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# The Power of Prices: How Fast Do Commodity Markets Adjust to Shocks?

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**The Power of Prices: How Fast Do Commodity Markets Adjust to Shocks?**

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Authorized for distribution by Petya Koeva Brooks
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**ABSTRACT:** This paper establishes supply and demand elasticities for a broad set of commodities based on a consistent dataset and identification methodology. We apply granular IV methods to a new cross-country panel dataset of commodity production and consumption from 1960-2021. The results indicate that commodity demand and supply are typically price inelastic. Demand and supply tend to be the most inelastic for minerals, whereas they are most elastic for agricultural commodities. The elasticities of energy commodities fall somewhere in between. Supply and demand become more elastic at longer time horizons for mineral and energy commodities, but not for most agricultural commodities.

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WORKING PAPERS

# The Power of Prices: How Fast Do Commodity Markets Adjust to Shocks?

Prepared by Christian Bogmans, Andrea Pescatori, Ivan Petrella, Ervin Prifti, and Martin Stuermer[1]

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# 1 Introduction

This paper presents a consistently identified and estimated set of price elasticities of demand and supply for a broad range of commodities. Price elasticities of demand and supply play a crucial role in commodity markets: The lower these elasticities, the more sensitive commodity prices are to unexpected shifts in market fundamentals and other commodity-specific disturbances (Albrizio et al., 2023). Estimating these elasticities, however, is fraught with problems since in equilibrium aggregate demand must equal supply (up to a change in inventories). This typically induces a possibly severe reverse causality bias, which makes estimates potentially invalid.

This paper attempts to solve this identification problem by applying the granular instrumental variable approach by Gabaix and Koijen (2020) and others. When there are sizeable consumer or producer countries, idiosyncratic demand (supply) shocks in one or more of these countries can shift the global demand (supply) curve, thereby moving the global commodity price, i.e., data show substantial, so-called granularity. Such shifts, in turn, allow us to exploit these granular shocks to trace the average slope of the supply (demand) curve across countries. In practice, we do this by constructing instrumental variables (IV) for commodity price changes based on the sum of idiosyncratic consumption (production) shocks across countries, weighted by their market share in the global consumption (production) of the given commodity.

Our analysis uses a new cross-country panel dataset that covers all major commodity classes, including food, agricultural raw materials, energy, and metals. For each commodity, the dataset includes annual global prices, country-level production and consumption, and relevant control variables during the period 1960 to 2021, drawn from a broad set of sources.

The results suggest that the demand and supply of commodities are generally inelastic. However, a closer examination reveals interesting differences. For example, even within the class of agricultural commodities, the supply of perennial crops is more inelastic than that of annual crops. This may explain why wheat prices, which spiked at the start of the war in Ukraine, have since fallen below prewar levels and why, at the time of writing, there is no end in sight for the global cocoa crisis that emerged in 2023 due to cocoa bean supply shortages. Demand elasticities may also have played a role when it comes to wheat, since within cereals cross-elasticities of demand allow for substitution. Mineral commodities exhibit particularly inelastic demand and supply. Energy commodities are in between agricultural commodities and minerals. At the same time, supply and demand become more elastic for minerals and energy commodities over longer time horizons, whereas the elasticities of most agricultural goods do not increase.

Our paper builds upon a broad literature that estimates elasticities for individual goods, including commodities. Surveys of commodity-related estimates in the literature include Dahl (2020) and Fally and Sayre (2018). Most of these estimates are based on different methodologies. They are also mostly based on correlations and suffer from biases as argued by Roberts and Schlenker (2013). This is a pitfall when using these estimates in models that include several commodities simultaneously (see, e.g., Fally and Sayre, 2018; Bolhuis et al., 2023, and others). This paper contributes to the literature by establishing a broad set of commodity demand and supply elastities with a consistent dataset and methodology across commodities. We also contribute to the recent literature employing time series models to estimate supply and demand elasticities in oil markets. Kilian (2022), Baumeister and Hamilton (2020) and Kilian and Zhou (2023) provide overviews of the recent literature and discuss the different approaches.

The remainder of the paper is structured as follows. Section 2 describes the new dataset. Section 3 presents the econometric methodology of the granular instrumental variable approach. Section 4 presents stylized facts and first-stage results on granularity in commodity markets. Section 5 lays out the baseline results. Finally, Section 6 concludes.

