Uncovering The Causal Effects of Commodity Price Shocks

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May 28, 2023

Abstract

This study uses high-frequency data and the methodology of identification through heteroskedasticity to investigate the effects of commodity price shocks. The primary objective is to estimate the contemporaneous causal impact of grain and oil prices on various financial indicators. Notably, I exploit a novel source of price heteroscedasticity, the USDA Grain Stocks report, which triggers price changes one standard deviation above other days. The results reveal that heteroscedasticity-based coefficients are significantly lower than OLS estimates, with some approaching zero. This finding highlights the risk of overestimating commodity price effects when neglecting endogeneity. Additionally, the results indicate that: i) oil and grain prices exhibit a two-way relationship; ii) higher grain prices decrease risk premiums in emerging markets; iii) within the US economy, increases in grain prices reduce uncertainty and positively influence stock markets, while oil price shocks increase inflation and interest rates.

Keywords: High-Frequency Identification, Heteroskedasticity, USDA, OPEC

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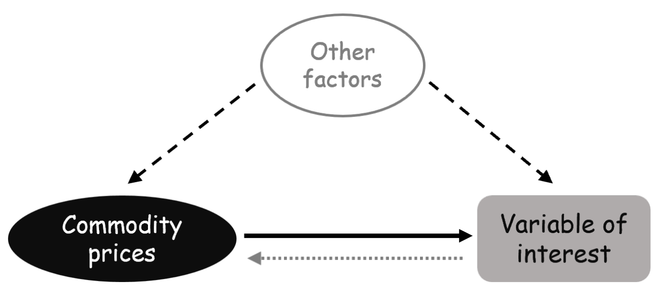
1 Introduction

A significant amount of research documents various impacts of commodity prices on different dimensions of the economy, such as exchange rates, domestic business cycles, monetary and fiscal policies, among others. However, many studies assume that commodity prices are exogenous and the primary source of external shocks, disregarding potential identification problems.

Disentangling causal effects from correlations between commodity prices and other macroeconomic variables is challenging due to their joint determination and potential simultaneous impacts from unobserved factors (Figure 1). This identification challenge is relatively straightforward for large developed countries, as commodity prices can affect these economies and respond to their shocks simultaneously. However, the issue is more nuanced for small open economies. While reverse causality is likely absent, many global factors can simultaneously influence commodity prices and the small open economy, blurring the identification.

Figure 1: Simultaneous determination of commodity prices



Consider, for example, the global instability caused by the COVID pandemic in early 2020. Within a short period, stocks and commodity prices plummeted, many currencies experienced sharp devaluation against the US dollar, while risk premiums on a wide range of debt securities soared. Production, consumption, and investment collapsed globally. Any empirical model where commodity prices are exogenously determined and regarded as the primary source of external shocks will attribute most of the aforementioned domestic developments to these prices.

An additional layer of confoundedness must be considered when focusing on the effects of a specific commodity rather than a composite index. Commodity prices are characterized by a high level of co-movement with each other. Besides the predominant role of common macroeconomic factors, this synchronism is also related to the interconnection of each commodity's specific supply and demand. For instance, crude oil can affect the prices of other products through production costs (transport, fertilizers, plastic packaging). Likewise, soybean price rises may lead farmers to shift part of their land from other crops. Moreover, as biofuels made from corn and soybeans are substitutes for gasoline and diesel, fluctuations in the prices of these agricultural commodities can affect the demand for crude oil (and vice versa).

In this study, I employ a high-frequency identification approach and a novel source of heteroskedasticity to uncover the contemporaneous causal effects of global agricultural price shocks. Specifically, I use data from the United States Department of Agriculture (USDA) to distinguish between two volatility regimes for soybean, corn, and wheat prices. I then use identification through heteroskedasticity methodology (Rigobon and Sack, 2004) to estimate the effect of grain prices on financial indicators from six countries (Brazil, Chile, Colombia, Mexico, Peru, and the United States), as well as on the prices of other commodities.

In addition to analyzing grain prices, I estimate the effects of oil price shocks using announcement dates from the Organization of the Petroleum Exporting Countries (OPEC) - an identification tool also adopted by Känzig (2021). Nonetheless, my estimations differ from his in two dimensions. First, instead of using the identified shock series as an external instrument in a VAR model, I directly estimate the causal parameter on high-frequency financial indicators, an approach that requires weaker assumptions. Second, I expand the analysis to include five emerging countries and other commodity prices rather than focusing solely on the US economy.

I present evidence that the USDA Grain Stocks Report has a far more significant effect on daily prices than the OPEC announcements. On average, the grain price changes are one standard deviation greater on days when the USDA publishes its Grain Stocks report, whereas this difference is around 0.4 standard deviations for crude oil prices on OPEC announcement days. This evidence is further supported by an F-test that rejects the null hypothesis of weak identification in the case of USDA releases, but not for OPEC announcements. Despite the limited identification power, OPEC announcements offer valuable insights into the direction of the bias in the Ordinary Least Squares (OLS) estimator. Also, the inference distortions caused by weak identification conditions tend to be minimized when the estimated effects are considerably large.

I show that the impact of commodity price shocks differs between grains and oil and is considerably overestimated when endogeneity is ignored. There is a striking pattern across countries and indicators: the magnitude of coefficients estimated using the heteroskedasticity-based approach is considerably lower than the naive OLS estimates, with some shrinking towards zero.

A bidirectional causal relationship is found between oil and grain prices, which differs from previous findings.[1] The CDS responses suggest that grain price shocks are associated with a slight decrease in credit risk for Latin American countries, in contrast to oil price shocks which do not seem to affect risk premiums. The results for emerging market stock indices are inconclusive, but the possible positive effects are likely minimal. Most countries experience a modest appreciation in their nominal exchange rates after grain and oil price shocks. Finally, the results show that for the US economy, grain price spikes reduce uncertainty and positively impact equities, while increases in oil prices lead to rising inflation and interest rates.

The findings for emerging markets CDS and the US indicators differ from recent studies emphasizing credit spreads as a relevant transmission mechanism for commodity price shocks in resource-exporting countries (Fernández et al., 2018; Drechsel and Tenreyro, 2018). While my results corroborate the hypothesis of improved financial conditions in response to a positive grain price shock, they also indicate that this effect is half of what a naive estimate suggests. Moreover, there is no evidence of oil price shocks affecting credit spreads, but they do seem to push inflation up. Therefore, this financial channel does not apply to all commodities.

[1] According to Fernandez-Perez et al. (2016), crude oil directly impacts agricultural commodities, while the reverse effect is not observed. Similarly to the current study, their research takes advantage of the heteroskedasticity in daily data to achieve identification. However, their methodology differs as they employ variance rolling windows to differentiate between volatility regimes, which contrasts with the approach adopted here, based on institutionally driven events. Furthermore, their sample period is approximately half of the period examined in the current study.

The remainder of this introduction discusses the related literature. In Section 2, I discuss the heteroskedasticity-based identification methodology and describe the estimation procedure. Section 3 presents the USDA and OPEC institutional information used to differentiate the volatility regimes. This Section also provides empirical evidence on the identification power of these two volatility sources. Section 4 describes the data and the empirical setup before presenting the results. Section 5 concludes the paper.

1.1 Related Literature

Numerous studies have examined the effects of commodity price shifts on various aspects of distinct economies. For example, in the exchange rates literature, Chen and Rogoff (2003) explore the relevance of commodity prices for the currencies of three developed commodity-exporting countries during the 1980s and 1990s, while Cashin et al. (2004) conduct a similar investigation across a panel of 58 countries between 1980-2002. Both studies find evidence that commodity price fluctuations significantly influence exchange rates in resource-rich nations.

Regarding policymaking, Céspedes and Velasco (2014) show that fiscal policy is typically more procyclical in commodity-exporting countries during price booms. Ferrero and Seneca (2019), in turn, propose a theoretical framework to assess the unique challenges faced by economies with abundant natural resources when implementing monetary policy. According to their argument, a downward shock in commodity prices usually leads to an economic slowdown along with inflationary pressures due to exchange rate depreciation. These developments exacerbate the trade-off between stabilizing inflation or output.

On inflationary effects, Gelos and Ustyugova (2017) and Choi et al. (2018) find empirical evidence that the share of food and transport in the CPI basket explains most of the cross-country differences in the pass-through of commodity prices. Both studies also suggest that a more credible monetary policy helps anchor inflation expectations and thus reduces the second-round effects of commodity price shocks.

Three papers must be mentioned in the literature on the drivers of domestic business cycles. First, Fernández et al. (2017) estimate a Structural Vector Autoregression (SVAR) model in which multiple commodity prices, rather than terms of trade, transmit the effects of global shocks to domestic business cycles. Their analysis, based on quarterly data between 2000 and 2015, indicates that commodity prices account for two-thirds of output fluctuations in the median country. Second, Fernández et al. (2018) employ a Dynamic Stochastic General Equilibrium (DSGE) framework with an embedded commodity sector and find that commodity price shocks are responsible for over a third of the variance in output across four Latin American countries. They emphasize the role of a common factor driving commodity prices and the spillover effect from commodity prices to interest rates. Finally, Drechsel and Tenreyro (2018) use a dataset spanning over a century of the Argentine economy to estimate a structural model and find that commodity price shocks are the primary drivers of domestic business cycles. Their model incorporates an arbitrary inverse relationship between interest rate premiums and commodity prices, augmenting the beneficial effects of higher commodity prices on the emerging economy.

Almost none of these studies discuss the causes of commodity price swings. Instead, they implicitly or explicitly assume that commodity prices are driven by external shocks unrelated to other disturbances. This assumption means that their frameworks are not concerned with whether an increase in commodity prices results from strong global demand, specific supply shortages, or higher financial liquidity. This disregard for the source of price fluctuations is further worrying when considering Alquist et al. (2020), who find that most commodity price movements are due to non-commodity shocks.

In contrast to the literature on aggregate commodity price shocks, research on the oil market has long acknowledged the need to disentangle the causal effects of price innovations (see Kilian and Zhou (2020) for a recent survey). Despite its early focus on implausible recursive restrictions, notable progress has been made in this research area. Of particular relevance to the current study, Känzig (2021) adapts the high-frequency identification strategy from the literature on monetary policy shocks (Rigobon and Sack, 2004; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). First, he explores oil price variations on days when the Organization of the Petroleum Exporting Countries (OPEC) announces its production policy to identify a news shock on oil prices. He then uses it as an external instrument in a VAR model to identify a structural oil supply shock.

