CHAPTER 1

COMMODITY SPECIAL FEATURE: ONLINE ANNEX 1.1

This online annex describes the data, empirical methodology, and additional results.

1. Selection of Commodities

The sample includes annual data from 1960 to 2021 for 20 agricultural, energy, and mineral commodities. In choosing the commodities in our sample, we first follow Alvarez et al (2023) and consider the top 10 most traded commodities (by USD value of exports 2019, BACI data) among agricultural goods and minerals, respectively. Alvarez et al (2023) also add commodities on the US, and the UK critical raw materials lists. They include palm oil due to its importance for food production and as a biofuel.

We exclude those commodities, where data-availability is an issue. That's why we do not consider silicon, sunflower seeds, tobacco, and titanium. We add bananas, bovine, tea, and cereals because of the availability of data and their importance as food commodities. Cereals is the calorie-weighted average of wheat, maize, soybeans, and rice based on global production numbers. For metals, we use refined production and consumption data, where data quality is high enough, and revered to mined production data if necessary. Natural gas has been excluded due to significant market segmentation between Europe, North-America, and Asia over the sample period.

Food and beverage commodities: Bananas, Bovine, Cocoa, Coffee, Maize, Palm Oil, Rice, Soybeans, Sugar, Tea, Wheat, and Cereals.

Raw agricultural commodities: Cotton and Rubber (natural).

Energy: Crude oil and Coal.

Minerals: Aluminum, Copper, Lead, Tin, and Zinc.

2. Data Sources

For the production and consumption of agricultural commodities, by-country data from the Food and Agricultural Organization's (FAO, 2023) Food Balances database are used. The International Energy Agency provides the by-country data for the consumption and production of crude oil and coal in its Energy Balances database.

By-country data on the refined consumption of aluminum, copper, lead, tin, and zinc is gathered from Stuermer (2017) until 1994. The data-series are then extended based on spliced data from the World Bureau of Metals Statistics (WBMS, 2024) for the period from 1995 to 2021. Data on aluminum production, refined lead production, and mined copper production are from the British Geological Survey (BGS, 2023) for the period 1960 to 2021, whereas data from mined copper, tin and zinc production are based on Bems et al (2023) for the period 1960 to 1994. Both data are then spliced onto series from WBMS (2024) for the years 1995 to 2021.

Price data are from the World Bank (2024) as well as Schwerhoff and Stuermer (2020). Series are adjusted for inflation using the US consumer price index from the Bureau of Labor Statistics (2024).

Working with historical data for a large set of countries poses the challenge of inconsistent series with breaks and zero observations among others. We use an algorithm to sort out unreliable data series. We keep those country series that fulfill the following criteria:

1. All observations are larger than zero in levels.
2. Log changes of all observations are within the 10th and the 90th percentile of the distribution.
3. Less than 20 zero entries in log changes.
4. The country is above the 25th percentile in terms of its volume of consumption (or production).

These criteria are applied to agricultural and energy commodities. For the five mineral commodities, we check for consistency of the series by hand. Crude oil series are exempted from criterion 4.

3. Empirical Methodology

To estimate the supply and demand elasticities, we use the granular instrumental variable (GIV) method following Gabaix and Koijen (forthcoming). The basic idea is to use country-specific idiosyncratic shocks to production and consumption as an exogenous instrument.

3.1 Constructing the granular instrumental variables

The following two equations represent supply and demand (in log-differences) for country *i* in year *t*:

$$y_{it}^d = \phi^d p_t + \lambda_i^d \eta_t^d + u_{it}^d, \quad \lambda_i^d \eta_t^d = \sum_{f=1}^{f=r} \lambda_i^{d,f} \eta_t^{d,f}$$

$$y_{it}^s = \phi^s p_t + \lambda_i^s \eta_t^s + u_{it}^s, \quad \lambda_i^s \eta_t^s = \sum_{f=1}^{f=r} \lambda_i^{s,f} \eta_t^{s,f}$$

The idiosyncratic shocks $u_{it}^d \sim N(0, \sigma_{d,u}^2)$ and $u_{it}^s \sim N(0, \sigma_{d,u}^2)$ are assumed mutually independent. This means that they are uncorrelated with the common shocks, between supply and demand, and across countries. As for the factor loadings for the common shocks, note that the simplest case is when the factor structure is that of a single time-fixed effect, i.e., $\lambda_i^d \eta_t^d = \eta_t^d$ and $\lambda_i^s \eta_t^s = \eta_t^s$.