# 2 A New Data-Set

We assemble a new dataset of by-country commodity production and consumption data for all countries in the world.

## 2.1 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 those commodities that are among the top 10 most traded commodities (by USD value of exports 2019, BACI data) in agricultural goods and minerals, respectively. Alvarez et al. (2023) also add those commodities that are on the US or UK critical minerals 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, notably silicon, sunflower seeds, tobacco, and titanium. Natural gas is excluded because of significant market segmentation between Europe, North America, and Asia during the sample period. We add bananas, bovine, tea, and cereals because of 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 when the data quality is high enough, and revered to mined production data if necessary.

**Commodities in our sample:**

- **Food and beverages**: Bananas, Bovine, Cocoa, Coffee, Maize, Palm Oil, Rice, Soybeans, Sugar, Tea, Wheat, and Cereals.
- **Raw agricultural materials**: Cotton and Rubber (natural).
- **Energy:** Crude oil and Coal.
- **Minerals:** Aluminum, Copper, Lead, Tin, and Zinc.

## 2.2 Data Sources

For the production and consumption of agricultural commodities, by-country data are from the Food and Agricultural Organization (FAO, 2023). The International Energy Agency (IEA, 2024) provides the by-country data for the consumption and production of crude oil and coal.

By-country data on 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 the production of aluminum, lead (refined), and copper (mined) are from the British Geological Survey (2023) for the period 1960 to 2021, while data for the production of tin and zinc are based on Bems et al. (2023) for the period 1960 to 1994. The 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 (2019). Series are adjusted for inflation using the US consumer price index from US Bureau of Labor Statistics (2024).

Working with historical data for a large set of countries faces the challenge of inconsistent series with breaks, zero observations, and other issues. To deal with that, we use an algorithm to sort out unreliable consumption and production 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 Methodology

To estimate the supply and demand elasticities, we use the granular instrumental variable (GIV) method following Gabaix and Koijen (2020). 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

Let the following two equations represent supply and demand (in log-differences) for country $i$ in deviation from its steady state in year $t$:

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

$$y_{it}^s = \phi^s p_t + \lambda_i \eta_t^s + u_{it}^s, \quad \lambda_i^s \eta_t^s = \sum_{f=1}^{f=r} \lambda_i^{s,f} \eta_t^{s,f} \tag{2}$$

It is assumed that the idiosyncratic shocks $u_{it}^d \sim N\left(0, \sigma_{d,u}^2\right)$ and $u_{it}^s \sim N\left(0, \sigma_{s,u}^2\right)$ are country-specific and 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 year 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. Let us refer to the set of countries on the consumption and production side that fulfill the four criteria described in section 2 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:

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

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

2. Following Bai (2009), country-specific components are extracted from $\hat{\epsilon}_{it}$:

$$\hat{\epsilon}_{it} = \Lambda F_t + u_{it}, \tag{3}$$

where $F_t$ is a matrix of factors, and $\Lambda$ is a matrix of heterogeneous (i.e., country-specific) loadings.[1] We save the residuals $\hat{u}_{it}$ and the estimated factors $\hat{F}_t$, as the latter can be 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 $\hat{u}_{it}^d$ and $\hat{u}_{it}^s$ respectively.

3. The consumption (production) instrument can then be constructed as the share-weighted

[1] To estimate a model with interactive fixed effects à la Bai (2009) we use the STATA module "regife" developed by Gomez (2021).

average of the estimated idiosyncratic shocks:

$$z_t^k = \sum_{i=1}^{I_k} \omega_i^k \hat{u}_{it}^k \quad \text{with } k \in \{d, s\}, \tag{4}$$

where $\omega_i^k$ represents the time-invariant share of country $i$ in total production (consumption) over the entire sample. If there is one common factor with homogeneous loadings, i.e., a year fixed effect, to estimate the idiosyncratic shocks, equation (4) reduces to the following expression which can be used to obtain the instrument directly from the data:

$$z_t^k = \sum_{i=1}^{I_k} \left( \omega_i^k - \frac{1}{I_k} \right) y_{it}^k \quad \text{with } k \in \{d, s\} \tag{5}$$