Outside the oil market literature, Fernandez-Perez et al. (2016) use the heteroskedasticity of daily data to estimate the contemporaneous interactions between energy (oil and ethanol) and agricultural commodities (corn, soybean, and wheat). Also, Stein (2022) employs a high-frequency identification strategy for New Zealand dairy prices.

2 Heteroskedasticity-based Identification

In their highly influential paper on the response of asset prices to monetary policy shocks, Rigobon and Sack (2004) propose an estimator based on the heteroskedasticity of high-frequency data as an alternative to the traditional "event-study" approach. In this Section, I present the main aspects of this seminal study in the context of commodity price shocks and briefly describe the empirical implementation of their estimator. A more detailed derivation of the estimator is presented in Appendix A.

2.1 Identification

To estimate the impact of a commodity price p_t on any other variable x_t, one considers estimating the following regression:

$$x_t = \alpha p_t + u_t \tag{1}$$

As is well known, estimating Equation (1) using OLS will only provide a consistent estimator of the parameter α under very restrictive assumptions. To illustrate the econometric problems of such estimation, consider the case where x_t and p_t are part of a system of two equations where both variables are affected by each other (endogeneity) and by a set of unobserved exogenous variables w_t (omitted variables):

$$p_t = \beta x_t + \gamma_p w_t + \varepsilon_t \tag{2}$$

$$x_t = \alpha p_t + \gamma_x w_t + \eta_t \tag{3}$$

Two remarks are worth highlighting. First, for ease of notation, I consider x_t and w_t as single variables, but this system can be easily extended to the multivariate case, where

x_t is a set of domestic indicators for a given country and w_t represents various unobserved variables. Second, I assume all variables are measured as log differences and thus follow a stationary process with no autocorrelation, which is a reasonable assumption for high-frequency financial data.

In such a system, the expected value of the OLS estimator of Equation (1) is given by:

$$\mathrm{E}\left[\widehat{\alpha}_{\text{ols}}\right] = \alpha + (1-\alpha\beta)\frac{\beta\sigma_\eta + \left(\beta\gamma_x^2 + \gamma_p\gamma_x\right)\sigma_w}{\sigma_\varepsilon + \beta^2\sigma_\eta + \left(\beta\gamma_x + \gamma_p\right)^2\sigma_w}, \tag{4}$$

which is clearly biased unless $\beta = \gamma_p = \gamma_x = 0$ or $\sigma_\eta = \sigma_w = 0$.

The OLS estimator will still be potentially biased, even if the researcher has good reasons to assume $\beta = 0$ (no reverse causality). For example, suppose one is interested in estimating the impact of daily commodity price changes (p_t) on the risk premium of a small open economy (x_t). In this case, it is unlikely that x_t has any effect on p_t, so $\beta = 0$. However, there is still a wide range of external variables (w_t) that can potentially affect both p_t and x_t simultaneously. It can be a global macroeconomic variable only measured for a lower frequency (such as GDP or inflation) or a poorly measured international variable such as growth expectations or financial conditions. In this context, the expected value of the OLS estimator remains biased and can be expressed as:

$$\mathrm{E}\left[\widehat{\alpha}_{\text{ols}}\right] = \alpha + \frac{\gamma_p\gamma_x\sigma_w}{\sigma_\varepsilon + \gamma_p^2\sigma_w}. \tag{5}$$

Based on the discussion and methodology developed by Rigobon and Sack (2004), I employ two identification strategies, namely Event Study (ES) and Identification through Heteroskedasticity (IH), to address the above problem. Both approaches are built on the premise that it is possible to distinguish two sample periods: E for “event,” characterized by higher volatility, and R for “regular.”

For the ES approach, the critical assumption is that the structural commodity price shock is the primary (preferably the only) source of innovations in period E:

$$\sigma_\varepsilon^E \gg \sigma_\eta^E, \tag{6}$$

$$\sigma_\varepsilon^E \gg \sigma_w^E. \tag{7}$$

In the limit case, as the ratios $\sigma_\varepsilon/\sigma_\eta$ and $\sigma_\varepsilon/\sigma_w$ go to infinity, the estimation of Equation (1) using only the sample period E will be consistent. In practice, however, the ratios $\sigma_\varepsilon/\sigma_\eta$ and $\sigma_\varepsilon/\sigma_w$ tend to be finite, making the ES approach likely biased.

The IH technique, in turn, requires assumptions much weaker than (6) and (7). It also demands two distinct variance regimes, but instead of becoming infinitely large, the variance of commodity price shocks only needs to change between regimes, while the variance of the other shocks must remain unchanged:

$$\sigma_\varepsilon^E > \sigma_\varepsilon^R, \tag{8}$$

$$\sigma_\eta^E = \sigma_\eta^R, \tag{9}$$

$$\sigma_w^E = \sigma_w^R. \tag{10}$$

With these assumptions, one can implement the identification by estimating the covariance matrix for each subsample and then subtracting them:

$$\mathrm{E}[\Delta\Sigma] = E\left[\widehat{\Sigma}^E\right] - E\left[\widehat{\Sigma}^R\right] = \frac{\left(\sigma_\varepsilon^E - \sigma_\varepsilon^R\right)}{(1-\alpha\beta)^2}\begin{bmatrix} 1 & \alpha \\ \cdot & \alpha^2 \end{bmatrix} \tag{11}$$

It turns out that Equation (11) offers three identifying moments for α:

$$\mathrm{E}\left[\widehat{\alpha}_{\mathrm{ih}}\right] = \mathrm{E}\left[\frac{\widehat{\Delta\Sigma}_{12}}{\widehat{\Delta\Sigma}_{11}}\right] = \mathrm{E}\left[\frac{\widehat{\Delta\Sigma}_{22}}{\widehat{\Delta\Sigma}_{12}}\right] = \mathrm{E}\left[\sqrt{\frac{\widehat{\Delta\Sigma}_{22}}{\widehat{\Delta\Sigma}_{11}}}\right] = \alpha. \tag{12}$$

Note that conditions (8) through (10) do not simply provide an alternative unbiased estimator, the $\widehat{\alpha}_{\mathrm{ih}}$. They also make the biased ES estimator valuable. It is possible to see from Equation (4) that, if these conditions hold, the bias of the ES estimator is smaller than that of the naive OLS and thus indicates the direction of the bias. For example, if $\widehat{\alpha}_{\mathrm{ols}} = 0.5$ and $\widehat{\alpha}_{\mathrm{es}} = 0.25$, both estimators are upward biased.

2.2 Estimation

The estimation using the ES method involves employing simple OLS regression to the period characterized by high volatility in structural commodity price shocks (period E).

In turn, there are two methods available to estimate Equation (11) when adopting the IH approach: Instrumental Variables (IV) and Generalized Method of Moments (GMM). As shown by Rigobon and Sack (2004), the IV technique involves constructing synthetic instruments that penalize the correlation in sample R. Although simple, the IV approach uses only one of the conditions in Equation (12) at a time, in contrast to the more efficient GMM estimator that considers all three moments together.

Focusing on the GMM estimator used in Section 4's empirical analysis, its implementation begins by expressing Equation (11) as a unified set of moments:

$$b_t = \mathrm{vech}\left(\left(\frac{N}{N_E}\tau_t^E - \frac{N}{N_R}\tau_t^R\right)[p_t x_t]'\,[p_t x_t] - \lambda[1\alpha]'[1\alpha]\right), \tag{13}$$

where N_E, N_R, and N are the number of observations in each subsample and the whole sample; τ_t^E and τ_t^R are dummy variables for the subsamples; and $\lambda \equiv \frac{\left(\sigma_\varepsilon^E - \sigma_\varepsilon^R\right)}{(1-\alpha\beta)^2}$ summarizes the degree of heteroskedasticity. Then, the estimation consists in minimizing the following objective function:

$$\left\{\hat{\alpha}_{\mathrm{ih}}, \hat{\lambda}\right\} = \mathrm{argmin}\left[\sum_{t=1}^{N} b_t\right]' W_N \left[\sum_{t=1}^{N} b_t\right], \tag{14}$$

where W_N is the optimal weighting matrix.

3 Distinguishing variance regimes

As discussed in Section 2, the fundamental premise of heteroskedasticity-based identification is that the researcher can distinguish variance regimes. Rigobon (2003), for instance, uses several international crises to differentiate between "tranquil" and "crisis" periods. Ehrmann et al. (2011) also identify "crisis" periods, but instead of using external information, they compute rolling window variances and characterize the regimes based on arbitrary criteria.[2] In contrast, other studies exploit institutionally driven events, such as monetary policy announcements (Rigobon and Sack, 2004; Gertler and Karadi, 2015;

[2]According to their criteria, a "crisis" regime must have at least 16 observations for which the relative variances of an asset surpass one standard deviation from its mean.

Nakamura and Steinsson, 2018) or legal rulings (Hébert and Schreger, 2017). In this study, I follow this second approach, using the unexplored USDA Stocks Report releases, as well as OPEC announcements updated from Känzig (2021).

Several studies have documented the price effects of USDA reports and OPEC announcements (Adjemian, 2012; Adjemian and Irwin, 2018; Loutia et al., 2016; McKenzie and Ke, 2021; Schmidbauer and Rösch, 2012). Nonetheless, it is worth revisiting this assessment to compare these two events and to evaluate their suitability for the empirical analysis outlined in Section 4. Therefore, in this Section, I present institutional information, along with empirical evidence on the identification power of these two volatility sources.

The empirical results presented in this Section are based on two datasets. In the initial two subsections, I illustrate intraday patterns in the grain and oil futures markets using price and trade volume at a 15-minute frequency. As intraday data have limited availability, subsequent subsections rely on daily data.[3] For the intraday data, each commodity's price and trade volume is the average of second and third nearby futures contracts traded at the Chicago Board of Trade (CBOT) and the New York Mercantile Exchange (NYMEX) from 2021-09-20 to 2022-10-31. Daily commodity prices are measured by applying principal component analysis (PCA) to the six nearby futures contracts traded on those same exchanges from January 1995 through October 2022.[4] Using the first PC for several maturities, an approach also employed by Känzig (2021), avoids the liquidity distortions of spot prices and mitigates potential noise from the term structure in individual future contracts. In simpler terms, the first PC tends to reflect better the impact of new information than single futures or spot prices.