To estimate the supply and demand elasticity pair $\{\phi^d, \phi^s\}$, we implement the following algorithm. The set of countries on the consumption and production side that fulfill the four criteria in section 2 are denoted as I_d and I_s respectively.

1. A panel regression is performed for both consumption and production. Using consumption as an example, we estimate:

   $$y_{it}^d = \alpha_i + \delta_t + \epsilon_{it} \ \ for\ i \in I_d,$$

   which gives us $\hat{\epsilon}_{it}$. The time fixed effects δ_t capture the price and any other common factors. There are, however, common factors in the residuals if these have heterogenous impacts on the country. The next step accounts for this possible residual common factor.

2. Following Bai (2009) country specific components are extracted from $\hat{\epsilon}_{it}$ using the STATA package "REGIFE" by Gomez (2021):

$$\hat{\epsilon}_{it} = \Lambda F_t + u_{it},$$

where F_t is a matrix of factors, and Λ is a matrix of heterogenous (i.e., country-specific) loadings. We save the residuals $\hat{u}_{it}$ and the estimated factors $\widehat{F_t}$. The latter are used to increase the efficiency of the IV regressions. The same steps 1 and 2 are executed for production with $i \in I_s$. To differentiate between demand and supply, we refer to the saved residuals as $\hat{u}^d_{it}$ and $\hat{u}^s_{it}$ respectively.

3. The consumption (production) instrument can then be constructed as the share-weighted average of the estimated idiosyncratic shocks:

$$z^k_t = \sum_i^{I_k} \omega^k_i \, \hat{u}^k_{it}\,, \quad with \;\; k \in d, s,$$

where ω^k_i represents the time-invariant share of country *i* in total production (consumption) over the entire sample. Under the assumption of one common factor with homogenous loadings, i.e., a year-fixed effect, to estimate the idiosyncratic shocks, the previous equation is equivalent to the following expression which can be used to obtain the instrument directly from the data:

$$z^k_t = \sum_i^{I_k} (\omega^k_i - 1/I_k)\, y^k_{it} \quad with \;\; k \in d, s.$$

In addition to using z^k_t and z^s_t as instruments, the difference $z^d_t - z^s_t$ can also be used as an instrument (as suggested in Appendix H14 of Gabaix and Koijen (forthcoming)). Thus, we have a consumption-based GIV, a production-based GIV, and the difference of the two, which is the preferred approach according to Gabaix and Koijen (forthcoming). Furthermore, we create three variations of each instrument: one with a single time fixed effect (for which thus step 2 of the algorithm is skipped), one with one common factor with heterogenous loadings, and one with two common factors with heterogenous loadings. This implies there are nine GIVs in total for each commodity.

3.2 Regression analysis

The unweighted average of consumption (or production) is defined as $y^k_{Et} = \frac{1}{I^k} \sum_i^{I^k} y^k_{it}$. To estimate the supply and demand elasticities at different horizons, we then estimate the following series of local projections with instrumental variables for each horizon $h = 0,1,2 \ldots 5$:

$$y^k_{E,t+h} = \delta^k_h(L) y^k_{E,t} + \beta^k_h(L) p_t + \phi^k_h p_t + \varepsilon^{s,IV}_{i,t+h}$$

Where $y^k_{E,t+h}$ is the *h+1* period log-difference, that is, $y^k_{E,t+h} \equiv \frac{1}{I^k} \sum_i^{I^k} y^k_{it+h}$ with $y^k_{it+h} = ln\left(Y^k_{i,t+h}\right) - ln\left(Y^k_{i,t-1}\right)$, such that at horizon *h=0* we are back at the simple annual log-difference, while $\delta_h(L)$ and $\beta_h(L)$ are polynomials in the lag operator *L=5*. The efficiency of the local projections estimates is further improved by adding the estimated factors from step 2 of the GIV algorithm. The standard errors are heteroskedasticity consistent.

