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Who moves first? Resource price interdependence through time-varying Granger causality

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Abstract

This paper investigates the interdependence among natural resource prices. Commodities belonging to three different groups (energy commodities, metals, agricultural commodities) are considered. The analysis is performed via a battery of time-varying Granger causality tests. They allow to assess whether price interdependence occurs and to identify the candidate first movers. These tests also allow observing how long and in which subperiods these causality relationships occur. The approach is applied to the monthly prices of 11 natural resources over the 1980–2021 period. Results suggest that interdependence is weak for energy and agricultural commodities and often concerns limited time periods, while it seems stronger and longer lasting among metals. Moreover, if an overall price driver has to be identified, agricultural commodities more than oil seem to be the best candidates.

KEYWORDS

commodity prices, natural resources, price interdependence, time-varying Granger causality

Recommendations for Resource Managers

- This paper investigates the interdependence among commodity prices belonging to three different

groups (energy commodities, metals, agricultural commodities).

- The analysis is performed via a battery of time-varying Granger causality tests.
- These tests also allow observing how long and in which subperiods these causality relationships occur.
- The approach is applied to the monthly prices of 11 commodities over the 1980–2021 period.
- Results suggest that interdependence is weak and short for energy and agricultural commodities, stronger and longer lasting among metals.
- Agricultural commodities are more often first movers than energy prices.

1 | INTRODUCTION

The large and rapid surge of most commodity prices in 2021 reiterated a well-known stylized fact: commodity prices tend to move together. The policy relevance of this possible interdependence is immediate. If a shock in one commodity is transmitted to other commodities, this shock will generalize and will transmit downstream to all consumption prices, thus shocking the inflation rate itself (Amaglobeli et al., 2022; Bürgi et al., 2023; Esposti, 2023; Ha et al., 2023). The economics of this interdependence consists of those underlying market linkages eventually generating cross-commodity price transmission (Listorti & Esposti, 2012). Though the progressive financialization of these markets may have increased this interdependence (Ding et al., 2021), what essentially connects commodities among them are the real cross-market linkages. These may be either vertical or horizontal. The former case prevalently occurs when one commodity enters as a cost into another commodity production process. The latter case may concern commodities behaving as either substitute or complementary goods in some intermediate or final demand set.

From this perspective, price interdependence signals that these commodities are connected either directly along the same supply chains (or networks) or indirectly through economy-wide (or system) linkages. An in-depth investigation of these real cross-market linkages would require complex structural approaches modeling those underlying market fundamentals (supply, demand, storage), eventually leading to price formation. Nonetheless, even without a complete and detailed structural representation of these connections, investigating the multivariate stochastic price generation process may still be highly informative.

As recently discussed by Byrne et al. (2020), the empirical literature on the common movement of commodity prices is vast. In this literature, communality of price dynamics comes from a shared (i.e., multivariate) data generation process (DGP), usually represented via vector autoregression (VAR) or vector error correction (VEC) models, or through more sophisticated representation of the underlying common drivers (for instance, common latent factors) (Esposti, 2021). The main interest in these reduced-form approaches is the identification of first-moving prices, that is, those standing at the core of these supply chains of networks and whose shock induces a response by the other prices (Esposti, 2023). In time-series econometrics, this idea is typically captured by the concept of Granger causality (Baum et al., in press; Shi et al., 2018, 2020).

One limitation of this concept is that Granger causality testing assumes time invariance. Over a period of observation, which has to be long enough to allow statistical reliability and robustness, the parameters linking the interdependent prices among them (and, consequently, also the Granger causation) are assumed constant. But if we care about price interdependence and this can vary over time, we have to admit the nonstability in causal relationships (Shi et al., 2020). Another issue with Granger causality testing concerns stationarity since, originally, the concept was introduced in the context of stationary variables. Shi et al. (2018, 2020) have developed an approach to Granger causality dealing with these two issues. On the one hand, they propose the notion of time-varying Granger causality to investigate whether causal relationships change over time. On the other hand, their approach also adapts to nonstationary series by testing Granger causality within a Lag-augmented VAR (LA-VAR) modeling framework (Dolado & Lütkepohl, 1996; Yamada & Toda, 1998).

Though some applications of this extended Granger causality testing have been presented (Baum et al., in press), also with specific reference to commodity prices (Adeosun et al., in press; Aharon et al., 2023; Shahzad et al., 2021), the present study is the first implementation of such approach to price interdependence among a large set of quite heterogeneous commodities over a long time period: monthly price series of 11 commodities over 42 years. Results here obtained suggest that interdependence is weak for energy and agricultural commodities and often concerns limited time periods, while it seems stronger and longer lasting among metals. Moreover, if an overall price driver has to be identified, agricultural commodities more than oil seem to be the best candidates. As emphasized by recent studies, this evidence points to the need for a further careful investigation of the energy-food price linkage (Adeosun et al., in press).

The rest of the paper is structured as follows. Section 2 presents the adopted data set and the main stylized facts by also discussing the relevant recent literature in the field. Section 3 details the adopted methodological approach and its novelty. Results are illustrated in Section 4 where their robustness is also discussed. Section 5 draws some policy and methodological implications and concludes.

2 | PRICE SERIES UNDER SCRUTINY AND LITERATURE REVIEW

The present analysis concerns the price of 11 selected commodities belonging to three different categories: three energy commodities (crude oil, natural gas, coal); four metals (aluminum, copper, zinc; nickel); four agriculture commodities (corn, wheat, soybean, beef).[1] All price series are monthly and cover the period January 1980 (1980M1)–December 2021 (2021M12) (504 observations), with the only exception of natural gas whose series starts in 1985M1 (444 observations). All series are taken from the International Monetary Fund (IMF) commodity price data set.

Appendix 1 provides details about which product quality these prices refer to and where they have been collected. As the intention of the IMF is to express, through these market prices, the global price dynamics, all these market places concern the most, or one of the most, important market worldwide usually adopted as reference price also by agents operating in more local markets. Therefore, they can be legitimately considered as proxies of the unavailable global market prices. It remains true, however, that some commodity prices may be more regional in nature than others (for instance, agricultural compared to energy commodities). In interpreting and commenting on results about price interdependence and reciprocal causation, therefore, this aspect should not be disregarded: global market prices are more likely to affect commodity prices that are more local in nature than the other way round. It must be also noticed that, as detailed in Appendix 1, several price series concern US markets and, in any case, all prices are expressed in US$. Therefore, we do not incur here the risk, often encountered when local or national prices are used, of commodity price shocks and movements actually induced by respective exchange rate adjustments (Antonio & Luis, 2022).

Unlike many previous studies (Esposti, 2021; Peterson & Tomek, 2000), commodity prices are here not deflated. The same strategy is followed for the possible presence of seasonality, particularly for agricultural prices (Crain et al., 1996): no seasonal adjustment is performed on price series and indexes. The logic behind this choice is twofold. On the one hand, we prefer to analyze the price series the economic agents really confront with and on which they take decisions. On the other hand, as stressed by Wang and Tomek (2007) and Corradi and Swanson (2006), any data transformation has to be taken with care as it could introduce artifacts within the series under investigation. In principle, purging inflation from these series, thus using the same deflator, is not expected to affect Granger causality tests under investigation here. However, deflated series may show different time-series properties compared to nondeflated series, especially in terms of stationarity (Esposti, 2021). Moreover, it remains true that a possible source of price interlinkage, especially during times of turbulence, could be represented by changes in macroeconomic variables such as interest rates and general price levels. Therefore, some robustness checks on the results here obtained with respect to correction for inflation and seasonality may still be informative. They are provided in Appendix 3 and discussed in Section 4.3.