3.1 USDA Grain Stocks report

The USDA is a government agency whose activities include collecting and publishing agricultural statistics from the United States and other countries. In particular, the Grain Stocks report, published every quarter since 1973, has been closely watched by market

[3]The data source used for this paper only provides intraday transaction data for the last 140 days.

[4]The first PC explains at least 90% of the variance in the six nearby future contracts for all the commodities considered.

participants looking to understand the current state of the grain market.[5] The report provides estimates of the domestic volume of grain stored in on-farm and off-farm storage facilities, broken down by state. The estimates are based on surveys conducted during the first two weeks of the last month of a quarter. The in-farm figures come from a survey based on a sampling procedure designed to ensure that any US producer can be selected. Off-farm statistics comprise all known commercial grain storage facilities, such as mills, elevators, warehouses, terminals, and processors. Despite giving special attention to corn, soybean, and wheat, the report also includes estimates for sorghum, oats, barley, flaxseed, canola, rapeseed, rye, sunflower, safflower, and mustard seed. The report is released at 12:00 p.m. EST, and before around 30 pages of tables, there is a highlight session summarizing the results.[6,7]

The release of the Grain Stocks report has a striking effect on markets. Figure 2 compares the intraday price and trade volume behavior on the days when the report is released (referred to as "event" days) to behavior on all other days (referred to as "regular" days) for corn, soybean, and wheat. On "event" days, at the time of the report release (session hour 16), there is often a price jump (shown in panels (a), (c), and (e)) and always a substantial increase in trade volume (panels (b), (d), and (f)). Remarkably, in the 15 minutes following the release, the trade volume of these three commodities is, on average, more than ten times higher than the median trade volume observed at the same hour on a "regular" day.

3.2 OPEC announcements

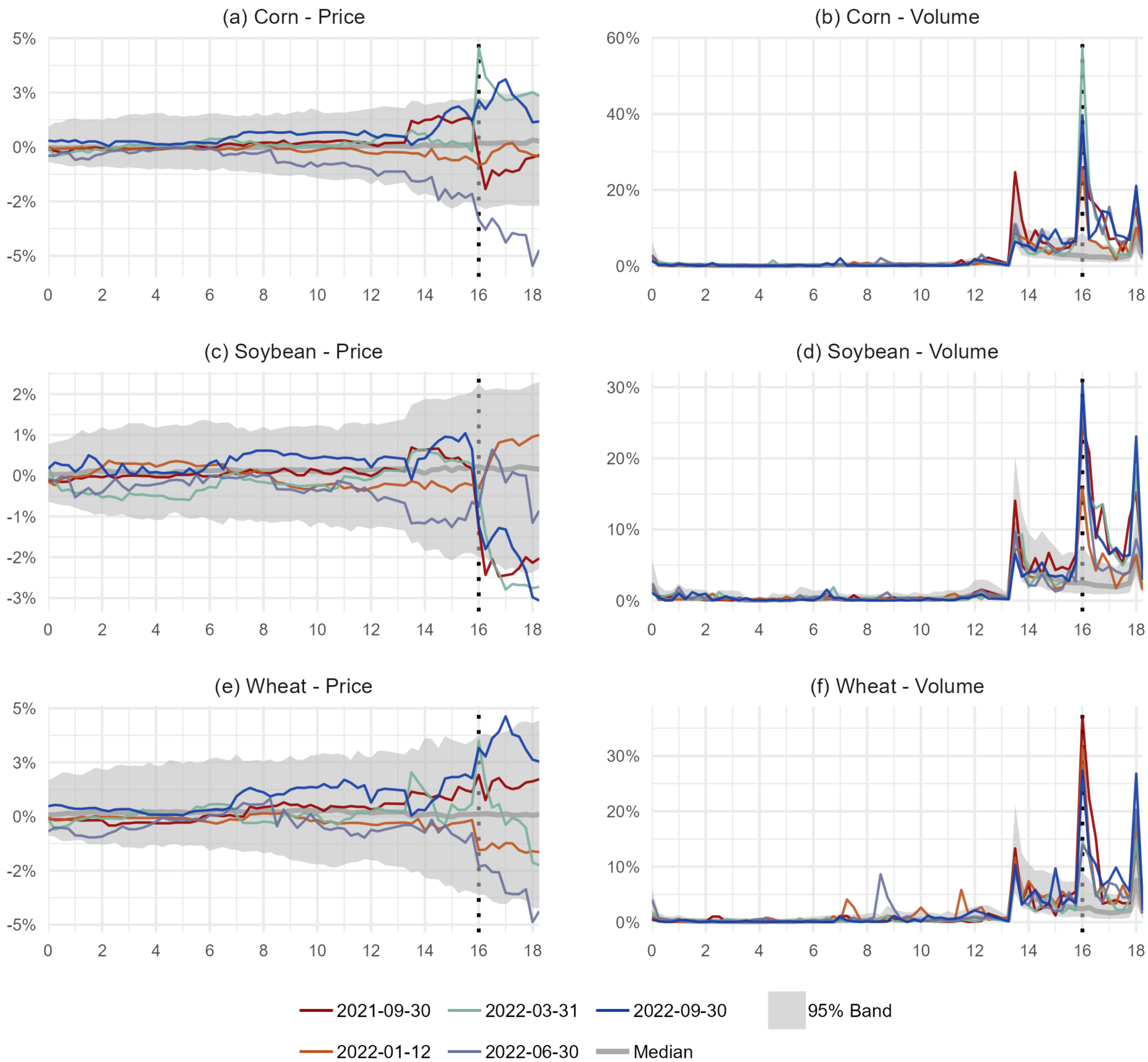
OPEC is a multinational organization created in 1960 that operates as a cartel in international markets, coordinating its members' oil production to achieve price and market

[5]Since 1987, it has been published in mid-January and on the last business day of March, June, and September.

[6]USDA reports used to be released after the close of the Chicago Board of Trade (CBOT) trading session until 1994 when they began to be published before the market opening. Starting in 2013, the report release time was changed to 12:00 p.m. EST, allowing markets to absorb the new information at a moment of high liquidity.

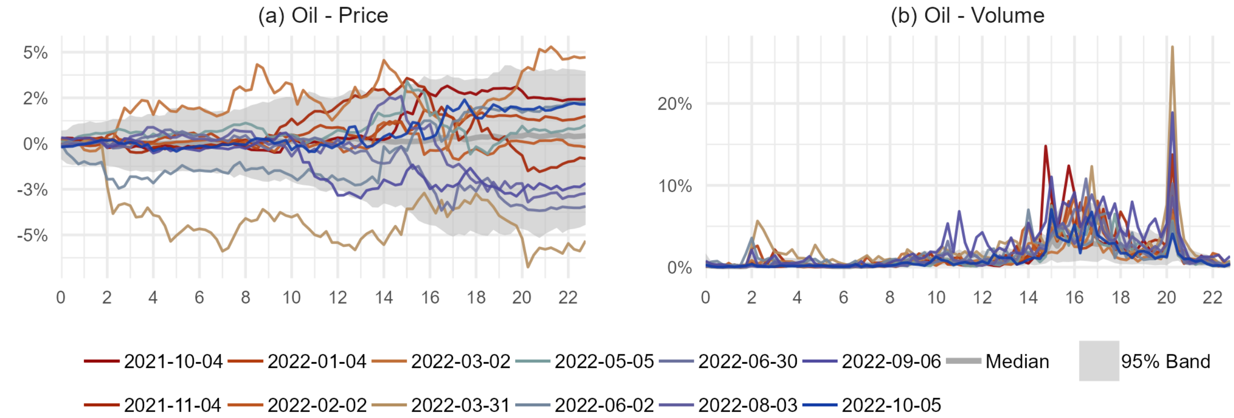
[7]Figure 10 in the Appendix provides an example of the Grain Stock report summary.

Figure 2: Intraday Grain Market



Note: X-axes denote the session hours, beginning at 8:00 p.m. the day before and closing at 2:20 p.m. (EST). The colored lines refer to the days of the Grain Stocks report, released at hour 16 of the session (depicted by a vertical dotted line). Panels (a), (c), and (e) show the accumulated price change from the previous session's closing price. Panels (b), (d), and (f) present the intraday volume distribution as a share of the last session's total volume. Shaded areas denote bands between 2.5% and 97.5% quantiles. Figure 11 in the Appendix shows the 15-minute absolute price changes for grains.

Figure 3: Intraday Crude Oil Market



Note: X-axes denote the session hours, beginning at 6:00 p.m. the day before and closing at 5:00 p.m. (EST). The colored lines refer to the days of the OPEC announcements (one "OPEC Conference" on 2022-03-31 and 11 "OPEC and non-OPEC Ministerial Meetings"). Panel (a) shows the accumulated price change from the previous session's closing price. Panel (b) presents the intraday volume distribution as a share of the last session's total volume. Shaded areas denote bands between 2.5% and 97.5% quantiles. Figure 13 in the Appendix shows the 15-minute absolute price changes for oil.

share goals.[8] At least twice a year, member delegations meet at the headquarters in Vienna, the "OPEC Conference," to discuss the overall production target and individual quotas. In recent years, OPEC and non-OPEC oil-producing countries formalized an alliance that is commonly referred to as OPEC+.[9] The formal agreement was first signed in December 2016 and was designed to run for six months, but it has already been extended several times and is currently set to last until December 2023. The decision sphere of OPEC+ is the so-called "OPEC and non-OPEC Ministerial Meeting," which has occurred every month since 2021. Both the traditional conferences and the recently created ministerial meetings are often surrounded by speculations about the outcome, which is eventually announced in a press release on OPEC's website without a pre-established schedule.[10]

In contrast to the strong impact of the Grain Stocks report on agricultural markets, the effects of OPEC announcements on intraday oil market behavior are not as clear (Fig-

[8] Currently, OPEC has 13 members: Algeria, Angola, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Congo, Saudi Arabia, United Arab Emirates, and Venezuela.

[9] The non-OPEC countries are Azerbaijan, Bahrain, Brunei, Kazakhstan, Malaysia, Mexico, Oman, Russia, Sudan, and South Sudan.