To identify a causal effect of prices on average production (consumption) we instrument p_t with both the contemporaneous and lagged GIVs, that is, we use the instrument pair $\{z_t^k, L.z_t^k\}$. We thus have nine such pairs of instruments for each commodity, on both demand and supply side.

We select the instrument pair that exhibits the strongest first stage, as measured by the F-score, conditional on the elasticity (so the 2nd stage) also having the right sign for our baseline results (see Miranda-Pinto and Young, 2022, for a similar approach). If that second condition is not met (so the elasticity has wrong sign), we go to the second-best IV pair, and so forth until we find a specification with the right sign.

The charts in the main text represent dynamic causal effects represented as impulse response functions $\left(h, \phi_h^k\right)$.

4. Additional Results

After the GIV algorithm described is implemented for each commodity to construct the nine different instruments, local projections with the instrumental variables are used to estimate the elasticities.

Annex Table 1.SF.1. compares our elasticity estimates against a range of estimates from previous papers, as summarized by Fally and Sayre (2018). The table shows first that our results are not only the first that provide consistent estimates across a broad set of commodities, but that our exercise generates new estimates in about half of the cases. Comparing our estimates to those that can be found in the literature, our results point towards a higher supply elasticity for coal; the demand elasticity for rice is not statistically different from zero and it is at the upper bound of the Fally and Sayre (2018)'s range of estimates. The point-estimate for the soybean short-term demand elasticity is higher than in the literature, while for wheat the elasticity is towards the low-end range. The long-run copper supply elasticity is within the range of estimates in the literature, while demand seems more elastic than previously estimated.

Annex Table 1.SF.2. shows the detailed local projection estimation results of the supply and demand elasticities at different horizons for all 20 commodities. The table also indicates whether the specification that was chosen for the baseline based on the strongest instrument uses a consumption-based IV, a production-based IV, or an IV based on the difference of these two IVs.

Annex Table 1.SF.3. provides a comparison between the supply shocks identified by narrative identification in Caldara et al (2019) and those identified by the GIV approach at the example of the oil market. The table shows all episodes of large country-specific oil production drops considered by Caldara et al (2019), and check marks those that are identified as exogenous by the authors. Note that there are major differences in the frequency and scope of these episodes. While Caldara et al (2019) identify monthly oil supply shocks at the global level and then attributes them to outages in individual countries, the GIV identifies shocks at the annual frequency and at the country-level in our setup.

The comparison is reassuring. In those cases where the monthly supply shocks identified by Caldara et al (2019) lead to a supply shock at the annual frequency, the shocks based on the narrative approach are broadly like those identified using the GIV. For example, take the case of the USA in September 2005, when hurricane Rita hit oil production the Gulf of Mexico. In Caldara et al (2019), the actual decline in US monthly output of -18.9% leads to a negative supply shock of -1.3% in global oil output. This monthly decline spills over to an actual annual decline of -5.2% in our data, and to an idiosyncratic shock in the GIV of -5.3%.

For other examples like Iran's supply shock in 1987 due to war with Iraq, there is not much overlap between the two instruments. However, this can be explained by the different frequencies. Iran's output declined by 22% in September but considering the annual average it increased by 12% in 1987. The GIV picks up the latter as an idiosyncratic shock. In other cases, e.g., Ecuador in 1987, our algorithm does not consider the country because data is not consistent over the entire sample length.

Overall, the results of this comparison show that the GIV method identifies similar shocks when the data is comparable at the monthly and annual frequency.[1]

[1] Differences with Caldara and Others (2018)'s are either related to the temporary nature of the shock (at most two months) and subsequent rebound (Iran Jan 1985, Nigeria Jun 1985, Qatar Apr 1986, UAE Aug 1990) or to a drop after a spike in production (Saudi Arabia Sept 1986, Iran Sept 1987, UAE Jan 1988). Caldara and others (2018) also compare their shock series to those identified in Kilian (2008). There are quite some notable differences that indicate that the literature is not settled on this question.