It is also worth reminding that, within the empirical literature in this field, the logarithm of prices rather than price levels is often used (Esposti & Listorti, 2013; Listorti & Esposti, 2012). Although an explicit justification for this data transformation is often missing, one possible motivation is that price logarithms are more likely to show a normal distribution than price levels, and normality is usually required by the estimation and inference approaches. However, as with any nonlinear transformation, taking the logarithms may substantially alter the stochastic properties of the series under analysis, thus it remains an artifact in assessing the commodity price dynamics. In particular, a log-linear specification of price interdependence implies a different relationship (namely, nonlinear) compared to the linear specification in the price levels (Esposti, 2023).[2] Consequently, also Granger causality entails a slightly different interpretation: in the linear case, Granger causality expresses the response of one price level to another price's change (Zhao et al., 2021); in the log-linear case, the response takes the form of a percentage change, that is, it behaves like an elasticity. Eventually, taking pros and cons into account, the present study initially considers both the price levels and their logarithms and assesses whether stochastic properties are robust across the transformation.

On these price series, the investigation is carried out as follows. First, three groups of commodities (energy commodities, metals, agricultural commodities) are separately considered. Then, three selected prices (one for each group) are mixed in the search for the first moving price.[3] The analysis concentrates on assessing if and when these price series show some form of interdependence. The literature on common commodity price dynamics is huge and it is mostly concentrated on the investigation of the determinants of this common movement (Esposti, 2023).[4] Especially after the 2007–2008 price turmoil, and primarily emphasizing the evident nonlinearities in price dynamics and interdependence, many empirical studies have investigated the common determinants of commodity price levels and price volatility. On this latter aspect, in particular, these contributions (Bredenkamp & Bersch, 2012; Devlin et al., 2011; OECD, 2010; Piot-Lepetit & M'Barek, 2011; to mention a few) identify four possible drivers. Two concern the possibly common demand and supply forces leading to the respective market equilibrium (for instance, population and economic growth on the demand side; increasing resource scarcity on the supply side). The other two forces concern the financial markets, that is, the growing speculative activity and the exchange rate volatility.[5] Most recent studies also emphasize a further aspect that may generate volatility in commodity prices, when measured in nominal terms as in the present study, which is the rapid change in the inflation rate (Antonio & Luis, 2022).

This focus on volatility transmission has led to approaches concentrating on price co-exceedance, which is a common movement only occurring in periods of price spikes, namely of highly nonlinear price dynamics (Esposti, 2023). In this respect, other approaches have been also proposed to investigate nonlinear commodity price interdependence. Some are grounded on the spectral analysis and in time–frequency approaches. Wavelet analysis, in particular, has emerged as a useful and powerful tool in assessing commodity price co-movement cycles (Mutascu et al., 2022). Another approach consists of dynamic time warping, a nonparametric pattern recognition method (Miljkovic & Vatsa, 2023).

The present paper aims to contribute to this recent literature on common commodity price dynamics with nonlinearities, but the focus here is not on the possible determinants of common movement or common volatility. Regardless of whether these common determinants exist or not and what they are, a common movement can imply that some commodity prices move first. The objective here is to investigate whether or not early movers can be identified, especially under large and temporary nonlinearities. The identification of these early movers may be helpful in understanding the underlying forces, and above all, in improving real-time surveillance policy tool mentioned in the future (Esposti, 2023). Even though we do not consider here the abovementioned recent alternative approaches to nonlinear price interdependence, however, the comparison and combination of these different methods can open interesting developments for future research in this area.

Appendix 2 displays the 11 abovementioned individual commodity prices (Figures A1–A3), and the respective logarithms (Figures A4–A6), grouped in the three categories, over the 1980M1–2021M12 period. Visual inspection points to some general characteristics of the price dynamics. Within each group, commodity prices seem to show a common movement. This is only partially confirmed across groups: metals and agricultural commodities tend to share the same periods of rise and fall, while energy commodity prices seem more stable and less volatile at least until the very last years of the period under consideration. The logarithmic transformation does not change the general behavior of the series. Qualitatively, the patterns of the price levels and their logarithms are similar even though the latter are obviously smoother and this seems particularly evident for the energy commodity prices.

Besides this qualitative assessment, it seems necessary to more formally assess the univariate stochastic properties of these price series. Common properties are required to allow for a multivariate representation of the stochastic price formation process. In particular, as will be clarified in the next section, testing for time-varying Granger causality entails knowledge of the order of integration of the price series. Already Wang and Tomek (2007) noticed that in the empirical literature, the search for a unit root may be jeopardized by the characteristics of the respective tests (i.e., their power) and by their possible misspecification. To settle the robust evidence in this respect, here we use a battery of unit-root tests with complementary characteristics.

Following Baum et al. (in press), the first unit-root test is that originally proposed by Leybourne (1995). It achieves power gains over the standard Dickey and Fuller (1979) testing procedure by applying the augmented Dickey–Fuller (ADF) regression to the forward as well as the reverse realization of the time series of interest, testing for the presence of a unit root based on the maximum ADF *t*-statistic that results from the two regressions. Hence, the test is commonly referred to as *ADFmax* test. The second test was proposed by Elliott et al. (1996) and is often referred to as the Dickey–Fuller generalized least-squares (*DFGLS*) test. It aims to increase the test power over the standard DF approach through generalized least squares (GLS) removal of the underlying mean (or trend) in the variable of interest. The third test is the Kwiatkowski–Phillips–Schmidt–Shin (*KPSS*) test of Kwiatkowski et al. (1992) based on the null hypothesis of stationarity, while in the other cases, the null hypothesis is the presence of a unit root. Therefore, combined with them, the KPSS test compensates for the lack of power that typically affects these approaches.

Though from Figures A1 to A6 it is not so clear whether all prices are trending, especially for the large volatility in the second half of the observed period,[6] for all commodities and for any of the three abovementioned tests two alternative specifications are considered, as they seem both compatible with the observed price dynamics: with a drift; with a drift and a deterministic trend.

This set of unit-root tests is not actually exhaustive of all the different stochastic processes possibly underlying commodity prices. In particular, empirical literature in the field stresses the presence of structural breaks since a structural break within a stationary series may lead to accepting the presence of a unit root, thus wrongly concluding that the series is nonstationary (Baum, 2005; Glynn et al., 2007; Wang & Tomek, 2007). However, these further tests are not considered here as previous studies on the same series already excluded the presence of structural breaks for most commodities and, for a few exceptions, breaks do not change the (non)stationarity properties of the series (Esposti, 2021).[7]

Table 1 summarizes these unit-root test results.[8] First of all, no significant differences emerge comparing price levels and logarithm of price levels. As stochastic properties emerging from these tests are very similar, and even though the whole analysis is repeated in parallel for these two cases, henceforth we only present and comment on the results referring to price levels. The evidence obtained with the logarithm of prices is substantially equivalent. Some of these results are reported in Appendix 2, while the others are available upon request (see next section).

With few exceptions, results are largely correspondent across the three tests. Unit root is accepted (ADFmax and DFGLS tests) while stationarity is rejected (KPSS test) for all time series: all commodity prices contain a unit root and this remains valid for both specifications (drift and drift with a deterministic trend). The nonstationarity of these series excludes that they behave like mean-reverting processes, eventually determined by the respective long-term market fundamentals (Esposti, 2023), since they rather move as random walks possibly around a drift and/or a deterministic trend.

The few exceptions in this concordant unit-root evidence actually concern the DFGLS test, in the specification without a trend, for wheat, aluminum, and nickel. In these cases, the null of a unit root is rejected. However, nonstationarity remains the outcome for the ADFmax and

TABLE 1 Unit-root tests on the selected commodity price levels and logarithms (1980M1–2021M12).[a]