[10] Figure 12 in the Appendix shows one of the OPEC press releases.

ure 3).[11] This discrepancy may be due to the lack of official announcement time and the potential for pre-meeting signaling and leaks, which tend to spread the impact of OPEC announcements over time. Nevertheless, there are indications that OPEC announcements do affect markets. For example, half of the "event" days in panel (a) exhibit an accumulated price change outside the 95% band at least in one moment of the trading session. Additionally, in all the "event" days, there is at least one trade volume spike outside the band (panel (b)).

3.3 Daily price volatility

This subsection presents a more comprehensive analysis of price behavior on "event" days *vis-à-vis* "regular" days. As previously mentioned, I use the principal component of futures prices from January 1995 to October 2022. The sample starts in January 1995 to eliminate the period when USDA reports were released after the end of the trading session. To begin, Table 1 summarizes the variances in daily price changes across the four commodities. The first line shows equal and unitary variances in the entire sample period, a mechanical consequence of the normalization. Line two reveals that corn, soybeans, and wheat prices experience considerably higher volatility when the USDA releases its Grain Stocks report, with corn price volatility being almost four times higher on these days than on the full sample. According to the third line, the same occurs with the volatility of oil prices on OPEC announcement days, but at a lower extent - 65% higher.

Table 1: Variances of daily price changes

	Corn	Soybeans	Wheat	Oil
Full sample (7,161 obs.)	1.00	1.00	1.00	1.00
Grain Stocks report (112 obs.)	4.82	3.79	3.20	0.93
OPEC announcements (108 obs.)	1.04	0.91	1.10	1.65

Note: Since the commodity price change series are normalized to zero mean and one standard deviation, all commodities have the same variance when considered the full sample.

[11] The occurrence of 12 OPEC announcements in such a short period had not occurred before. This is due to the recent creation of OPEC+ and the subsequent establishment of a monthly periodicity for the "OPEC and non-OPEC Ministerial Meetings." Interestingly, it is unlikely to happen again in the future, as the meeting of October 5th adjusted the frequency of the monthly meetings to every two months, and the subsequent one (December 4th) announced that the next meeting would take place on June 2023.

To control for possible seasonality or persistence in price volatility, as well as to identify any spillovers into the vicinity of the event days, I estimate the following OLS regression for each of the four commodities:

$$|p_d| = \rho\,|p_{d-1}| + \underbrace{\theta_1 S_{d+1} + \theta_2 S_d + \theta_3 S_{d-1}}_{\text{Grain Stocks report effects}} + \underbrace{\delta_1 O_{d+1} + \delta_2 O_d + \delta_3 O_{d-1}}_{\text{OPEC announcement effects}} + \underbrace{\xi_m + \xi_{wd}}_{\text{Fixed effects}} + \varepsilon_d, \quad (15)$$

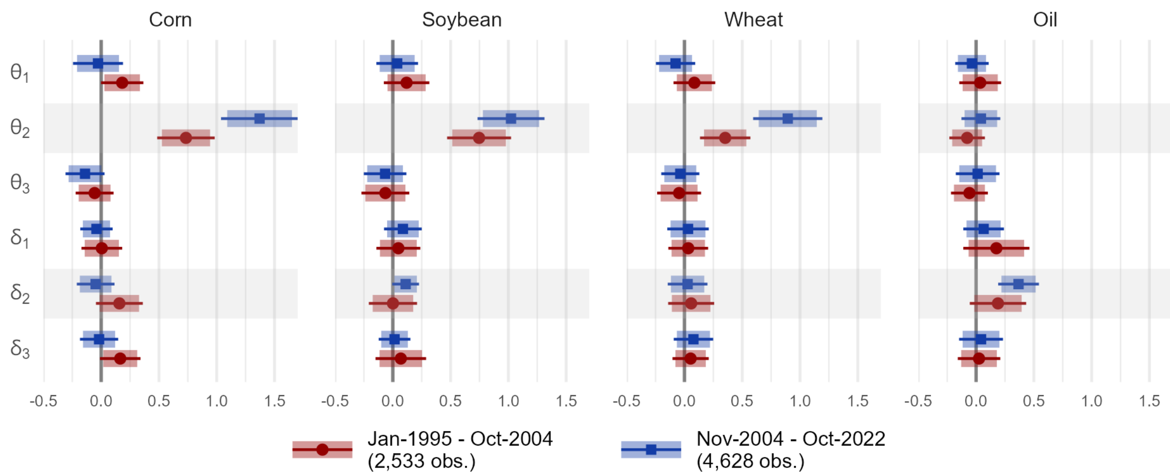
where $|p_d|$ represents the absolute change in the (log) price of a commodity at day d; S_d and O_d assume unitary value when the day d corresponds to a publication date of the Grain Stocks report or an OPEC announcement day, respectively (and zero otherwise). The remaining variables are a lag of the dependent variable and fixed effects of month and weekday. The coefficients θ_2 and δ_2 are designed to capture average differences observed on "event" days, while θ_1, θ_3, δ_1, and δ_3 capture possible spillover effects to the days preceding and following those days. For each commodity, I run two versions of Equation (15): one for the period between January 1995 and October 2004 (2,533 observations, 40 Grain Stocks reports, and 35 OPEC announcements) and another for the period from November 2004 to October 2022 (4,628 observations, 72 Grain Stocks reports, and 73 OPEC announcements).[12] The threshold between the two samples is determined by data availability for the empirical analysis in Section 4.[13] Despite not being used in the empirical analysis, the first sample is considered in this Section's exercises to assess the identification conditions for periods that may interest future studies.

The results in Figure 4 show that the prices of the four commodities exhibit larger fluctuations on their respective "event" days across both samples (θ_2 for grains and δ_2 for oil). Particularly, the price changes associated with the Grain Stocks report are far more prominent. In the second sample, the price changes of the three grains exceed one standard deviation from their usual rates, whereas, for OPEC and crude oil, this difference is approximately 0.4 standard deviations. In addition, the days before and after the "event" days show almost no effect in any of the eight regressions. These results suggest that both the release of the Grain Stocks report and the OPEC announcements induce price changes

[12] Table 3 in the Appendix contains the "event" dates for USDA and OPEC.

[13] In particular, the 2-year US breakeven inflation series starts in November 2004.

Figure 4: Coefficient estimates



Note: Estimates for eight versions of Equation (15). Rows represent the coefficients of interest, while each column refer to a different dependent variable, $|p_d|$. Since the commodity price change series are normalized to zero mean and one standard deviation, the coefficients express the average difference of the "event" days in terms of standard deviations. The solid dots are point estimates, while error bars/lines show the 90%/95% confidence intervals. Standard errors are robust to heteroskedasticity and autocorrelation.

that can be useful to distinguish volatility regimes.

Interestingly, the disparity between "event" and "regular" days is consistently higher in the sample starting in November 2004. This pattern may be linked to the increased financialization of commodity markets, characterized by a greater prevalence of futures contracts and derivatives instruments, which might have increased the liquidity and automation of the markets. With greater liquidity, agents can adjust their positions more quickly after new information, whereas automated trading algorithms are likely to amplify this effect.

3.4 Weak identification test

The preceding subsections provided evidence on how the volatilities of grains and oil prices are affected by the release of the USDA Grain Stocks report and OPEC announcements. However, those exercises do not allow for assessing the robustness of the identification eventually performed with these sources of price volatility. For this purpose, the test for weak identification in models identified through heteroskedasticity, proposed by Lewis (2022), can be used. This test consists of a first-stage F-test, similar to the traditional one proposed by Staiger and Stock (1997) for the basic instrumental variables setting.

His heteroskedasticity-robust first-stage F-statistic is given by:

$$F = \frac{\widehat{\Pi}^2 \left(\sum_{t=1}^{T} Z_t^2\right)^2}{\sum_{t=1}^{T} Z_t^2 \hat{v}_t^2} \tag{16}$$

where Z_t is an instrument constructed based on the observed innovations (commodity price) and regime dummies ($Z_t = 1$ for "event" days and $Z_t = -1$ for "regular" days); $\widehat{\Pi}$ is the OLS estimator of the coefficient from the first-stage regression of price innovations on Z_t; and $\hat{v}_t$ is the OLS residuals. He proposes a rule of thumb of F>23.11 for the first-stage F-statistic to reject the null hypothesis that the maximum relative bias associated to weak instruments is 10% (and F>37.42 for 5%).

Table 2 reports the outcomes of the above weak-instrument test for the studied commodity prices. The results for grains show mostly strong statistics, validating the USDA Grain Stocks report as an effective identification tool. When considering the sample beginning in November 2004, the statistics for the three grains considerably surpass the proposed rule of thumb, meaning that the null hypothesis of a weak instrument is rejected. However, both samples yield a low statistic for oil prices, indicating that OPEC announcements do not generate enough price volatility to enable a robust identification.

Table 2: Weak identification test (F-statistic)

	Corn	Soybeans	Wheat	Oil
Jan-1995 - Oct-2004 (2,533 obs.)	102.58	54.54	15.99	3.47
Nov-2004 - Oct-2022 (4,628 obs.)	661.87	277.02	173.26	7.15

Note: First-stage F-statistics of the weak-instrument test proposed by Lewis (2022). The instrument Z_t is constructed using the USDA Grain Stocks dates for corn, soybeans, and wheat prices. For oil price, the instrument is based on OPEC announcement dates. The critical values based on TSLS bias are: 37.42 (5%); 23.11 (10%); 15.06 (20%); and 12.05 (30%). For a given critical value, bias is greater than that indicated in 5% of repeated samples.

Through simulations, Lewis (2022) also demonstrates that the standard Wald test exhibits considerably high power for large effect sizes, even under weak identification conditions. His Monte Carlo simulations reveal that when the coefficient of interest is around 1, the power of the Wald test approaches 100%, regardless of the identification strength. Although these findings are specific to the calibration adopted in Lewis' study, they indicate that the inference distortions arising from the weak identification power of OPEC announcements tend to be mitigated for larger effects.

It is important to mention that the weak-instrument test for oil price does not necessarily invalidate the results of Känzig (2021). In that study, the author uses the OPEC announcements to build a monthly instrument, which is then used to identify the contemporaneous coefficients of a monthly VAR. Indeed, that approach might reduce weak identification issues caused by the lack of an official announcement time for OPEC decisions. However, it also requires stronger assumptions, equivalent to those needed for the event study identification discussed in Section 2.