In addition to using $z_t^d$ and $z_t^s$ as instruments, the difference $z_t^d - z_t^s$ can also be used as an instrument (as suggested in Appendix H14 of Gabaix and Koijen (2020)). 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 (2020). 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 heterogeneous loadings, and one with two common factors with heterogeneous 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 $y_{Et}^k = \frac{1}{I^k} \sum_{i=1}^{I^k} y_{it}^k$. To estimate the elasticities of supply and demand at different horizons, we then estimate the following series of local projections with instrumental variables for each horizon $h = 0, 1, 2, \ldots, 5$:

$$y^k_{E,t+h} = \delta^k_h(L) y^k_{Et} + \beta^k_h(L) p_t + \phi^k_h p_t + \epsilon^{k,IV}_{i,t+h} \tag{6}$$

Where $y^k_{E,t+h}$ is the average $h+1$ period log-difference, that is, $y^k_{E,t+h} \equiv \ln(Y^k_{i,t+h}) - \ln(Y^k_{i,t-1})$. 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.

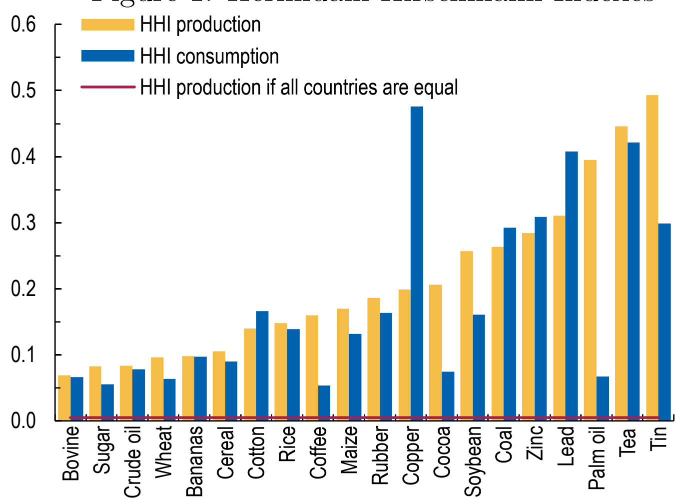
To identify a causal effect of prices on average production (consumption) we instrument $p_t$ with both the contemporaneous and lagged GIVs, that is, we use the pair $\{z^k_t, L.z^k_t\}$. We thus have nine such pairs of instruments for each commodity, on both demand and supply side.

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 silimar approach). If that second condition is not met (so the elasticity has the wrong sign), we go to the second-best IV pair, and so forth until we find a specification with the right sign.

# 4 Granularity in Commodity Markets

Identification requires granularity, which, in turn, manifests itself in a high degree of market concentration. Most commodity markets do satisfy this condition showing an elevated Herfindahl Index (HHI) for both production and consumption (Figure 1). or example, for palm oil (whose production is concentrated in Indonesia) the production HHI is 0.4, roughly 80 times higher than the value of the HHI if all 195 countries in the world were to have the same market shares. This means that an idiosyncratic shock in palm oil production in Indonesia most likely affects palm oil prices globally. Such a shock could is used to build an instrument to estimate average global price elasticities for both consumption and production.