	ADFmax (drift)	ADFmax (drift and trend)	DFGLS (drift)	DFGLS (drift and trend)	KPSS (drift)	KPSS (drift and trend)
Price levels						
Oil	−1.873	−2.895	−1.124	−1.748	1.920*	0.312*
Coal	−1.753	−3.008	−0.764	−2.192	1.780*	0.271*
Natural gas[b]	−0.348	−2.306	0.589	−2.474	1.950*	0.241*
Aluminum	−2.196	−2.819	−2.523*	−2.784	1.030*	0.193*
Copper	−0.503	−2.186	−0.142	−1.843	2.130*	0.247*
Zinc	−1.699	−2.219	−0.826	−2.862	1.880*	0.236*
Nickel	−2.368	−2.985	−2.933*	1.830	1.230*	0.225*
Wheat	−2.144	−2.917	−2.010*	−2.267	0.889*	0.264*
Corn	−2.907	−1.842	−1.284	−2.793	1.370*	0.242*
Soy	−1.615	−2.772	−1.198	−2.389	1.580*	0.272*
Beef	0.567	−1.054	0.310	−0.511	1.880*	0.597*
Logarithm of the price levels						
Oil	−1.682	−2.358	−0.986	−1.281	1.940*	0.381*
Coal	−1.385	−2.636	−0.736	−1.920	1.780*	0.331*
Natural gas[b]	−0.350	−1.651	0.059	−1.318	1.340*	0.372*
Aluminum	−2.441*	−3.032	−2.447*	−2.740	1.160*	0.172
Copper	−0.945	−2.194	−0.624	−1.717	2.150*	0.220*
Zinc	−1.569	−3.030	−0.471	−2.990*	2.010*	0.254*
Nickel	−2.123	−3.091	−1.426	−2.775	1.640*	0.279*
Wheat	−2.354	−3.035	−2.040*	−2.162	0.831*	0.221*
Corn	−2.079	−3.028	−1.151	−2.614	1.450*	0.247*
Soy	−2.234	−3.200	−1.343	−2.372	1.570*	0.288*
Beef	0.036	−1.010	−0.284	−0.656	1.760*	0.577*
Price first difference						
Oil	−12.332*	−12.328*	−4.224*	−4.718*	0.078	0.041
Coal	−7.066*	−7.061*	−5.866*	−5.912*	0.124	0.037
Natural gas[b]	−2.646*	−3.160*	−2.916*	−3.193*	0.220	0.097
Aluminum	−8.532*	−8.529*	−2.802*	−3.335*	0.085	0.035
Copper	−6.379*	−6.459*	−2.635*	−4.058*	0.144	0.043
Zinc	−13.967*	−13.975*	−2.675*	−3.250*	0.051	0.023
Nickel	−12.834*	−18.823*	−4.430*	−5.146*	0.030	0.028

(Continues)

TABLE 1 (Continued)

	ADFmax (drift)	ADFmax (drift and trend)	DFGLS (drift)	DFGLS (drift and trend)	KPSS (drift)	KPSS (drift and trend)
Wheat	−8.193*	−8.239*	−3.969*	−5.389*	0.104	0.038
Corn	−5.155*	−5.211*	−2.703*	−3.677*	0.057	0.033
Soy	−7.184*	−7.218*	−5.154*	−5.383*	0.053	0.031
Beef	−7.564*	−7.801*	−3.697*	−6.161*	0.340	0.030
Logarithm of the price first differences						
Oil	−11.758*	−11.770*	−3.490*	−5.131*	0.131	0.061
Coal	−11.391*	−11.436*	−5.034*	−5.427*	0.104	0.031
Natural gas[b]	−21.920*	−21.958*	−5.128*	−5.083*	0.174	0.056
Aluminum	−7.957*	−7.950*	−2.608*	−3.824*	0.078	0.035
Copper	−6.117*	−6.137*	−2.609*	−3.162*	0.132	0.054
Zinc	−16.330*	−16.322*	−2.965*	−2.983*	0.036	0.025
Nickel	−15.395*	−15.381*	−2.553*	−3.947*	0.036	0.032
Wheat	−17.384*	−17.368*	−3.822*	−5.324*	0.097	0.035
Corn	−16.316*	−16.321*	−2.144*	−3.168*	0.054	0.031
Soy	−16.042*	−16.039*	−4.691*	−5.150*	0.053	0.030
Beef	−6.587*	−6.796*	−3.256*	−5.646*	0.320	0.038

Abbreviations: ADF, augmented Dickey–Fuller; DFGLS, Dickey–Fuller generalized least squares; KPSS, Kwiatkowski–Phillips–Schmidt–Shin.

[a]Statistically significant at the 5% confidence level.

[b]1985M1–2021M12.

*The test specification in terms of lags is established following Schwert (1989) and using $c = 12$ and $d = 4$ in his terminology.

KPSS tests. These few cases vanish in the lower part of Table 1 where the same tests on the first difference of prices and of the logarithm of prices are reported. Here results are totally concordant across all commodities, specifications, data transformation (levels or logarithms): the presence of a unit root (ADFmax and DFGLS tests) is always rejected, and stationarity (KPSS) is always accepted. Overall, this whole battery of tests provides a robust enough evidence to conclude that all prices share common stochastic properties: they have a single unit root, thus behaving like $I(1)$ series around a drift or, possibly, a deterministic trend.

The combination of purely visual inspection and unit-root tests makes the key research objective of the present study surface. Commodity prices seem to move together, particularly within the same category and during periods of turbulence, and this would suggest a common stochastic process. Such a multivariate process has to be properly identified and estimated to formally test for the presence of this interdependence and for its "nature," that is, its direction and variation over time. Time-varying Granger causality testing seems the appropriate tool for this research objective.

3 | THE METHODOLOGICAL APPROACH

Consider N commodities whose price is observed over T time periods (months in the present case). Assume that for any ith commodity there exists an unobserved fundamental price depending on the underlying real market drivers (supply, demand, storage, expectations). The ith price dynamics has two main components. One consists of adjustments to its own lagged values toward this fundamental long-run level. The other consists of the ith price response to the jth commodity price movements whenever the ith and jth markets show some of the abovementioned linkages. The stochastic DGP representing the ith price movement can be thus written as follows:

$$p_{it} = \alpha_i + \delta_i t + \sum_{s=1}^{S} b_{is} p_{it-s} + \sum_{s=1}^{S} c_{js} p_{jt-s} + u_{it}, \quad i,j \in N, \;\; i \neq j\,t, \;\; s \in TS < T, \tag{1}$$

where p_{it} is the ith commodity price (or the logarithm of price) at time t and α_i, δ_i, b_{is}, and c_{js} are commodity-specific unknown parameters to be estimated. α_i expresses the drift, while δ_i is the deterministic trend coefficient. Thus, α_i and δ_i indicate the long-term fundamental price level or the long-term deterministic trend, respectively, to which the actual price is expected to revert. The error term u_{it} is assumed to be normally, independently, and identically distributed, $u_{it} \sim NID(0, \sigma_i^2)$.

An analogous DGP can be specified for the jth commodity price:

$$p_{jt} = \alpha_j + \delta_j t + \sum_{s=1}^{S} b_{js} p_{jt-s} + \sum_{s=1}^{S} d_{is} p_{it-s} + u_{jt}, \quad i,j \in N, \;\; i \neq j\,t, \;\; s \in TS < T, \tag{2}$$

Equations (1) and (2) are two simultaneous autoregressive equations. Systems (1) and (2) thus behaves like a bivariate VAR(S) model. Once model coefficients have been estimated, price p_j (p_i) is said to Granger cause (henceforth, G-cause) price p_i (p_j) if the past values of p_j (p_i) have predictive power for the current value of p_i (p_j), conditional on the past values of p_i (p_j) itself. Formally, the null hypotheses of no Granger causality from p_j (p_i) to p_i (p_j) involves testing the joint significance of parameters c_{js} (d_{is}) ($\forall\, s = 1, ..., S$) by means of a heteroskedastic-consistent Wald test (Baum et al., in press).[9] This statistic follows a standard χ^2 distribution. The VAR model and the consequent testing approach can be generalized to a multivariate VAR model with $m \geq 2$ prices, thus equations.[10]

Dealing with commodity price series, this conventional testing framework may come across two main issues. First, the VAR model must include stationary variables while, as shown in the previous section, this is not the case for the commodity price series under investigation here. To account for the possibility of nonstationary and integrated variables, an LA-VAR model can be adopted (Dolado & Lütkepohl, 1996).[11] It simply consists of the original VAR(S) specification augmented with additional d lags for the possible maximum order of integration of the variables, that is, a VAR($S+d$) specification, though Granger causality testing remains confined to the original S lags.