4 Empirical analysis

4.1 Data

This paper seeks to estimate the contemporaneous causal effect of commodity prices on certain financial variables, assuming that the system of Equations (2) and (3) describes this relationship. I consider the prices of grains (corn, soybeans, and wheat) and crude oil as p_t. The variables x_t are categorized into three groups: i) prices of commodities (grains, crude oil, soybean oil, live cattle, and heating oil); ii) indicators from emerging economies (Credit Default Swap (CDS), nominal exchange rate, and stock index for Brazil, Chile, Colombia, Mexico, and Peru); and iii) US indicators (Dollar Index, S&P 500, Implied Volatility Index (VIX), breakeven inflation, and interest rate). All variables are standardized log changes of daily quotes from November 2004 to October 2022 (4,628 observations).[14]

The selection of variables, countries, and time range primarily relies on their availability and suitability to the econometric model adopted. Among the set of variables for which the response to a commodity price shock may be of interest, only those measured daily can be selected. The chosen emerging countries are those whose financial market is open during the release of the USDA Grain Stocks report and for which there is at least 95% of daily quotes for CDS in the established period. In addition, the US economy is included due to its relevance and data availability. Finally, the beginning of the sample is constrained by the availability of short-term breakeven inflation data for the US.

[14] Additional data details are provided in the Appendix. Tables 4 and 5 present information on the data sources used in this empirical analysis, while Figure 14 depicts the dynamics of the series employed.

Despite the emphasis on data availability, it turns out that primary commodities hold significant economic value for all six countries selected. Most of these countries are major players in the global market for at least one primary product. Among the commodities considered in this study, Brazilian grains and Colombian oil stand out, accounting respectively for 10% and 36% of these countries' merchandise exports.[15]

It should be noted that using a daily window rather than intraday frequency is not necessarily a drawback. On one side, there is an increased possibility of other shocks confounding the observed price response. On the other hand, as agents can take time to interpret new information and adjust their positions, daily data tends to be less susceptible to possible overreactions right after an event. Moreover, the challenges of accurately timing OPEC announcements (as detailed in Section 3) provide additional justification for employing daily frequency.

4.2 Empirical framework

Three estimates of α are provided for each pair of price p_t and variable x_t : i) a standard OLS estimate, which may be biased; ii) an ES approach that tends to reduce the bias but does not eliminate it; and iii) an IH approach (estimated using GMM) that is expected to give an unbiased estimate - mainly when applied to grains. By comparing these three estimates, I can evaluate the distortion caused by endogeneity issues.

An important consideration is how to differentiate the impacts of price innovations for corn, soybeans, and wheat. As the Grain Stocks report provides information on the three inventories simultaneously and their prices can influence each other, disentangling the effects of individual shocks is a complex econometric task beyond the scope of this paper. To overcome this problem, I compute the principal components (PC) of the three price series (which are themselves PC of their future prices) and use their first component to gauge price innovations. As a result, this empirical study estimates the joint causal effect of these three crops.

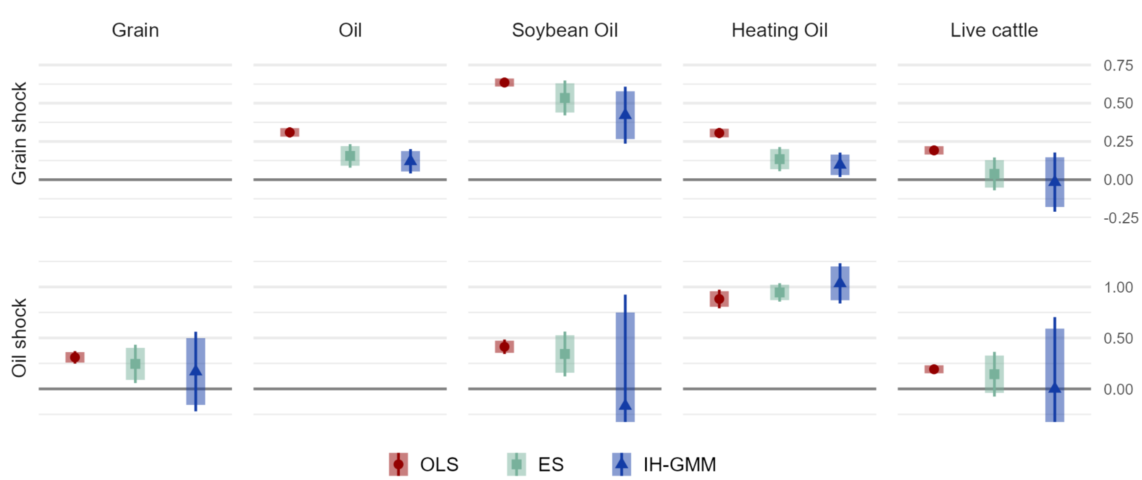
[15] Table 6 in the Appendix provides an overview of the commodities' relevance to the external trade of these six countries.

Another issue to consider is whether to present the coefficients for crude oil using OPEC announcements, given the results of the weak-instrument test shown in the previous Section. I have opted to present and discuss these results for three reasons. First, comparing OLS and ES estimates gives an idea of the bias sign, thus shedding light on the true effects of oil price shocks. Second, as discussed earlier, inference distortions caused by weak identification conditions tend to be reduced in the case of sizable coefficients. Lastly, the wide confidence intervals obtained with the IH approach for most of crude oil effects are enough to highlight the unreliability of the estimates, which can be contrasted to the more robust identification obtained for grains.

4.3 Results

The various α estimates are presented in Figures 5 to 9. Rows refer to grains and oil prices (p_t), while each column represents a different response variable (x_t). As all variables have been normalized to zero mean and one standard deviation, a coefficient of 0.1 means that a positive one standard deviation shock in p_t leads to an elevation of 0.1 standard deviations in x_t.

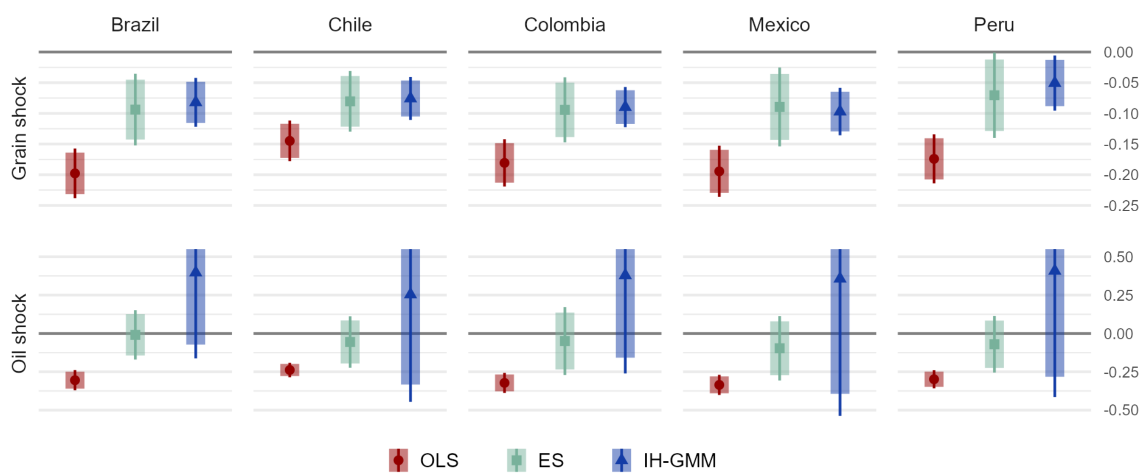
Figure 5: Effects on commodity prices



Note: Estimates of α in Equation (3) for distinct pairs of commodity price p_t (rows) and response variable x_t (columns), according to different approaches (OLS, Event Study, and Identification through Heteroskedasticity). The sample period ranges from November 2004 to October 2022, with a total of 4,628 observations for OLS and IH-GMM estimates, 72 for Grain's ES, and 73 for Oil's ES. The solid dots are point estimates, while error bars/lines show the 90%/95% confidence intervals. Standard errors are robust to heteroskedasticity and autocorrelation. All variables have been normalized to zero mean and one standard deviation. In this Figure, the response variables are represented by other commodity prices.

Figure 5 depicts the responses of commodity prices, revealing that all OLS estimates are positive and statistically significant. For grain price shocks, the ES and IH methods produce coefficients consistently lower than the OLS estimate, indicating an upward bias in the latter. Notably, grain price shocks positively affect oil prices, a finding that contrasts with previous research. Regarding oil price shocks, the wide confidence intervals around ES and IH estimates do not allow one to rule out the equality of the three coefficients. However, by examining the point estimates, one can still infer an indication of bias, as the direction of the change from OLS to ES is always the same as from ES to IH. Finally, it is worth highlighting the effect of a crude oil price shock on heating oil, for which ES and IH confidence intervals are relatively narrow, and the point estimates are higher than the OLS. This result aligns with the premise that the weak-instrument issue does not hinder the identification when the underlying effect is sufficiently large.

Figure 6: Effects on emerging market CDS

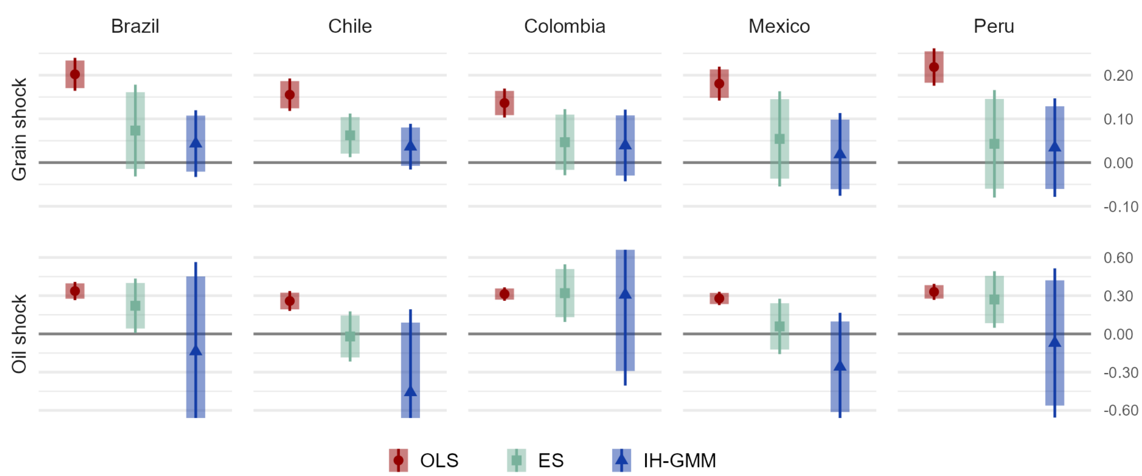


Note: Same as Figure 5, except for the response variables, here represented by emerging market CDS quotes.