Figure 1: Herfindahl-Hirschmann Indexes



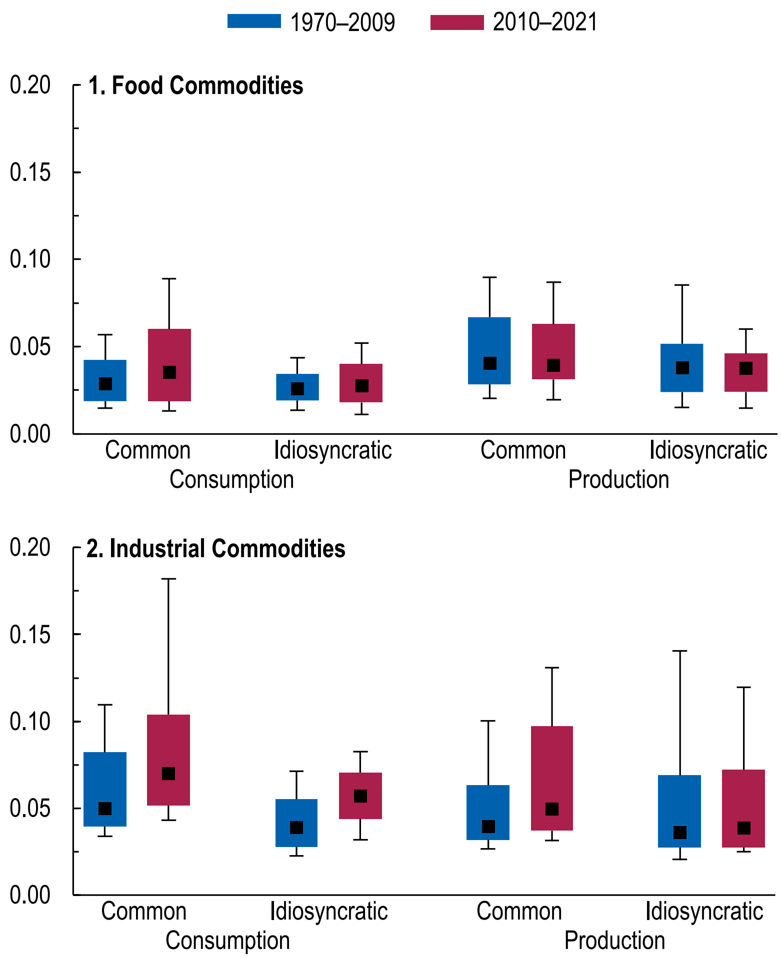

Sources: Boehnert et al. (2023); Food and Agriculture Organization; International Energy Agency; International Historical Statistics; Stuermer (2017); World Bureau of Metal Statistics; and IMF staff calculations.
Note: For each commodity, the Herfindahl-Hirschman index (HHI) is calculated by summing the squares of each country's share in global production (consumption). The HHI ranges indicating perfectly equal production across the 195 countries in our sample and 1 (indicating perfect inequality).

Based on Bai (2009)'s approach for panel data models with interactive fixed effects, we assess the contribution of common global factors versus country-specific factors in driving global consumption and production growth over time for each commodity in the sample. Common factors are generally believed to exert a greater influence on the demand rather than the supply of a commodity, as the global economic cycle stimulates co-movement in commodity consumption across countries (see, e.g., Kilian, 2009; Jacks and Stuermer, 2020). This analysis, however, presents a more nuanced perspective.

The results show that common factors are more relevant than idiosyncratic factors in driving fluctuations not only for commodity-consumption but also for commodity-production, on average across the commodities in the sample (Figure 2). One explanation is global supply chains. Shocks to these supply chains (e.g., shipping) following a trade network can manifest as a common factor on the production side. In line with this, results reveal that common factors have particularly increased in the case of industrial commodities production over the last decade (see Figure 2).

What's more, common factors across countries have become more important in driving consumption over time (for both food and industrial commodities). The increased synchronization of the global business cycle may explain this phenomenon (Gaillard and de Soyres, 2020). Third, it still holds that for food commodities the relevance of idiosyncratic shocks in production is greater than consumption, while this is not the case for the typical industrial commodity. Agricultural production, in fact, can be more affected by idiosyncratic country-specific factors such as droughts, floods, temperature anomalies, or biological stressors such as pests that can affect yields locally but not globally.

Figure 2: Common versus idiosyncratic factors in commodity demand and supply




Sources: Boehnert et al. (2023); Food and Agriculture Organization; Stuermer (2017); World Bureau of Metal Statistics; and IMF staff calculations.
Note: The y-axis shows the standard deviation of the common and idiosyncratic components of the country-specific residuals. The residuals are obtained from panel regressions using countries' commodity consumption or production as dependent variables and time fixed-effects as controls. Whiskers indicate the 10th and 90th percentiles; the bars show the 25th and the 75th percentiles; black markers indicate the median.