Under nonstationary prices, Granger causality could be still assessed within a first-difference VAR model, but this might misspecify the underlying relationship if a long-run linkage (canceled out in first differentiation) occurs. Nonetheless, for the sake of completeness and comparison, Granger causality test results are also obtained for the first-difference VAR model specification (see Section 4.3 and Appendix 3).[12]

The second issue is that the conventional Wald test rejects or accepts Granger causality on the whole period T while, in fact, it might only occur in limited subperiods. In this latter case, it would be also helpful to date these subperiods of emerging causality. To overcome this latter limitation, it can be helpful to adapt the logic developed by Phillips et al. (2011, 2015) and Phillips and Shi (2020) to test and date episodes of asset price bubbles (i.e., explosive roots) via right-tailed unit-root tests (Baum & Otero, 2021). The extension of this logic to Granger causality testing has been proposed by Shi et al. (2018, 2020). In short, the method consists of recursive estimation algorithms that generate a sequence of Wald test statistics of Granger causality, one for each subperiod of interest. Three alternative strategies can be adopted: the forward expanding window (FE), the rolling window (RO), and the recursive evolving (RE) algorithms.[13]

In all cases, the first step consists of establishing the number Tr corresponding to the integer part of the product T by r with $0 < r < 1$. $[1, Tr]$ thus denotes a subsample starting at p_{i1} and ending at p_{iTr}. The VAR$(S + d)$ model can be estimated, provided that $(S + d) \ll Tr$, over this subsample and the respective Wald test statistic indicates the Granger causality in this subperiod. In the FE algorithm, this is firstly performed for the minimum window length going from p_{i1} to p_{iTr}. Then, this minimum sample is expanded sequentially by one observation until the final test statistic is computed on the entire sample, that is, from p_{i1} to p_{iT}. The FE algorithm thus returns a sequence of $(T + 1 - Tr)$ Wald test statistics, one for each of the $(T + 1 - Tr)$ subsamples with the same starting point (the first data observation) and an increasing size. In the RO algorithm, the VAR model is estimated on subsamples containing a fixed number of Tr observations, starting from the subsample $[1, Tr]$. Then, this window is rolled through the sample advancing one observation at a time. The Wald test statistic is computed for each of the $(T + 1 - Tr)$ windows, that is, subsamples, of constant size.

Finally, the RE algorithm is a sort of combination of the previous ones. The VAR model is estimated, and the Wald test statistics are computed, for the initial $[1, Tr]$ subsample. Then, estimation is repeated over the progressively expanded subsamples as in the FE algorithm. In turn, this procedure is reiterated, like in the RO algorithm, for the whole sequence of subsamples from $[n + 1, Tr + n]$ to $[T - Tr, T]$, with $n = 1, \ldots, (T - Tr)$. It follows that for any observation in the sample, apart from the first subsample that defines the minimum window size Tr, the RE algorithm produces a set, that is, a vector, of Wald test statistics. To manage this abundance, Phillips et al. (2015) and Shi et al. (2020) propose an inference based, for each observation, on the maximum absolute value of this set or vector.

This maximum value of the Wald statistic is also called supremum, or supremum norm, and it is indicated as SW. Thus, the RE algorithm is based on a sequence of $(T + 1 - Tr)$ test statistics that are these SWs at each observation. It is worth noting that these SWs are extracted from a sequence of Wald tests, which, unlike the FE and RO algorithms, for any observation have a different sample size. This might pose an issue with the reliability of the inference based on these maximum statistics.[14] However, Shi et al. (2020, Theorem 1 and Section 6.6) demonstrate how this heterogenous size is handled in deriving the limiting distribution (i.e., for $T \to \infty$) of SW and, on the basis of these asymptotic properties, in computing the critical values on which inference is performed.

As the RE algorithm encompasses both the FE and RO ones as special cases, its results can be regarded as the most robust and reliable evidence on time-varying Granger causality. The practical implementation of this time-varying approach to Granger causality implies the estimation of the underlying VAR (or LA-VAR) model using moving windows of different lengths. As suggested by Baum et al. (in press), the large number of resultant statistics can be efficiently stored and displayed for analysis as follows. For each observation (month in the present case) an upper triangular square matrix can be arranged in with column and row dimensions equal to the largest number of usable observations. The FE Wald statistic is the leading entry in each column, the RO Wald statistic is located on the main diagonal, and the largest element of each column is the RE statistics, that is, the SW.

Two sets of test results are generated and presented here. First, for any algorithm, a single test statistic is computed to test whether a commodity price G-causes another one at any time over the whole sample. The null hypothesis is that there is no evidence of any Granger causality between that couple of prices. This single test consists of the largest FE, RO, and RE statistics, respectively, that is, the supremum norms of the sequence of FE and RO Wald test statistics (i.e., the largest element of the first row of the upper triangular matrix of test statistics and the largest element of the main diagonal of the matrix, respectively), and the supremum norm of the sequence of SWs returned by the RE algorithm (i.e., the largest element of the entire upper triangular matrix). Second, the sequence of RE statistics over the whole $(T+1-Tr)$ period is displayed graphically. In this case, whenever the test result exceeds its critical value, we date the emergence of this Granger causation.

To perform all these tests, the minimum window size, Tr, is set at 72 observations (i.e., months), corresponding to one-seventh of the whole sample of 504 observations. The empirical distribution of the test statistics under the null hypothesis is computed by bootstrapping, with 400 replications, and controlling for size (Shi et al., 2020). Critical values are then obtained from this empirical distribution.

4 | RESULTS

4.1 | Full sample analysis: Price interdependence and first movers

In the present application, Granger causality testing aims to reveal price independence and assess its "nature," that is, whether it is multidirectional or unidirectional. In this latter case, tests also identify the price behaving as first mover. Tables 2–4 report the three time-varying Granger causality tests (FE, RO, RE) for the selected energy commodities, metals and agricultural commodities, respectively.[15] Reported results are the heteroskedastic-consistent Wald tests computed from an LA-VAR$(S+d)$ model. The optimal lag S of the unaugmented VAR can be selected using the conventional criteria, the Akaike information criterion and Schwarz's Bayesian information criterion, in particular.[16] As the data are monthly, the maximum number of lags is set to 12. In the present case, these two criteria are not concordant as they indicate an optimal lag of $S=4$ and $S=2$, respectively. Following Shi et al. (2020) and Baum et al. (in press), a lag length of $S=2$ is selected as it offers a more parsimonious representation of the variables in the system.[17] The lag of the augmented part of the LA-VAR model is set at $d=1$ consistently with the order of integration observed for all price series, $I(1)$. The adopted specification is thus an LA-VAR $(2+1)$ model.[18] Finally, following Baum et al. (in press) and previous studies on these price series (Esposti, 2023), the adopted LA-VAR model specification always includes both a drift and a deterministic trend to avoid the risk of misspecification. Therefore, the differences in the reported maximal statistics are solely due to the different subsampling schemes employed by the three algorithms and discussed in the previous section.

TABLE 2 Time-varying Granger causality tests for energy commodities prices (1985M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Oil G-caused by			
Coal	14.477	15.497	15.699
	(24.981)	(23.802)	(26.614)
	[35.244]	[33.079]	[35.486]
Natural gas[a]	11.921	14.857	14.857
	(19.894)	(19.864)	(21.302)
	[23.535]	[23.159]	[25.249]
Coal G-caused by			
Oil	56.545**	32.569**	56.545**
	(25.574)	(26.060)	(27.747)
	[34.131]	[31.537]	[34.131]
Natural gas[a]	47.407**	36.053**	53.329**
	(15.384)	(15.142)	(15.945)
	[22.915]	[22.602]	[23.230]
Natural gas G-caused by			
Oil	8.606	16.759	23.360
	(23.382)	(22.766)	(23.669)
	[30.919]	[28.656]	[30.919]
Coal	50.230**	23.090**	50.230**
	(19.003)	(19.295)	(19.751)
	[26.531]	[23.430]	[26.531]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

[a]1985M1–2021M12.

*,**Statistically significant at 5% and 1% confidence level, respectively.