The responses of CDS in emerging markets are shown in Figure 6. The OLS estimates show a negative correlation between commodity prices and credit risk for Latin American countries, but these coefficients are clearly overestimated as they stand far outside the confidence intervals derived from the most robust approaches. Although grain price shocks do result in a statistically significant reduction in credit risk when estimated using ES and IH methods, their effects are about half of those predicted by OLS estimates. For oil price shocks, the ES estimates yield coefficients close to zero and statistically different from the OLS ones, while the unreliable IH estimates indicate a positive impact instead. These findings indicate that grain price fluctuations have less influence on credit risk than naive estimations suggest and provide no evidence of reduced risk premiums in developing economies resulting from oil price shocks. A reasonable explanation for this result is that aside from enhanced competitiveness, shocks to commodity prices also elevate final goods production costs, pushing inflation up and hampering economic activity - ultimately worsening a country's indebtedness. In this case, the results indicate that the adverse effects of oil price hikes are greater than those caused by grain prices and are large enough to offset any benefits from improved terms of trade.

Turning to the responses of stock indexes in emerging markets, Figure 7 shows a similar pattern to previous results: OLS tends to overestimate the effects of grain and oil prices. In this case, however, the possible positive causal effects are likely minimal since none of the IH estimates is statistically different from zero. The results indicate that oil price shocks positively impact the Colombian stock index. This conclusion is based not only on the statistical significance of the ES estimate (which also applies to grain for Chile and oil for Brazil and Peru) but also on the similarity between point estimates obtained through three different approaches.

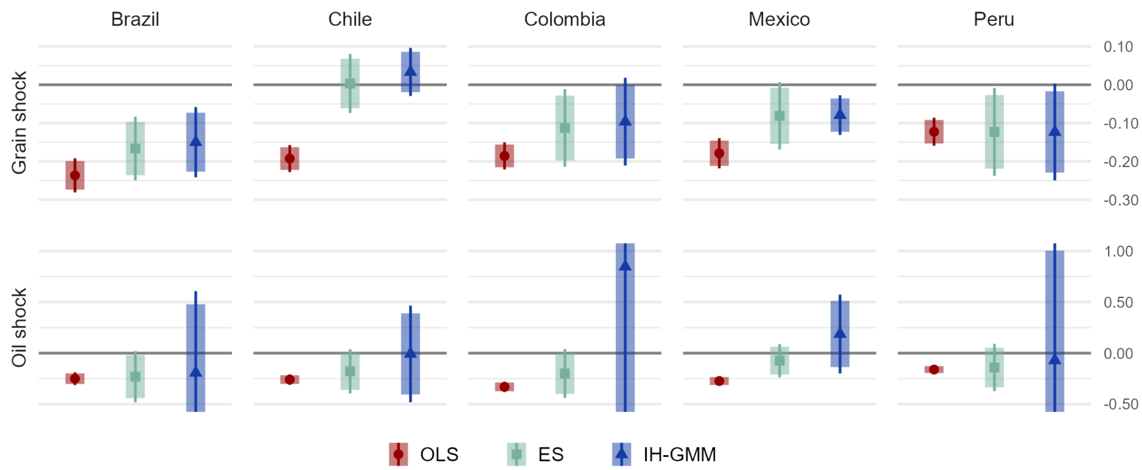
Figure 7: Effects on emerging market stock index



Note: Same as Figure 5, except for the response variables, here represented by emerging market stock indexes.

Completing the set of emerging market indicators, Figure 8 displays the nominal exchange rate responses. Although OLS overestimation persists, it is now less pronounced since most ES and IH confidence intervals overlap those of the OLS. Apart from Chile regarding grain price shocks and Mexico for oil price shocks, all other estimates point toward a slight exchange rate appreciation. This evidence is robust for Brazil, Colombia, Mexico, and Peru in the case of grain price shock, as ES and IH estimates are statistically significant. Likewise, Brazil's exchange rate appears to appreciate in response to an oil price shock, as suggested by the statistically significant ES estimate and three nearly identical point estimates.

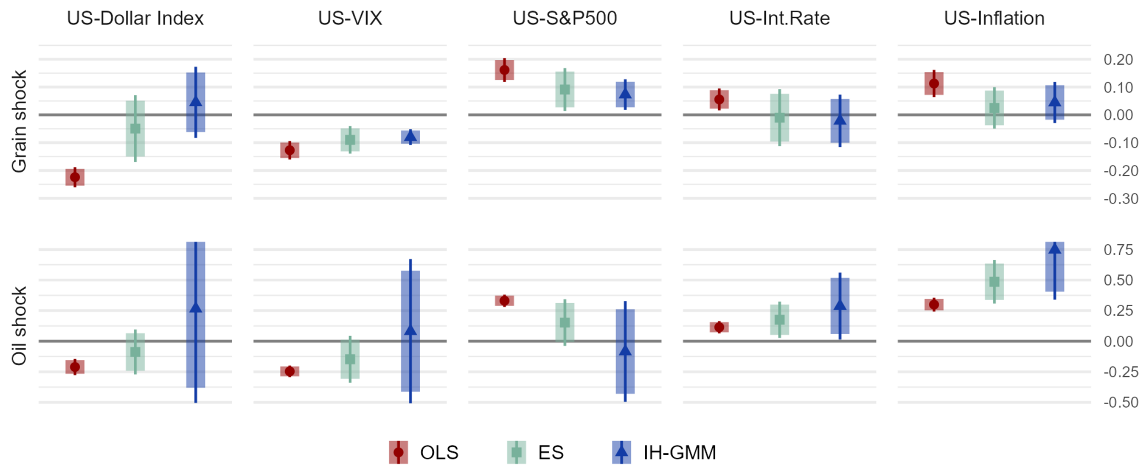
FIGURE 8: EFFECTS ON EMERGING MARKET EXCHANGE RATE



Note: Same as Figure 5, except for the response variables, here represented by emerging market exchange rates.

Finally, Figure 9 presents the estimates for US indicators responses. Aside from the ever-present OLS bias, there are three noteworthy observations. First, none of the shocks significantly impact the US dollar. Second, a grain price shock reduces volatility and positively affects the S&P 500 index without putting pressure on inflation or interest rate, which is an essentially favorable outcome. Third, an oil price shock worsens economic conditions by increasing inflation and interest rate. These findings are coherent with those in Figure 6, where the credit risk of developing countries decreases following the grain price shocks but not due to the oil price ones. Furthermore, the IH estimate for the impact of an oil price shock on US inflation seems to be another example of a large enough effect mitigating the distortions caused by weak identification conditions.

Figure 9: Effects on US variables



Note: Same as Figure 5, except for the response variables, here represented by US financial indicators.

5 Concluding remarks

Commodity prices are highly correlated with various other financial and macroeconomic variables. However, extracting cause-and-effect relationships from these co-movements can be challenging due to their simultaneity. In this paper, I use the increased volatility produced by relevant information releases to isolate the causal effects of grains and oil prices on several financial indicators. Notably, I explore a novel source of grain price volatility, the USDA Grain Stocks report.

I document that the impact of the Stocks Report on daily grain prices is more significant than that of OPEC announcements on oil prices, which enables a more precise identification. I show that the naive OLS approach consistently overestimates the effects of commodity price shocks. The results further indicate a bidirectional relationship between oil and grain prices, which differs from previous research suggesting that agricultural prices do not affect oil prices. Also contrasting with other studies, my findings suggest that grain price shocks only slightly impact emerging markets' risk premiums, while oil price shocks seem to have no effect. Regarding the US economy, I show evidence that grain price shocks reduce uncertainty and positively affect equities, while oil price shocks increase inflation and interest rate.

The results of this paper reveal that the effects of commodity price shocks are not uniform across different commodity classes and are considerably overestimated when endogeneity is neglected. These findings may have significant implications for macroeconomic models and policymaking. As models rely on precise coefficient estimates to accurately depict the domestic effects of changes in international commodity prices, the estimate distortions highlighted here may determine whether such models are helpful. Additionally, the evidence presented in this paper allows one to infer that the appropriate policy response to changes in commodity prices will depend on whether the underlying cause is a global factor or a specific shock to a particular commodity.

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Appendix A Derivation details

The goal is to estimate the parameter α from the following system:

$$p_t = \beta x_t + \gamma_p w_t + \varepsilon_t \tag{17}$$

$$x_t = \alpha p_t + \gamma_x w_t + \eta_t \tag{18}$$

With three shocks and two observed variables, if the researcher is unable to impose restrictions on β, γ_p, and γ_x, she can only estimate the covariance matrix. To see this, I first solve for the two observed variables:

$$p_t = (1-\alpha\beta)^{-1}\left[\left(\gamma_p + \beta\gamma_x\right) w_t + \beta\eta_t + \varepsilon_t\right], \tag{19}$$

$$x_t = (1-\alpha\beta)^{-1}\left[\left(\gamma_x + \alpha\gamma_p\right) w_t + \eta_t + \alpha\varepsilon_t\right]. \tag{20}$$

Next, I derive the covariance matrix as a function of the parameters and structural variances:

$$\Sigma = \mathrm{E}\left[[p_t x_t]' \cdot [p_t x_t]\right] = (1-\alpha\beta)^{-2}\begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \cdot & \Omega_{22} \end{bmatrix} \tag{21}$$

where:

$$\Omega_{11} = \sigma_\varepsilon + \beta^2\sigma_\eta + \left(\gamma_p + \beta\gamma_x\right)^2 \sigma_w,$$

$$\Omega_{12} = \alpha\sigma_\varepsilon + \beta\sigma_\eta + \left(\gamma_p + \beta\gamma_x\right)\left(\gamma_x + \alpha\gamma_p\right)\sigma_w,$$

$$\Omega_{22} = \alpha^2\sigma_\varepsilon + \sigma_\eta + \left(\gamma_x + \alpha\gamma_p\right)^2 \sigma_w.$$

It is easy to see that this system is not identified since the covariance matrix provides three moments (the variances of x_t and p_t, and the covariance between them), whereas there are seven unknowns: $\alpha, \beta, \gamma_p, \gamma_x, \sigma_\varepsilon, \sigma_\eta, \sigma_w$.