# 5 Results

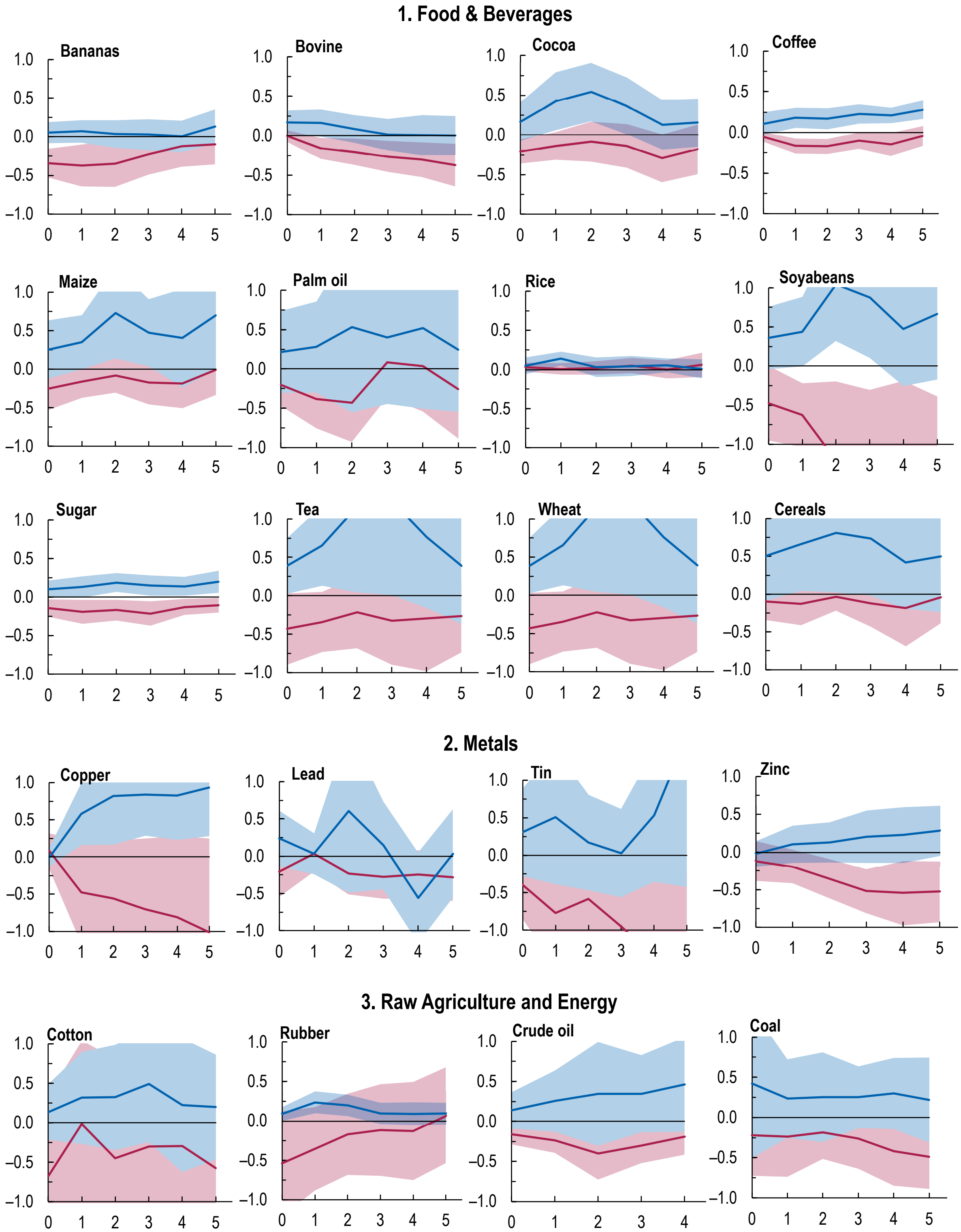
## 5.1 Commodities are Mostly Inelastic

On the supply side, results for the one year elasticities show that metals, especially copper and zinc, tend to have the lowest elasticities, while agricultural commodities generally have the highest (see Figure 3 and Table 2). For example, copper and zinc show supply elasticities close to zero. In contrast, the results for cereals show that the supply elasticity is around 0.6, implying that a 10 percent increase in prices raises output by 6 percent within a year. This is in line with the fact that crop switching or applying more fertilizer are relatively easy within a year, whereas the expansion and opening of mines is subject to longer lead times.

In the same vein, there is also an important distinction within agriculture between multi-year perennial crops such as coffee, cocoa, palm oil, and rubber on the one hand, and annual crops for cereals like maize and soybeans on the other hand. Perennial crops are characterized by smaller supply elasticities compared to annual crops due to the extended growing period needed for palm oil trees, coffee trees, and cocoa trees, which typically take at least two, three, and five years respectively, to bear fruit. The supply elasticities of energy commodities tend to be in-between those for the mineral and agricultural commodities.