The three algorithms return largely concordant results with only few and marginal exceptions. Therefore, for the reasons discussed above, we will comment only on the evidence resulting from the RE algorithm.[19] In the case of energy commodities, it emerges that price interdependence mostly involves coal and natural gas: the shock on one of the two prices generates a response by the other. On the contrary, oil is not caused by any other price while it G-causes coal but not natural gas. Therefore, oil seems to behave as the first mover: its shocks are transmitted to coal, then coal and natural gas prices are interdependent. Metals show a larger degree of interdependence with all prices G-caused by at least two of the other metals. This means that it is not possible to identify a clear causal channel in this price interdependence, that is, an indisputable first moving price. Nonetheless, for the following analysis, we select copper price as representative of metal prices for its relevance and because it is the only case in which one Granger causation is statistically missing, linking copper to nickel price. Moreover, as will be shown in the following section, the effects of copper price on other metal prices seem more persistent.

The group of agricultural commodities shows a limited interdependence, overall. Two different price linkages seem to emerge. One concerns the interdependence between crops, in

TABLE 3 Time-varying Granger causality tests for metals prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Alum G-caused by			
Copper	16.679**	20.169**	62.005**
	(12.181)	(12.786)	(12.978)
	[14.967]	[15.406]	[15.794]
Zinc	25.258**	22.308**	37.055**
	(10.859)	(11.113)	(11.895)
	[16.726]	[15.699]	[18.167]
Nickel	79.717**	80.034**	85.770**
	(18.253)	(17.850)	(18.747)
	[25.251]	[24.385]	[26.026]
Copper G-caused by			
Alum	18.039**	16.866**	30.407**
	(15.197)	(14.473)	(15.961)
	[16.636]	[17.170]	[17.275]
Zinc	23.020**	52.371**	56.478**
	(15.222)	(14.787)	(16.032)
	[18.754]	[20.286]	[20.783]
Nickel	10.439	14.641	24.905
	(17.116)	(15.844)	(24.954)
	[20.442]	[19.906]	[26.545]
Zinc G-caused by			
Alum	11.441	22.137**	23.809**
	(11.584)	(11.797)	(12.761)
	[13.731]	[15.008]	[16.645]
Copper	22.361**	49.659**	51.899**
	(15.594)	(14.885)	(16.675)
	[21.844]	[18.859]	[21.844]
Nickel	21.035*	20.895*	24.463*
	(19.348)	(19.779)	(21.979)
	[27.476]	[31.144]	[31.710]
Nickel G-caused by			
Alum	25.055**	19.234*	31.071**
	(17.414)	(18.505)	(19.132)
	[22.913]	[23.698]	[24.403]
Copper	55.271**	49.812**	55.271**
	(13.555)	(15.229)	(15.445)
	[25.340]	[25.980]	[26.318]
Zinc	10.631	14.648	28.202**
	(21.436)	(20.624)	(21.909)
	[25.340]	[25.980]	[26.318]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

*,**Statistically significant at 5% and 1% confidence level, respectively.

TABLE 4 Time-varying Granger causality tests for agricultural commodities prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Wheat G-caused by			
Corn	10.850	15.212	20.245*
	(17.066)	(18.002)	(18.667)
	[23.061]	[23.469]	[23.637]
Soy	8.799	21.465*	21.476*
	(18.272)	(17.680)	(19.417)
	[28.447]	[29.076]	[30.244]
Beef	25.975**	18.182**	28.720**
	(8.401)	(9.072)	(9.593)
	[13.924]	[12.746]	[13.924]
Corn G-caused by			
Wheat	17.447	24.082	25.718
	(28.875)	(29.006)	(29.682)
	[38.674]	[40.274]	[43.679]
Soy	4.808	25.339*	25.339*
	(21.452)	(22.180)	(23.166)
	[31.766]	[33.799]	[34.839]
Beef	11.218	11.663	11.663
	(13.269)	(13.253)	(14.183)
	[18.528]	[18.399]	[19.367]
Soy G-caused by			
Wheat	8.103	15.592	19.129
	(20.992)	(22.915)	(23.406)
	[28.306]	[30.191]	[32.574]
Corn	8.690	18.809	25.669*
	(21.580)	(20.013)	(22.618)
	[30.739]	[29.682]	[31.893]
Beef	13.107	14.633	14.859
	(14.756)	(14.936)	(15.642)
	[18.489]	[18.675]	[19.636]
Beef G-caused by			
Wheat	37.325**	54.189**	56.397**
	(7.965)	(8.441)	(8.881)
	[11.739]	[11.241]	[13.289]
Corn	10.015	9.999	12.430
	(13.786)	(12.196)	(14.344)
	[16.340]	[19.251]	[20.183]
Soy	8.936	12.929	13.606
	(13.512)	(14.284)	(15.308)
	[18.589]	[16.900]	[21.338]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

*,**Statistically significant at 5% and 1% confidence level, respectively.

TABLE 5 Time-varying Granger causality tests for a mixed set of commodity prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Oil G-caused by			
Copper	18.736	14.822	19.649
	(24.508)	(24.772)	(26.375)
	[33.311]	[32.258]	[35.208]
Wheat	9.561	21.668*	21.668*
	(17.445)	(17.472)	(18.288)
	[26.017]	[24.554]	[29.015]
Copper G-caused by			
Oil	13.992	12.472	14.234
	(23.524)	(24.641)	(25.757)
	[30.947]	[31.983]	[34.554]
Wheat	18.954*	10.835	20.138*
	(15.432)	(17.472)	(18.667)
	[21.732]	[25.177]	[25.177]
Wheat G-caused by			
Oil	8.606	16.759	23.360
	(23.382)	(22.766)	(23.669)
	[30.919]	[28.656]	[30.919]
Copper	50.230**	23.090**	50.230**
	(19.003)	(19.295)	(19.751)
	[26.531]	[23.430]	[26.531]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

*,**Statistically significant at 5% and 1% confidence level, respectively.

particular soybean and corn. The other concerns the bidirectional causal channel between wheat and beef. Given its relevance, but also because wheat is vertically integrated with the downstream beef production, here we select wheat as representative of the agricultural commodities for the following analysis.

Table 5 finally reports the results of this second level of investigation, that is, time-varying Granger causality tests for a further group of commodities obtained by mixing the most representative and/or first movers of the three categories: oil, copper, and wheat. As could be expected, price interdependence is here a little weaker that in the more homogeneous subgroups. Nonetheless, some interesting results are worth noticing. First of all, oil does not seem to be the driver of the other prices. Second, wheat is the only price that G-causes the other two. Third, copper and wheat show reciprocal Granger causation. The implication of these results is that the first mover may be either wheat or copper, then the shock is transmitted to the other price and, in the case of wheat, also to the oil price. This result would suggest that agriculture remains the most critical sector, that is, a sector not only satisfying basic needs but also feeding a large number of downstream activities and, therefore, is strategic relevance for the overall economy. Supply-side shocks (for instance, natural disasters) and demand-side shocks (for instance, periods of economic downturn or sudden changes in consumption habits) firstly affect primary needs. But then, these effects are transmitted downstream along the supply chains by eventually changing the demand for energy and materials (like metals) whose prices are then indirectly affected.

These results here obtained do not constitute a real novelty. Early works in the field have suggested that energy behaves as a major driver of agricultural production, agricultural production choices, and, therefore, of agricultural commodity prices (Christensen et al., 1981; Dvoskin & Heady, 1977; Sands et al., 2011). Results of the present paper seem to contradict or, at least, to question this evidence, particularly on the lag relationship between oil and agricultural commodity prices. However, it is worth noting that if more recent contributions using similar prices, though adopting different methodologies, are considered, the here presented results remain remarkable but far less surprising. Vatsa et al. (2023) investigate the impact of natural gas price shocks on three major cereal crops (maize, rice, and wheat) and find that the response of cereal prices has been relatively small, instantaneous, and transitory. Shahzad et al. (2021) show evidence of significant time changes in the relationships across different pairs of commodity prices. More specifically, it emerges that temporary spillovers between energy and agricultural commodities are more frequent than between agricultural commodities and precious metals, but these spillovers are bidirectional and do not point to energy prices as the driving prices.

With reference to the specific relationship between oil and agricultural prices, Miljkovic and Vatsa (2023) conclude that oil price is generally anticipated by crop prices; however, there are also periods when the former leads the latter. In this effort of understanding the predictive relationship between energy and food commodities, Adeosun et al. (in press) notice that a feedback between Brent oil and six food commodity prices (corn, rice, sugar, coffee, meat, and palm oil) occurs but, again, it is bidirectional. During specific periods of crisis, however, a causal effect mostly running from wheat and soybean prices to Brent oil price is observed and this highlights the importance of the predictive power of agricultural prices in the trajectory of oil prices.