Online Annex Table 1.SF.1. CSF Estimates versus Fally & Sayre

(Percent)

		Short-Run		Long-Run	
		CSF	Fally & Sayre	CSF	Fally & Sayre
Bananas	Demand	–0.342***	–0.738 to –0.566	–0.099	N/A
	Supply	0.052	0.2 to 0.4	0.133	N/A
Bovine	Demand	–0.004	N/A	–0.375**	N/A
	Supply	0.171*	N/A	0.004	N/A
Cereal	Demand	–0.099	N/A	–0.040	N/A
	Supply	0.507	N/A	0.498	N/A
Coal	Demand	–0.223	–0.7 to –0.3	–0.489**	N/A
	Supply	0.421	0.0565	0.218	0.11
Cocoa	Demand	–0.209**	–0.14 to –.01	–0.181	–0.63 to –0.13
	Supply	0.167	0.03 to 0.12	0.156	0.15 to 0.38
Coffee	Demand	–0.055	–0.54 to –0.07	–0.042	–0.339
	Supply	0.110	0.02 to 0.55	0.282***	0.11 to 0.95
Cotton	Demand	–0.674	–0.684	–0.572	N/A
	Supply	0.136	0.497	0.199	0.0503
Maize	Demand	–0.251	N/A	–0.010	N/A
	Supply	0.253	N/A	0.698	N/A
Palm Oil	Demand	–0.205	N/A	–0.257	N/A
	Supply	0.217	N/A	0.242	N/A
Rice	Demand	0.032	–0.487 to 0.007	0.062	N/A
	Supply	0.049	0.032 to 0.302	0.009	N/A
Rubber	Demand	–0.539	N/A	0.069	N/A
	Supply	0.091*	N/A	0.096	N/A
Soybean	Demand	–0.475	–0.329 to –0.05	–1.870**	N/A
	Supply	0.358	0.061 to 0.705	0.666	N/A
Sugar	Demand	–0.143**	–0.643 to –0.010	–0.106*	–0.47 to –0.03
	Supply	0.101	0.1216 to 0.14	0.196**	0.15 to 0.71
Tea	Demand	–0.433	N/A	–0.267	N/A
	Supply	0.389*	N/A	0.391	N/A
Wheat	Demand	–0.192	–1.6 to –0.095	–0.363	N/A
	Supply	0.197	0.059 to 0.355	0.148	N/A
Crude oil	Demand	–0.157**	–0.08 to –0.003	–0.191	–0.32 to to –0.005
	Supply	0.138	<0 to 0.09	0.462	0.1 to 1.1
Copper	Demand	0.082	–0.42 to –0.0346	–1.011	–0.82 to –0.12
	Supply	–0.006	0.06 to 1.2	0.937**	0.87 to ≈6
Lead Refined	Demand	–0.209	–0.22 to –0.1108	–0.281	N/A
	Supply	0.238	0.109 to 1.84	0.033	0.27 to 0.81
Tin	Demand	–0.394	–0.55 to –0.0968	–1.223**	–1.6 to –0.41
	Supply	0.309	0.032 to 1.11	1.593	0.18 to 2.09
Zinc	Demand	–0.118	–0.47 to –0.064	–0.527**	N/A
	Supply	–0.020	0.085 to 1.75	0.285	0.08

Sources: Fally & Sayre (2018); and IMF staff estimates.
Note: Short-run are 1-year contemporaneous elasticities while long-run are the cumulative 5-year response (with the exception of crude oil which uses 4-year responses). * represents a p-value less than 0.1, ** less than 0.05, and *** less than 0.01.

Online Annex Table 1.SF.2. Baseline Regression Results
(Percent)