The demand side is less determined by the type of commodity. Instead, commodity specific characteristics seem to play a larger role. This is in line with the fact that there are several mechanisms on the demand side that allow for adjustment: substitution by other commodities, more efficient use, and the substitution of downstream products by other products. For agricultural goods, rice is atypical, showing a price elasticity of demand close to

Figure 3: Impulse response functions of commodity demand and supply




Sources: Food and Agriculture Organization; World Bureau of Metal Statistics; and IMF staff estimates.
Note: Impulse response functions (IRFs) show the change in the quantity supplied (blue line) or demanded (red line) due to a 1 percent increase in prices as a function of time measured in years. IRFs are based on a combination of local projections and the granular instrumental variable approach (Gabaix and Koijen, forthcoming). 90 percent confidence bands are shown.

zero, probably reflecting that only about 10 percent of rice production is traded internationally. Being a staple food in Asia, rice prices are also typically subsidized. Elasticities for tea, cotton, and wheat are above 0.4. For crude oil and coal, the results show demand elasticities below 0.2 in line with the difficulties to switch from one fuel to the other due to technical constraints over the short term. Finally, copper and zinc show demand elasticities close to zero, whereas those for lead and tin are between 0.2 and 0.3. The former metals are essential for electrical appliances and steel production, respectively, while lead and tin are much easier to substitute.

Table 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 half of our estimates are for new commodities in the literature. When comparing our estimates with those found in the literature, our results point to a higher supply elasticity for coal; the demand elasticity for rice is not statistically different from zero and 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.

Table 2 in the annex 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.

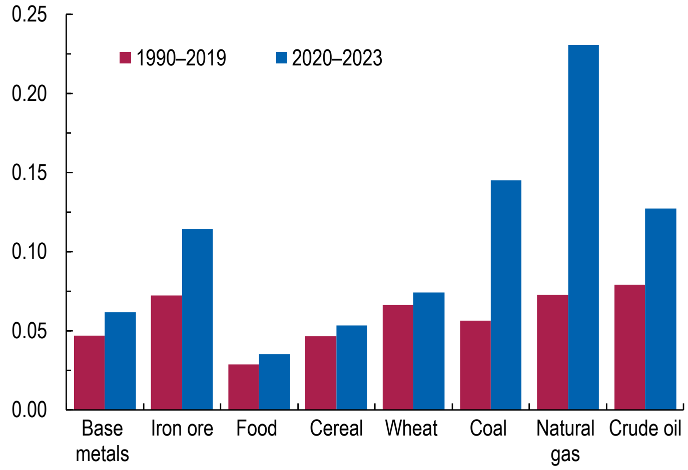
## 5.2 Supply and Demand Become More Responsive over Time

The results also demonstrate that commodities tend to become more responsive over time as markets adjust. However, based on long-run multipliers at different horizons the results show notable differences across the three different types of commodities. The results for agricultural commodities indicate that, for the most part, supply responses are relatively flat over a five-year horizon. At the same time, some commodities show a statistically significant strong peak about two to three years after the shock. This includes perennial multi-year crops such as rubber, coffee, and cocoa. For most of the metals and energy the supply elasticities are upward sloping, but only in a significant way for copper.

On the demand side, results are generally not very precisely estimated. Metals show the largest increases in the multipliers over the horizon. At the same time, for most agricultural commodities the demand multipliers have not become larger.

Overall, demand and supply for agricultural goods appear to be generally more responsive to shocks than minerals and energy commodities, which is consistent with the smaller price volatility observed for agricultural goods, compared to metals and energy commodities (Figure 4). Agricultural commodities also see the least increase in their responsiveness after a couple of years, whereas the responsiveness increases quite strongly for mineral commodities.

Figure 4: Commodity Price Volatility




Sources: IMF Primary Commodity Price System; and IMF staff calculations.
Note: Volatility is the standard deviation of log-differences in monthly prices over the repective periods. Base metal, food, cereal, coal, and natural gas are price indexes. The crude oil price refers to the IMF average petroleum spot price.

### 5.3 Comparison to Other Identification Methods

Table 3 in the Annex 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 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 attribute them to outages in individual countries, we identify 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 similar to those identified using the GIV. For example, take the case of the USA in September 2005, when hurricane Rita hit oil production in the Gulf of Mexico. In Caldara et al. (2019), the actual decline in US monthly output of -18.9 percent leads to a negative supply shock of -1.3 percent in global oil output. This monthly decline spills over to an actual annual decline of -5.2 percent in our data, and to an idiosyncratic shock in the GIV of -5.3 percent.