The bottom line of this comparison with recent studies suggests that the here presented results confirm and clarify what was previously obtained. Not only do they question the role of oil price as the key driver of all other prices, but also of the inflation rate Aharon et al., 2023; Antonio & Luis, 2022; Esposti, 2023). In addition, they stress that the critical role of agricultural commodities is very often overlooked if not disregarded. Another key evidence is that price interdependence across commodities may vary across time and this may depend both on the occurrence of short periods of crises or stress, but also on changes in some long-term market fundamentals (for instance, the use of crops for biofuel production). In this respect, the approach here adopted seems particularly suited in dating when these changes may have occurred.

4.2 | Dating Granger causality

The time-varying Granger causality tests reported in Tables 2–5 pick the largest FE, RO, and RE statistics. Therefore, this evidence may either concern only a very limited time window or persist over the whole period under investigation. Therefore, to assess whether this price interdependence is just occasional or more structural, we need to detect how long and when Granger causality occurs. The sequence of test statistics from the three algorithms can be graphically examined to investigate how the causal relationships change over time. In this respect, the patterns emerging from the three algorithms are largely correspondent even though RO and RE algorithms appear to have greater power than the FE approach to detect temporal instability of Granger causal relationship (Shi et al., 2020). As already discussed above, here we perform this dating analysis only using the RE algorithm.

Figures 1–3 display the whole sequence of the RE statistics for all commodity prices with respect to the other commodities of the same category. Figure 4 reports the same results for the

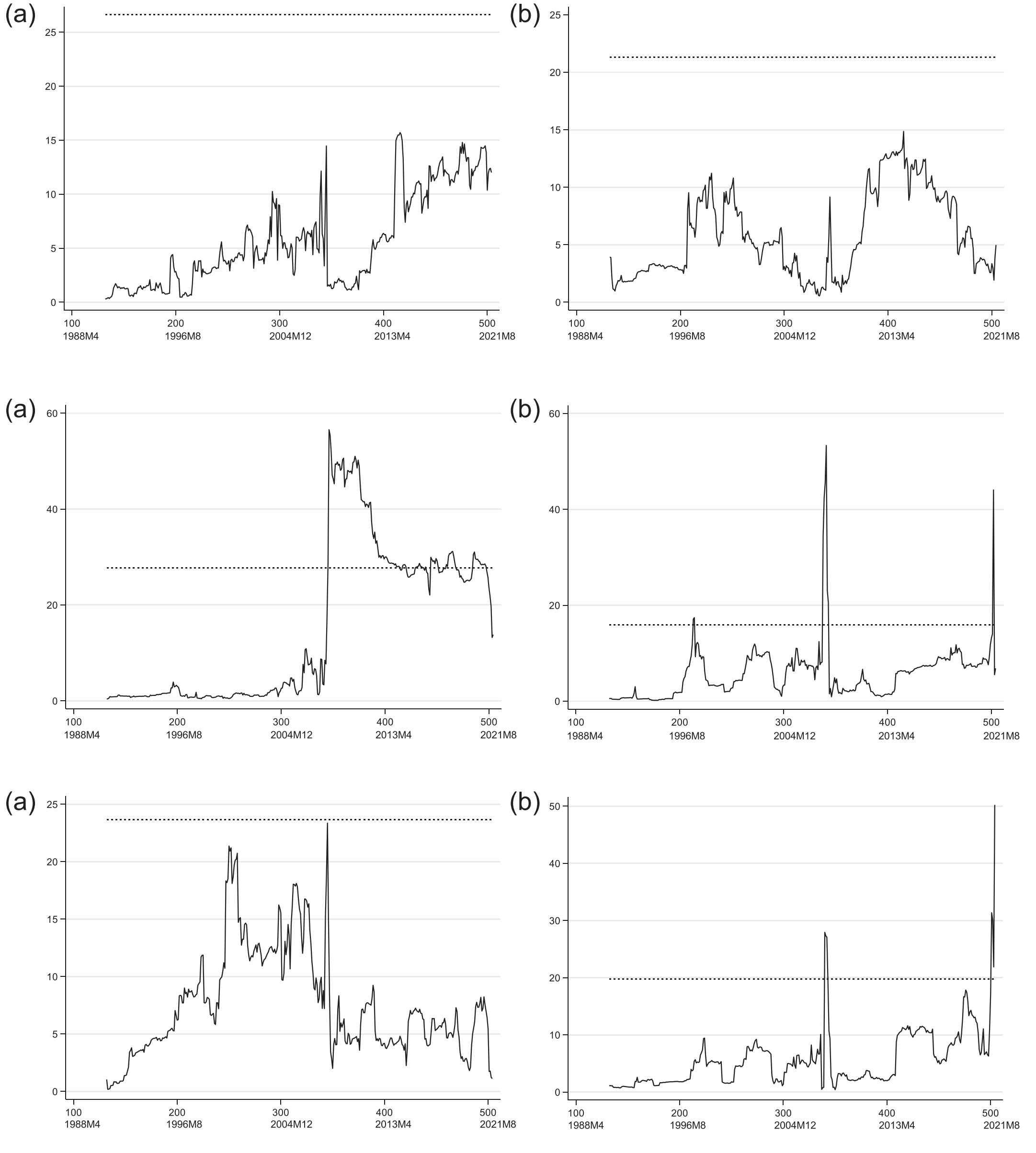

FIGURE 1 Recursive expanding Wald tests (Wald RE). The dashed line indicates the 95th percentile of bootstrapped test statistics. Progressive number of months in the horizontal axis (1 = 1980M1; 504 = 2021M12). Tests start from observation 61 (1985M1). Oil G-caused by coal (a) and natural gas (b). Coal G-caused by oil (a) and natural gas (b). Natural gas G-caused by oil (a) and coal (b).