		Horizon						IV type		
		0	1	2	3	4	5	Consumption	Production	Both
Bananas	Demand	-0.342***	-0.374**	-0.345*	-0.226	-0.125	-0.099			✓
		0.114	0.165	0.186	0.16	0.158	0.156			
	Supply	0.052	0.069	0.033	0.027	0.004	0.133			✓
		0.083	0.09	0.109	0.122	0.124	0.134			
Bovine	Demand	-0.004	-0.162**	-0.204**	-0.265**	-0.304**	-0.375**		✓	
		0.044	0.079	0.1	0.119	0.135	0.164			
	Supply	0.171*	0.160	0.084	0.015	0.006	0.004		✓	
		0.091	0.105	0.107	0.122	0.153	0.15			
Cereal	Demand	-0.099	-0.128	-0.033	-0.122	-0.186	-0.040			✓
		0.148	0.174	0.113	0.186	0.308	0.211			
	Supply	0.507	0.661*	0.813*	0.738	0.419	0.498		✓	
		0.364	0.375	0.479	0.461	0.372	0.448			
Coal	Demand	-0.223	-0.239	-0.185	-0.262	-0.419	-0.489**	✓		
		-0.304	-0.302	-0.201	-0.23	-0.262	-0.243			
	Supply	0.421	0.235	0.253	0.251	0.300	0.218	✓		
		0.562	0.297	0.338	0.233	0.267	0.321			
Cocoa	Demand	-0.209**	-0.137	-0.087	-0.138	-0.293	-0.181			✓
		0.092	0.107	0.153	0.168	0.183	0.192			
	Supply	0.167	0.423*	0.541**	0.364*	0.128	0.156		✓	
		0.147	0.221	0.224	0.218	0.19	0.184			
Coffee	Demand	-0.055	-0.166***	-0.170***	-0.102*	-0.146*	-0.042			
		0.037	0.056	0.056	0.062	0.086	0.075			
	Supply	0.110	0.183**	0.172**	0.231***	0.209***	0.282***		✓	
		0.085	0.076	0.078	0.072	0.058	0.068			
Cotton	Demand	-0.674	-0.014	-0.448	-0.303	-0.293	-0.572			✓
		0.62	0.64	0.762	0.707	0.803	0.866			
	Supply	0.136	0.316	0.322	0.488	0.223	0.199			✓
		0.212	0.355	0.404	0.444	0.515	0.403			
Maize	Demand	-0.251	-0.160	-0.085	-0.173	-0.190	-0.010			✓
		0.169	0.131	0.135	0.174	0.193	0.197			
	Supply	0.253	0.350	0.729**	0.472*	0.402	0.698		✓	
		0.229	0.213	0.36	0.265	0.389	0.426			
Palm oil	Demand	-0.205	-0.384*	-0.430	0.085	0.037	-0.257			✓
		0.159	0.226	0.302	0.267	0.352	0.384			
	Supply	0.217	0.278	0.531	0.401	0.519	0.242		✓	
		0.315	0.351	0.66	0.516	0.622	0.48			
Rice	Demand	0.032	0.010	0.022	0.052	0.004	0.062		✓	
		0.035	0.044	0.05	0.058	0.069	0.094			
	Supply	0.049	0.140***	0.032	0.046	0.054	0.009		✓	
		0.063	0.053	0.074	0.075	0.052	0.072			
Rubber	Demand	-0.539	-0.355	-0.171	-0.117	-0.129	0.069	✓		
		0.403	0.322	0.314	0.354	0.378	0.37			
	Supply	0.091*	0.237***	0.197**	0.097	0.093	0.096	✓		
		0.054	0.084	0.081	0.083	0.086	0.083			
Soybean	Demand	-0.475	-0.627**	-1.206**	-1.133**	-1.378*	-1.870**		✓	
		0.291	0.248	0.612	0.503	0.721	0.899			
	Supply	0.358	0.439	1.041**	0.873*	0.474	0.666		✓	
		0.241	0.27	0.437	0.469	0.444	0.508			
Sugar	Demand	-0.143**	-0.193**	-0.170**	-0.214**	-0.130**	-0.106*	✓		
		0.069	0.093	0.081	0.096	0.062	0.058			
	Supply	0.101	0.131	0.187***	0.150*	0.138*	0.196**			✓
		-0.066	-0.084	-0.073	-0.08	-0.074	-0.087			
Tea	Demand	-0.433	-0.342	-0.219	-0.327	-0.294	-0.267			✓
		0.283	0.239	0.283	0.346	0.418	0.286			
	Supply	0.389*	0.655**	1.160*	1.233*	0.762	0.391	✓		
		0.221	0.318	0.678	0.745	0.558	0.461			
Wheat	Demand	-0.192	-0.186	-0.562	0.036	-0.858	-0.363			✓
		0.527	0.3	0.652	0.409	0.561	0.601			
	Supply	0.197	0.583**	0.521**	0.656***	0.390*	0.148		✓	
		0.204	0.253	0.209	0.238	0.223	0.246			
Crude oil	Demand	-0.157**	-0.235**	-0.401**	-0.299**	-0.191		✓		
		0.079	0.094	0.199	0.134	0.137				
	Supply	0.138	0.255	0.345	0.346	0.462		✓		
		0.137	0.231	0.394	0.293	0.358				
Copper	Demand	0.082	-0.478	-0.556	-0.705	-0.812	-1.011	✓		
		0.145	0.422	0.474	0.58	0.663	0.767			
	Supply	-0.006	0.581**	0.819**	0.841**	0.828**	0.937**		✓	
		0.075	0.255	0.397	0.337	0.363	0.398			
Lead Refined	Demand	-0.209	0.030	-0.231	-0.274	-0.245	-0.281	✓		
		0.202	0.143	0.171	0.18	0.196	0.194			
	Supply	0.238	0.031	0.606	0.148	-0.558	0.033	✓		
		0.225	0.167	0.663	0.358	0.369	0.36			
Tin	Demand	-0.394	-0.774*	-0.581	-0.954	-1.346*	-1.223**	✓		
		0.282	0.438	0.394	0.616	0.772	0.589			
	Supply	0.309	0.508	0.168	0.028	0.531	1.593	✓		
		0.356	0.545	0.388	0.357	0.538	1.227			
Zinc	Demand	-0.118	-0.193	-0.355**	-0.521***	-0.546**	-0.527**	✓		
		0.16	0.137	0.159	0.178	0.263	0.246			
	Supply	-0.020	0.106	0.130	0.206	0.228	0.285	✓		
		0.102	0.149	0.161	0.211	0.223	0.201			

