluctuates between -0.4 and 0.6, averaging 0.25 for the whole period with the exception being the 2017-18 period. The high policy rate co-movement could be only given by global factors.

Online Annex 1.1 Figure 1.SF.8. Average Correlations between G20 Policy Rates and the US Policy Rate
(Percent)



Sources: IMF staff calculations.
Note: Last point is June 2023. Rolling windows 1999 to 2004 onwards.

However, granger-causality tests using monetary policy surprises for the US, Canada, Japan, ECB, and UK show that US monetary policy shocks Granger cause monetary policy surprises in Canada and the European union. These results, together with the effect of ECB monetary policy shocks on oil prices in Online Annex 1.1 Figure 1.SF.4 suggest that during periods of monetary policy coordination, the commodity-price channel could be amplified by the coordinated tightening or loosening of other central banks.

State-dependent passthrough of food and oil price shocks

In this part, we employ panel local projections a la Jordà (2005) to estimate the response of domestic inflation to global commodity price shocks, that is, we are interested in the so-called passthrough from commodity prices to domestic consumer prices. The novelty here lies in estimating the impulse response functions (IRFs) for different states, and then comparing the IRFs across different states (see Ramey and Zubairy, 2018). The state-dependence of the commodity price passthrough is assessed for three types of state-dependence: (i) commodity price boom phase versus bust phase, (ii) rising versus declining commodity prices, and (iii) large versus small commodity price shocks.

We consider two different exercises. In the first exercise, we regress domestic food inflation at various horizons on food commodity price shocks, while in the second exercise we regress domestic energy inflation on oil price shocks. For the first exercise we use a panel dataset of 130 advanced economies (AEs) and emerging markets (EMs) spanning the years 1991-2019, while for the energy exercise we use a more limited panel dataset of 30 AEs for the same time period.

Lag-augmented local projections (see Montiel Olea and Plagborg-Møller(2021)) are used to construct IRFs of the cumulative commodity price pass-through. All variables are included at a monthly frequency. For each horizon (or forward month) $h=0,1,2,...12$ the following equation is estimated for the food price exercise:

$$p_{i,t+h}^{f} - p_{i,t-1}^{f} = \alpha_i^h + I^{+}\left(\beta_{+}^{h}\Delta p_{i,t}^{f,int} + \boldsymbol{\gamma}_{+}^{\boldsymbol{h}}\Delta \boldsymbol{x}_{\boldsymbol{i},\boldsymbol{t}} + \delta_{+}^{h}(L)\Delta p_{i,t}^{f}\right) + I^{-}\left(\beta_{+}^{h}\Delta p_{i,t}^{f,int} + \gamma_{+}^{h}\Delta x_{i,t} + \delta_{+}^{h}(L)\Delta p_{i,t}^{f}\right) + \epsilon_{t,i+h} \tag{9}$$

where $p_{i,t}^{f}$ is the log of the food CPI for country *i* at time *t*, I^{+} is a dummy variable equal to 1 during state *A* (e.g., rising commodity prices) and 0 otherwise, and I^{-} is its complement meaning its equal to 1 during state *B* (e.g., falling commodity prices) and 0 otherwise, $p_{i,t}^{f,int}$ is the log of the IMF's (international) food and beverages commodity price index, and $\boldsymbol{x}_{\boldsymbol{i},\boldsymbol{t}}$ is a set of controls including a country's exchange rate (in logs) against the USD (in LCU/USD), and α_i^h is a country fixed effect. Following convention, the number of lags L on the dependent variable on the right-hand side is matched with the length of the horizon, i.e., its set to 12. Dynamic causal effects of food commodity prices during the two different states of the economy (e.g., commodity price booms vs. commodity price busts) are represented by the IRFs $(h, \beta_{+}^{h},)$ and (h, β_{-}^{h}).

The estimation of the response of domestic energy inflation to oil price shocks is done analogously to eq.(9). Here we use instead the log-difference of the energy CPI on the left-hand side, and use $\Delta p_{i,t}^{oil,int}$, that is, the monthly log-difference of the IMF's average petroleum spot price index as the shock variable of interest.

For some of the exercises we used external instruments to isolate exogenous variation in the commodity price shocks (LP-IV). For food commodity prices we instrumented with harvest shocks from de Winne and Peersman (2021), and for oil prices we instrumented with oil supply news shocks from Känzig (2021). Food CPI data, food commodity prices, and average petroleum spot prices are from the IMF's international finance statistics and the IMF's primary commodity price system. Energy CPI data is from the global inflation dataset assembled by Ha et al. (2023).

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