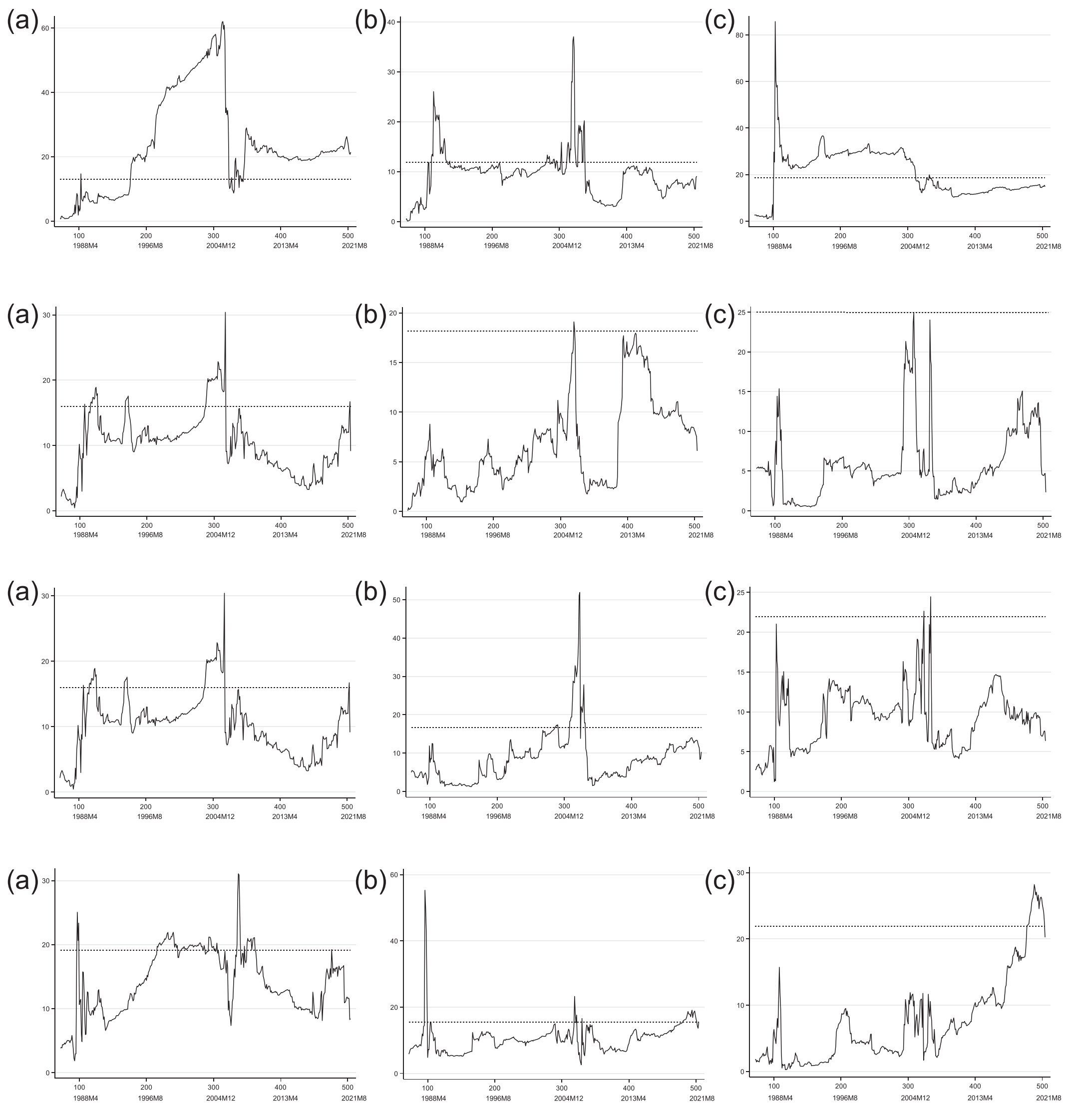

FIGURE 2 Recursive expanding Wald tests (Wald RE). The dashed line indicates the 95th percentile of bootstrapped test statistics. Progressive number of months in the horizontal axis (1 = 1980M1; 504 = 2021M12). Aluminum G-caused by copper (a), zinc (b), and nickel (c). Copper G-caused by aluminum (a), zinc (b), and nickel (c). Zinc G-caused by aluminum (a), copper (b), and nickel (c). Nickel G-caused by aluminum (a), copper (b), and zinc (c).

mixed group (oil, copper, wheat).[20] For the energy commodities (Figure 1), a poor interdependence is confirmed though some evidence of instability in the Granger causation channels still emerges. When Granger causality is observed (coal price G-caused by the natural gas price and the other way round), it occurs very occasionally (one or few months) and during periods of price exuberance, that is, at the end of the 1990s, during the 2008 price crisis, and in the very last year of the period of observation (i.e., 2021). The only exception is the oil price G-causing the coal price: also this effect opens around 2008 but it is more sustained and almost regularly remains for the following period until 2021.

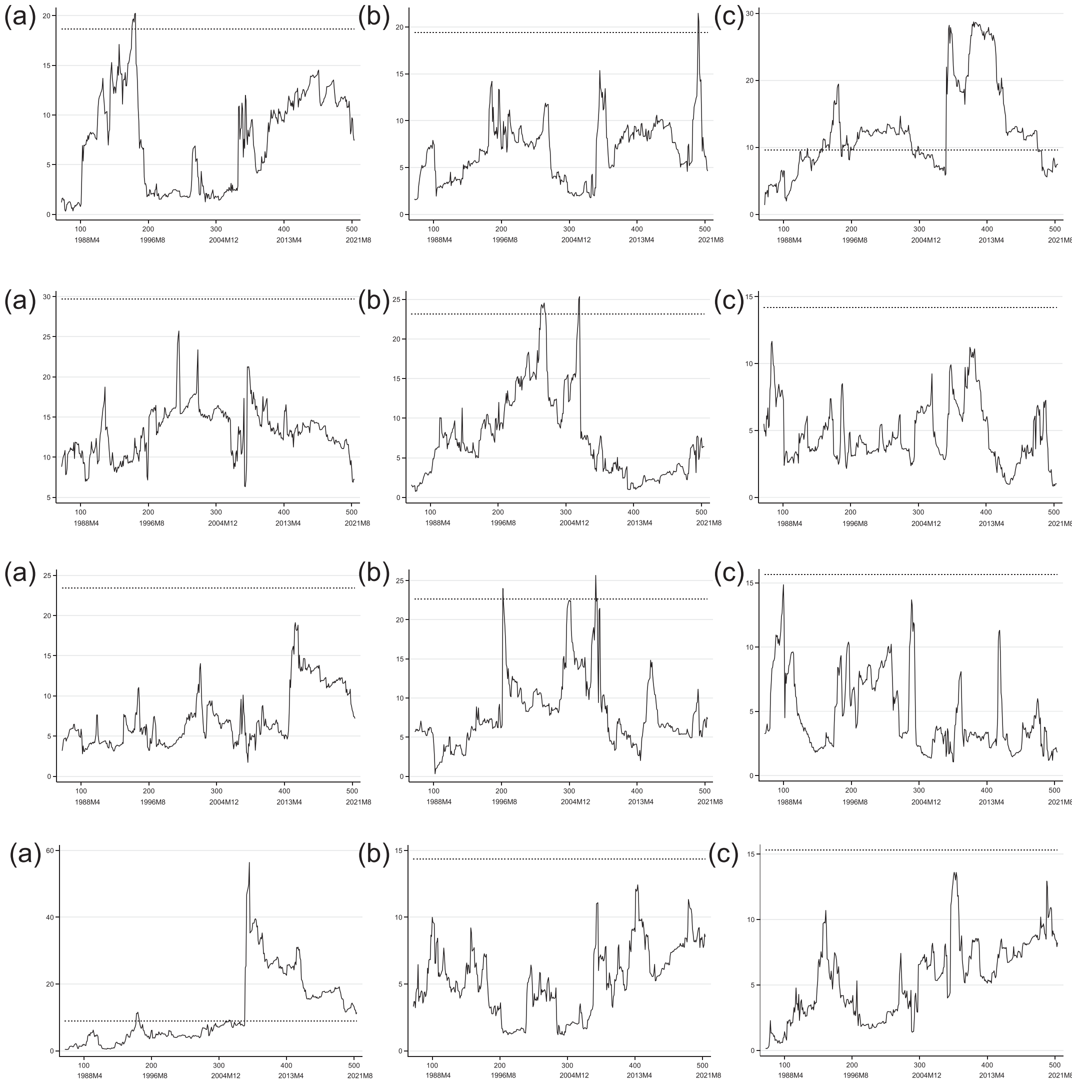

FIGURE 3 Recursive expanding Wald tests (Wald RE). The dashed line indicates the 95th percentile of bootstrapped test statistics. Progressive number of months in horizontal axis (1 = 1980M1; 504 = 2021M12). Wheat G-caused by corn (a), soy (b), and beef (c). Corn G-caused by wheat (a), soy (b), and beef (c). Soy G-caused by wheat (a), corn (b), and beef (c). Beef G-caused by wheat (a), soy (b), and corn (c).