Source: IMF staff estimates.
Note: Values show the change in the quantity supplied or demanded due to a 1 percent increase in prices as a function of time measured in years. Standard errors are shown below the estimated values. * represents a p-value less than 0.1, ** less than 0.05, and *** less than 0.01. ✓ represents the instrumental variable type that was used.

Online Annex Table 1.SF.3. Shock Identification at the Example of Oil Supply Shocks: Narrative versus GIV Approach
(Percent)

Year	Country	Event	Actual Change (Monthly)	Narrative Approach (Exogenous)	Actual Change (Annual)	GIV Approach (Idios. residual, annual)
1985	Iran	War	-22.32	✓	7.36	8.90
1985	Saudi Arabia	OPEC	-25.36		-24.13	-24.40
1985	Nigeria	OPEC	-24.15		7.41	6.65
1986	Nigeria	OPEC	-53.63		-2.18	-5.23
1986	Norway	Strike	-62.36	✓	–	–
1986	Qatar	N\A	-48.46		12.00	3.66
1986	Egypt	OPEC	-20.13		-9.13	-14.23
1986	Saudi Arabia	OPEC	-25.09		38.39	31.17
1986	Egypt	OPEC	-12.71		-9.13	-14.23
1987	Saudi Arabia	OPEC	-22.46		-16.77	-19.27
1987	Ecuador	Earthquake	-82.56	✓	–	–
1987	Iran	War	-22.24	✓	12.80	12.10
1988	U.A.E.	OPEC	-28.63		5.49	0.21
1989	Saudi Arabia	OPEC	-26.10		-0.78	-5.38
1990	Iraq	War	-70.59	✓	–	–
1990	Kuwait	War	-94.59	✓	–	–
1990	U.A.E.	Geopolitics	-19.51	✓	9.07	2.72
1992	Russia	Anticipated	-6.32		-13.45	-14.00
1995	Mexico	Hurricanes	-30.37	✓	-2.60	-7.38
1997	Iraq	Geopolitics	-54.33	✓	–	–
2000	Iraq	Geopolitics	-51.87	✓	–	–
2001	Iraq	Geopolitics	-61.96	✓	–	–
2002	Iraq	Geopolitics	-51.69	✓	–	–
2002	Venezuela	Geopolitics	-65.68	✓	-6.55	-1.09
2003	Iraq	War	-96.14	✓	–	–
2005	U.S.A.	Hurricane	-18.94	✓	-5.16	-5.26
2008	U.S.A.	Hurricane	-20.51	✓	-0.91	-1.85
2011	Libya	Civil War	-77.61	✓	–	–

Sources: Caldara et.al. (2019); and IMF staff calculations.
Note: Narrative oil supply disruption is from Caldara and others (2019) Table 1, monthly percent change. Idiosyncratic residual is from panel regression using annual data based on the GIV.

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