From (21), I can obtain the expected value of the OLS estimator of Equation (1):

$$\mathrm{E}\left[\hat{\alpha}_{\text{ols}}\right] = \frac{\mathrm{Cov}\left(p_t, x_t\right)}{\mathrm{Var}\left(p_t\right)} = \mathrm{E}\left[\frac{\widehat{\Sigma}_{12}}{\widehat{\Sigma}_{11}}\right] = \alpha + (1-\alpha\beta)\frac{\beta\sigma_\eta + \left(\beta\gamma_x^2 + \gamma_p\gamma_x\right)\sigma_w}{\sigma_\varepsilon + \beta^2\sigma_\eta + \left(\beta\gamma_x + \gamma_p\right)^2\sigma_w} \tag{22}$$

Using the assumptions (6) and (7) for the ES approach, in the limit case where the variance ratios go to infinity, the covariance matrix estimated using only the sample period E is given by:

$$\mathrm{E}\left[\hat{\Sigma}^E\right] \cong \frac{\sigma_\varepsilon^E}{(1-\alpha\beta)^2}\begin{bmatrix} 1 & \alpha \\ \cdot & \alpha^2 \end{bmatrix} \tag{23}$$

and hence the OLS estimator of Equation (1) using only the sample period S is consistent:

$$\mathrm{E}\left[\widehat{\alpha}_{\mathrm{es}}\right] = \frac{\mathrm{Cov}\left(p_t, x_t \mid t \in E\right)}{\mathrm{Var}\left(p_t \mid t \in E\right)} = \mathrm{E}\left[\frac{\widehat{\Sigma}_{12}^E}{\widehat{\Sigma}_{11}^E}\right] \cong \frac{\sigma_\varepsilon(1-\alpha\beta)^{-2}\alpha}{\sigma_\varepsilon(1-\alpha\beta)^{-2}} = \alpha. \tag{24}$$

Similarly, applying the IH approach based on assumptions (8) to (10):

$$\mathrm{E}[\Delta\Sigma] = E\left[\widehat{\Sigma}^E\right] - E\left[\widehat{\Sigma}^R\right] = \frac{\left(\sigma_\varepsilon^E - \sigma_\varepsilon^R\right)}{(1-\alpha\beta)^2}\begin{bmatrix} 1 & \alpha \\ \cdot & \alpha^2 \end{bmatrix}, \tag{25}$$

$$\mathrm{E}\left[\widehat{\alpha}_{\mathrm{ih}}\right] = \mathrm{E}\left[\frac{\widehat{\Delta\Sigma}_{12}}{\widehat{\Delta\Sigma}_{11}}\right] = \mathrm{E}\left[\frac{\widehat{\Delta\Sigma}_{22}}{\widehat{\Delta\Sigma}_{12}}\right] = \mathrm{E}\left[\sqrt{\frac{\widehat{\Delta\Sigma}_{22}}{\widehat{\Delta\Sigma}_{11}}}\right] = \alpha. \tag{26}$$

Appendix B - USDA and OPEC information

Figure 10: Highlights of a Grain Stocks report

Grain Stocks

ISSN: 1949-0925

Released January 12, 2022, by the National Agricultural Statistics Service (NASS), Agricultural Statistics Board, United States Department of Agriculture (USDA).

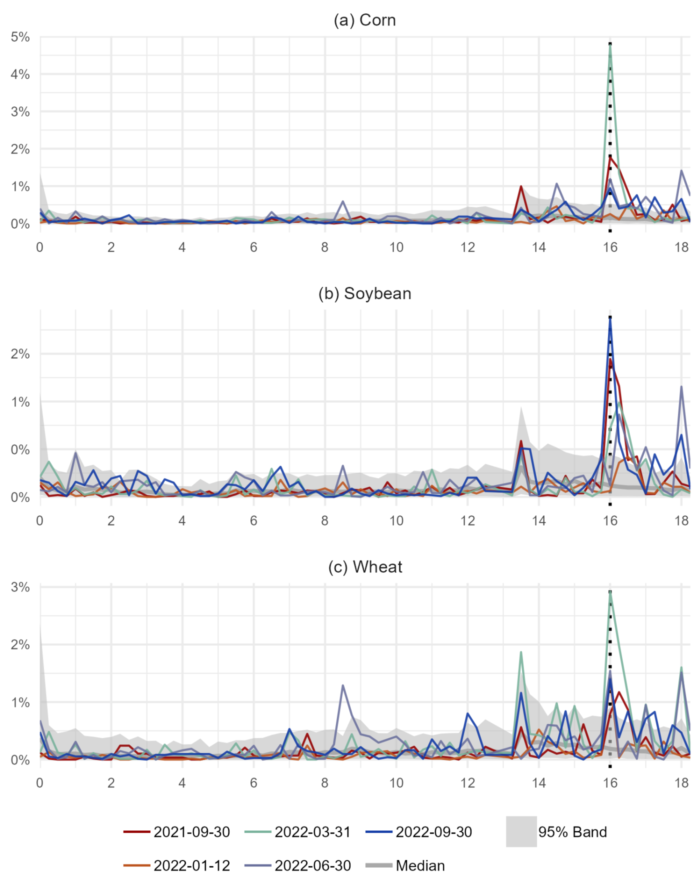
Corn Stocks Up 3 Percent from December 2020
Soybean Stocks Up 7 Percent
All Wheat Stocks Down 18 Percent

Corn stored in all positions on December 1, 2021 totaled 11.6 billion bushels, up 3 percent from December 1, 2020. Of the total stocks, 7.23 billion bushels are stored on farms, up 3 percent from a year earlier. Off-farm stocks, at 4.41 billion bushels, are up 4 percent from a year ago. The September - November 2021 indicated disappearance is 4.70 billion bushels, compared with 4.74 billion bushels during the same period last year.

Soybeans stored in all positions on December 1, 2021 totaled 3.15 billion bushels, up 7 percent from December 1, 2020. Soybean stocks stored on farms totaled 1.52 billion bushels, up 16 percent from a year ago. Off-farm stocks, at 1.63 billion bushels, are down 1 percent from last December. Indicated disappearance for September - November 2021 totaled 1.54 billion bushels, down 14 percent from the same period a year earlier.

All wheat stored in all positions on December 1, 2021 totaled 1.39 billion bushels, down 18 percent from a year ago. On-farm stocks are estimated at 273 million bushels, down 43 percent from last December. Off-farm stocks, at 1.12 billion bushels, are down 8 percent from a year ago. The September - November 2021 indicated disappearance is 384 million bushels, 16 percent below the same period a year earlier.

Figure 11: Intraday absolute price changes



Note: Panels (a), (b), and (c) show the 15-minute absolute price changes. All x-axes denote the session hours, beginning at 8:00 p.m. the day before and closing at 2:20 p.m. (EST). The colored lines refer to the days of the Grain Stocks report, released at hour 16 of the session (depicted by a vertical dotted line). Shaded areas denote bands between 2.5% and 97.5% quantiles.

Figure 12: OPEC Press Release


Organization of the Petroleum Exporting Countries

30th OPEC and non-OPEC Ministerial Meeting

The 30th OPEC and non-OPEC Ministerial Meeting was held via videoconference on 30 June 2022. In view of current oil market fundamentals and the consensus on its outlook, the OPEC and participating non-OPEC oil producing countries agreed to:

1. Reaffirm the decision of the 10th OPEC and non-OPEC Ministerial Meeting on 12th April 2020 and further endorsed in subsequent meetings including the 19th OPEC and non-OPEC Ministerial Meeting on the 18th July 2021.

2. Reconfirm the production adjustment plan and the monthly production adjustment mechanism approved at the 19th and 29th OPEC and non-OPEC Ministerial Meetings and the decision to adjust upward the monthly overall production for the month of August 2022 by 0.648 mb/d.

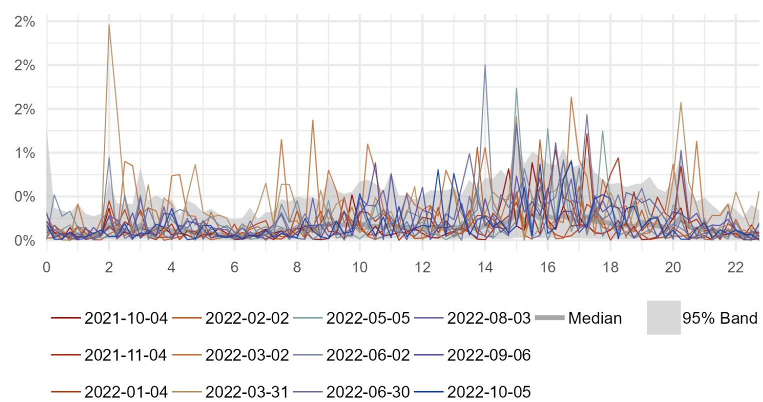
3. Reiterate the critical importance of adhering to full conformity and to the compensation mechanism. Compensation plans should be submitted in accordance with the statement of the 15th OPEC and non-OPEC Ministerial Meeting.

4. Hold the 31st OPEC and non-OPEC Ministerial Meeting on 3 August 2022.

Production table

Download document

Figure 13: Intraday oil price changes



Note: Intraday 15-minute absolute price changes. x-axes denote the session hours, beginning at 6:00 p.m. the day before and closing at 5:00 p.m. (EST). The colored lines refer to the days of the OPEC announcements. Shaded areas denote bands between 2.5% and 97.5% quantiles.