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 percent in September but considering the annual average it increased by 12 percent 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.

Differences with Caldara et al. (2019) are 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 et al. (2019) also compare their shock series with those identified in Kilian (2008). There are quite some notable differences that indicate that the literature is not settled on this question.

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.

# 6 Conclusion

This paper is the first to estimate a broad set of supply and demand elasticities for commodities based on a consistent dataset and identification methodology. These estimates are essential for calibrating macro-models and quantitative trade models with heterogeneous commodities as inputs. These models are key for better understanding the economic impact of geoeconomic fragmentation.

The results suggest that the price elasticities of demand and supply of commodities are generally inelastic, but interesting differences exist. Even within the class of agricultural commodities, perennial crops supply is more inelastic than that of annual crops. The difference in elasticities between annual and perennial crops may explain two recent phenomena: first, why wheat prices, which spiked at the start of the war in Ukraine, fell below prewar levels in less than a year; and second, why the global cocoa crisis that emerged in 2023 due to a worldwide cocoa bean supply deficit shows no signs of abating at the time of writing. Demand elasticities may have also played a role in the case of wheat, since within cereals cross-elasticities of demand allow for substitution. Mineral commodities are particularly inelastic. Energy commodities are in between agricultural commodities and metals. At the same time, supply and demand become more elastic for minerals and energy commodities over time.

Countries exposed to commodity markets with relatively low elasticities, especially metals, could build fiscal buffers and monetary policy space to prepare for the relatively larger impact of possible shocks. As elasticities ultimately reflect adjustment made by final consumers and producers, replacing energy and agricultural subsidies with targeted transfers would help increase the demand and supply elasticities of many commodities and reduce their price volatility. International trade can play a prominent role in smoothing commodity shocks and buffering against the economic impact of these shocks. This will be even more relevant in the context of increasing geopolitical tensions and trade fragmentation.

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# A Additional Tables and Figures

Table 1: Comparison of our estimates with survey estimates from Fally and Sayre (2018).

| | | Short-Run | | Long-Run | |
|---|---|---|---|---|---|
| | | GIV estimate | Fally & Sayre | GIV estimate | 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 $\approx$ 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 |

## Table 2: Detailed elasticity results

| | | 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 | | | X |
| | | 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 | | | X |
| | | 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** | | X | |
| | | 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 | | X | |
| | | 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 | | | X |
| | | 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 | | X | |
| | | 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** | X | | |
| | | -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 | X | | |
| | | 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 | | | X |
| | | 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 | | X | |
| | | 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*** | | X | |
| | | 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 | | | X |
| | | 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 | | | X |
| | | 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 | | | X |
| | | 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 | | X | |
| | | 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 | | | X |
| | | 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 | | X | |
| | | 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 | | X | |
| | | 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 | | X | |
| | | 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 | X | | |
| | | 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 | X | | |
| | | 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** | | X | |
| | | 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 | | X | |
| | | 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* | X | | |
| | | 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** | | | X |
| | | -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 | | | X |
| | | 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 | X | | |
| | | 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 | | | X |
| | | 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 | | X | |
| | | 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 | | X | | |
| | | 0.079 | 0.094 | 0.199 | 0.134 | 0.137 | | | | |
| | Supply | 0.138 | 0.255 | 0.345 | 0.346 | 0.462 | | X | | |
| | | 0.137 | 0.231 | 0.394 | 0.293 | 0.358 | | | | |
| **Copper** | Demand | 0.082 | -0.478 | -0.556 | -0.705 | -0.812 | -1.011 | X | | |
| | | 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** | | X | |
| | | 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 | X | | |
| | | 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 | X | | |
| | | 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** | X | | |
| | | 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 | X | | |
| | | 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** | X | | |
| | | 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 | X | | |
| | | 0.102 | 0.149 | 0.161 | 0.211 | 0.223 | 0.201 | | | |

Table 3: Comparison of IV variable for oil with Caldara et al. (2019)

| Year | Country | Event | Actual Change (Monthly) | Narrative Approach (Exogenous) | Actual Change (Annual) | GIV approach (Idiosyncratic 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 | ✓ | – | – |