Table 3: Event dates

(a)				(b)			
USDA Grain Stocks report				**OPEC anoucements**			
12/01/1995	11/01/2002	**12/01/2009**	**12/01/2016**	20/06/1995	31/07/2003	**10/09/2009**	**09/04/2020**
31/03/1995	28/03/2002	**31/03/2009**	**31/03/2016**	22/11/1995	24/09/2003	**22/12/2009**	**13/04/2020**
30/06/1995	28/06/2002	**30/06/2009**	**30/06/2016**	07/06/1996	04/12/2003	**17/03/2010**	**08/06/2020**
29/09/1995	30/09/2002	**30/09/2009**	**30/09/2016**	02/12/1996	10/02/2004	**14/10/2010**	**03/12/2020**
16/01/1996	10/01/2003	**12/01/2010**	**12/01/2017**	26/06/1997	31/03/2004	**13/12/2010**	**05/01/2021**
29/03/1996	31/03/2003	**31/03/2010**	**31/03/2017**	01/12/1997	03/06/2004	**08/06/2011**	**04/03/2021**
28/06/1996	30/06/2003	**30/06/2010**	**30/06/2017**	30/03/1998	15/09/2004	**14/12/2011**	**01/04/2021**
30/09/1996	30/09/2003	**30/09/2010**	**29/09/2017**	24/06/1998	**10/12/2004**	**14/06/2012**	**27/04/2021**
10/01/1997	12/01/2004	**12/01/2011**	**12/01/2018**	30/11/1998	**31/01/2005**	**12/12/2012**	**01/06/2021**
31/03/1997	31/03/2004	**31/03/2011**	**29/03/2018**	23/03/1999	**16/03/2005**	**31/05/2013**	**19/07/2021**
30/06/1997	30/06/2004	**30/06/2011**	**29/06/2018**	22/09/1999	**15/06/2005**	**04/12/2013**	**01/09/2021**
30/09/1997	30/09/2004	**30/09/2011**	**28/09/2018**	29/03/2000	**20/09/2005**	**11/06/2014**	**04/10/2021**
13/01/1998	**12/01/2005**	**12/01/2012**	**08/02/2019**	21/06/2000	**12/12/2005**	**01/12/2014**	**04/11/2021**
31/03/1998	**31/03/2005**	**30/03/2012**	**29/03/2019**	11/09/2000	**31/01/2006**	**05/06/2015**	**02/12/2021**
30/06/1998	**30/06/2005**	**29/06/2012**	**28/06/2019**	13/11/2000	**08/03/2006**	**04/12/2015**	**04/01/2022**
30/09/1998	**30/09/2005**	**28/09/2012**	**30/09/2019**	17/01/2001	**01/06/2006**	**02/06/2016**	**02/02/2022**
12/01/1999	**12/01/2006**	**11/01/2013**	**10/01/2020**	19/03/2001	**11/09/2006**	**28/09/2016**	**02/03/2022**
31/03/1999	**31/03/2006**	**28/03/2013**	**31/03/2020**	05/06/2001	**14/12/2006**	**30/11/2016**	**31/03/2022**
30/06/1999	**30/06/2006**	**28/06/2013**	**30/06/2020**	03/07/2001	**15/03/2007**	**12/12/2016**	**05/05/2022**
30/09/1999	**29/09/2006**	**30/09/2013**	**30/09/2020**	27/09/2001	**11/09/2007**	**25/05/2017**	**02/06/2022**
12/01/2000	**12/01/2007**	**10/01/2014**	**12/01/2021**	14/11/2001	**05/12/2007**	**01/12/2017**	**30/06/2022**
31/03/2000	**30/03/2007**	**31/03/2014**	**31/03/2021**	15/03/2002	**01/02/2008**	**22/06/2018**	**03/08/2022**
30/06/2000	**29/06/2007**	**30/06/2014**	**30/06/2021**	26/06/2002	**05/03/2008**	**25/06/2018**	**06/09/2022**
29/09/2000	**28/09/2007**	**30/09/2014**	**30/09/2021**	19/09/2002	**10/09/2008**	**07/12/2018**	**05/10/2022**
11/01/2001	**11/01/2008**	**12/01/2015**	**12/01/2022**	12/12/2002	**24/10/2008**	**01/07/2019**	
30/03/2001	**31/03/2008**	**31/03/2015**	**31/03/2022**	13/01/2003	**17/12/2008**	**02/07/2019**	
29/06/2001	**30/06/2008**	**30/06/2015**	**30/06/2022**	11/03/2003	**16/03/2009**	**06/12/2019**	
28/09/2001	**30/09/2008**	**30/09/2015**	**30/09/2022**	11/06/2003	**28/05/2009**	**05/03/2020**	

Notes:

1) The dates in bold correspond to the "event" days used in the empirical analysis.

2) For the USDA Grain Stocks report, the dates are just a compilation from the USDA website.

3) For OPEC announcements, I use two sources: i) the press releases available on the OPEC website starting from 2002; ii) the Appendix from Känzig (2021), who uses OPEC resolutions and Bloomberg news. In both cases, there are dates corresponding to weekends and holidays. For these cases, I report the next trading day, the one effectively used to compute the surprise.

Appendix C Data details

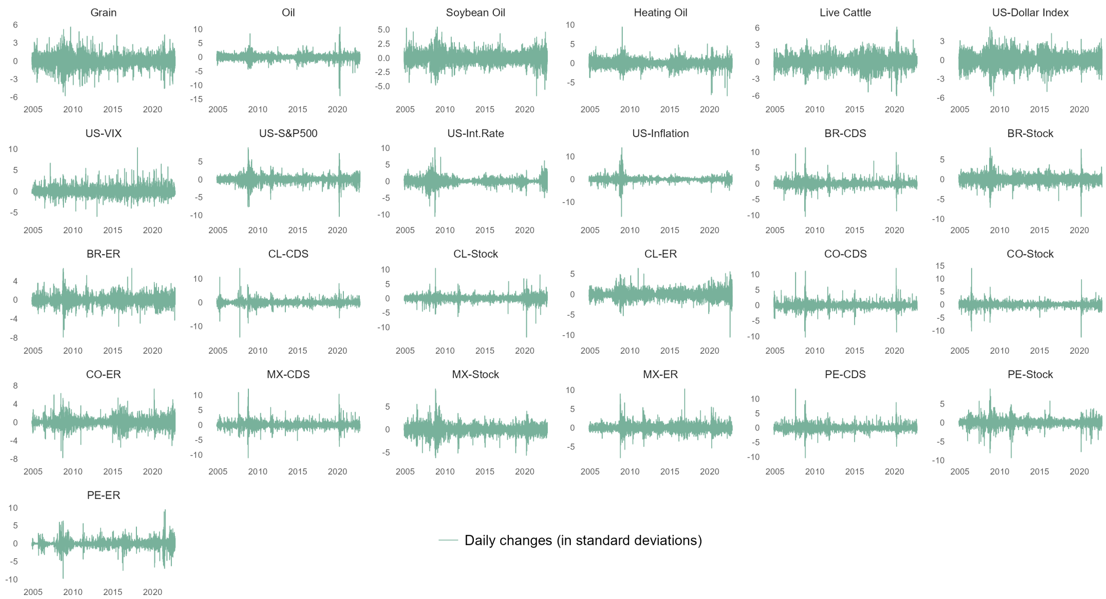
Table 4: Data sources: country indicators

Country	Indicator	Bloomberg Ticker
Brazil	Credit Default Swap (CDS)	CBRZ1U5 CBIN Curncy
Brazil	Stock Index	IBOV Index
Brazil	Currency rate against US dollar	BRL CMPN Curncy
Chile	Credit Default Swap (CDS)	CCHIL1U5 CBIN Curncy
Chile	Stock Index	IPSA Index
Chile	Currency rate against US dollar	CLP CMPN Curncy
Colombia	Credit Default Swap (CDS)	CCOL1U5 CBIN Curncy
Colombia	Stock Index	COLCAP Index
Colombia	Currency rate against US dollar	COP CMPN Curncy
Mexico	Credit Default Swap (CDS)	CMEX1U5 CBIN Curncy
Mexico	Stock Index	MEXBOL Index
Mexico	Currency rate against US dollar	MXN CMPN Curncy
Peru	Credit Default Swap (CDS)	CPERU1U5 CBIN Curncy
Peru	Stock Index	SPBLPGPT Index
Peru	Currency rate against US dollar	PEN CMPN Curncy
United States	US Dollar Index	DXY Curncy
United States	VIX	VIX Index
United States	S&P 500 INDEX	SPX Index
United States	Generic Government Bond Yield 2 Yr	GT2 Govt
United States	Zero-coupon inflation swap (ZCIS) 2 Yr	USSWIT2 BGN Curncy

Table 5: Data sources: commodity prices

Commodity	Nearby Future Contracts	Bloomberg Ticker
CBOT Soybean	1-6	S COMDTY
CBOT Corn	1-6	C COMDTY
CBOT Wheat	1-6	W COMDTY
CBOT Soybean Oil	1-6	BO COMDTY
CME Live Cattle	1-6	LC COMDTY
NYMEX Light Crude Oil	1-6	CL COMDTY
NYMEX Heating Oil	1-6	HO COMDTY

Figure 14: Transformed data series



Note: Daily series included in the empirical exercise. All the variables are standardized log changes.

Table 6: Commodities share in external trade

	Brazil	**Chile**	**Colombia**	**Mexico**	**Peru**	**USA**
Exports						
Commodities	**56.0**	**79.1**	**66.9**	**19.9**	**69.6**	**21.5**
Metal	**14.2**	**56.9**	**1.4**	**2.5**	**42.6**	**3.2**
Fuel	**9.3**	**1.4**	**51.1**	**10.7**	**8.5**	**8.7**
Oil	9.2	1.3	36.6	10.6	6.9	5.5
Food	**32.5**	**20.8**	**14.4**	**6.6**	**18.5**	**9.6**
Grains	10.5	0.2	0.0	0.1	0.0	2.5
Corn	*1.6*	*0.2*	*0.0*	*0.0*	*0.0*	*0.7*
Soybeans	*8.8*	*0.0*	*0.0*	*0.0*	*0.0*	*1.3*
Wheat	*0.1*	*0.0*	*0.0*	*0.1*	*0.0*	*0.5*
Imports						
Commodities	**25.5**	**29.9**	**19.4**	**16.4**	**27.3**	**21.7**
Metal	**3.5**	**1.9**	**2.0**	**2.5**	**1.1**	**2.3**
Fuel	**16.7**	**19.6**	**6.5**	**7.5**	**15.0**	**14.0**
Oil	11.4	16.0	6.2	5.4	14.3	12.8
Food	**5.2**	**8.3**	**10.9**	**6.3**	**11.2**	**5.3**
Grains	1.1	1.0	3.4	1.4	3.4	0.1
Corn	*0.1*	*0.5*	*2.0*	*0.6*	*1.6*	*0.0*
Soybeans	*0.1*	*0.1*	*0.4*	*0.5*	*0.2*	*0.0*
Wheat	*0.9*	*0.4*	*1.0*	*0.3*	*1.6*	*0.0*

Notes: Average for the 2004-2021 period. Source: own construction based on UN Comtrade and World Bank's WDI.