Also for metals, we observe that most Granger causality relationships tend to be occasional (Figure 2). For three metals (copper, zinc, nickel), when their price is G-caused by the others, this occurs only in two specific and very limited moments, that is, the price spikes in the late 1980s and Years 2006–2007. For the nickel price driven by the zinc price, we also detect Granger causation in the very final years of observation. The only exception to this occasionality is represented by the aluminum price which is G-caused by all the other metals more persistently over the period going from the 1980s to about 2006. Then, Granger causation vanishes for the zinc and nickel prices while it remains for the copper price. This latter case

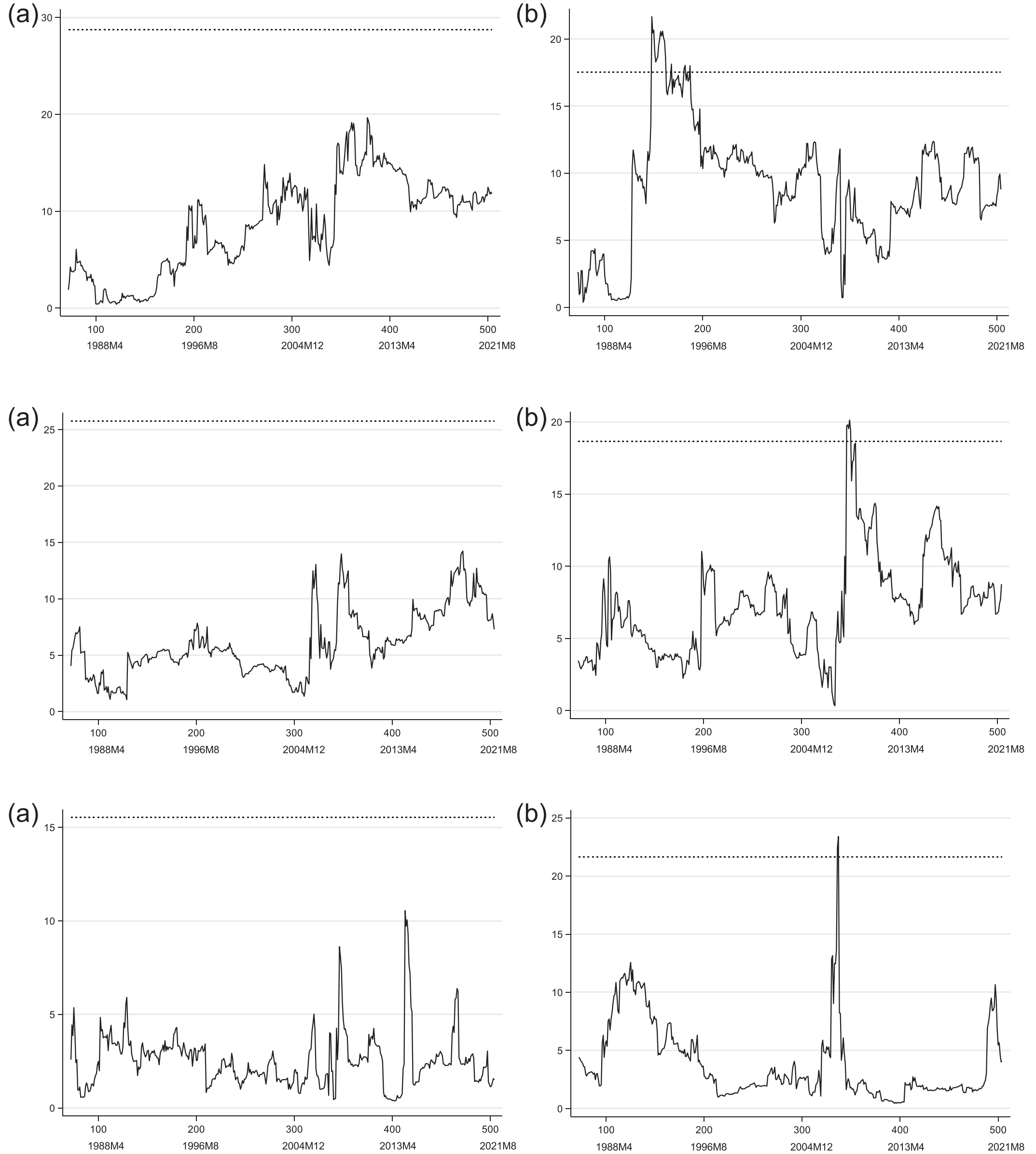

FIGURE 4 Recursive expanding Wald tests (Wald RE). The dashed line indicates the 95th percentile of bootstrapped test statistics. Progressive number of months in the horizontal axis (1 = 1980M1; 504 = 2021M12). Oil G-caused by copper (a) and wheat (b). Copper G-caused by oil (a) and wheat (b). Wheat G-caused by oil (a) and copper (b).

(aluminum price G-caused by the copper price) seems to be one of the most persistent price dependence observed in the present study.

The substantial occasionality of Granger causation, thus of price interdependence, is confirmed also in the case of agricultural commodities (Figure 3). Sporadic Granger causation is observed in different moments of time: in mid-1990s (wheat and soy prices G-caused by the corn price); different moments between 2002 and 2006 (corn price caused by the soy price and the other way round); the very final part of the period of observation, that is, between 2020 and 2021 (wheat price caused by the soy price). However, two more structural relationships seem to emerge. It has to do with the interdependence between wheat and beef prices that is observed from the very beginning, but discontinuously, and then becomes persistent from 2006 onward, though declining in the final part of the period.

A final evidence about the persistence of causation channels concerns the second level of the analysis, that is, the mixed subgroup made of oil, copper, and wheat (Figure 4). As could be expected, and as anticipated, only occasional Granger causality relationships emerge. Oil price is G-caused by the wheat price for several months between 1993 and 1996. Copper price is caused by the wheat price for very few months around 2009. The other way round is also observed (wheat price caused by the copper price) in the same period but for only 1 month.

4.3 | Robustness checks

To assess the robustness of the results presented and discussed above, the same analysis is repeated under four variants of either the price series or model specification. This further evidence is reported in Appendix 3 (Table A5), where, for the sake of space limitation, the only results displayed are the time-varying RE Granger causality tests (Max Wald RE) for the level of the mixed set of commodity prices (oil, copper, and wheat).[21]

The variants considered are the following. First, the real commodity prices rather than nominal prices are considered. This is obtained by deflating these series. As they are all expressed in US$, we use as deflator the monthly US Consumer Price Index (CPI) reported by the IMF Macroeconomic and Financial Data (see also Esposti, 2021). Second, seasonally adjusted prices are used. Following Pedace (2013), seasonal adjustment is performed by regressing the first-differenced original series on their two lags, a constant and a trend, and a set of 11 monthly dummies (January is excluded).[22] The estimated residuals are then added to the initial price level and to the first-difference mean to restore the scale of the original series.[23] Third, the original series (i.e., nominal and not seasonally adjusted prices) are first-differenced to obtain $I(0)$ series. Consequently, a VAR(2) model in the first differences of the series is estimated, instead of an LA-VAR($2+1$) model, and time-varying Granger causality tests are consequently performed. Finally, to assess the impact on results of alternative lag specification of the LA-VAR model, an LA-VAR($4+2$) model is estimated on the original series and respective tests computed.

By comparing Table A5 with Table 5, it clearly emerges that, though the value of statistics (as well as the critical values) may often slightly differ across the four different cases, and besides some differences in the significance level (95% instead of 99% or vice versa), results are largely concordant across the four alternatives and with what obtained and discussed above. Wheat G-causes oil and copper, while copper G-causes wheat. Oil is the driver of none of the two other commodities. The confirmation of these results should not surprise as none of the four alternatives, in either price series or model specification, should lead to major changes regarding Granger causality. For instance, it has been already noticed that, since Granger Causality is used for ascertaining whether one time series is useful in forecasting another in the short-run, LA-VAR, and first-difference VAR models are expected to bring about similar conclusions (Yamada & Toda, 1998). Nonetheless, the evidence reported in Appendix 3 confirms that test results remain stable across all these variants, that is, the Granger causation outlined above is essentially independent of the possible adjustments in the price series and in model specification.

5 | CONCLUSION AND POLICY IMPLICATIONS

This study investigated the interdependence within and among different groups (fossil fuels: oil, natural gas, and coal; metals: aluminum, copper, zinc, and Nickel; and agricultural commodities: wheat, corn, soybeans, and beef) of commodity prices. The analysis aimed to assess whether interdependence occurs and, more importantly, to characterize it in terms of direction and timing. The interest in this empirical assessment lies in the political concern about the rise of the inflation rate. If a single commodity price shock is transmitted to other commodities, then it will likely become a trigger for a generalized price increase, and therefore for an inflationary shock. The reduced model underlying Granger causality testing does not provide information on the structural drivers and mechanisms of price interdependence. Nonetheless, this approach remains extremely useful for forecasting purposes, that is, it indicates which commodity price can have a robust predictive power with respect to other prices.

Results indicated that a generalized price transmission across different commodity groups can be excluded. We also found that within groups interdependence is mostly weak. These linkages appeared to be occasional and mostly limited to periods of price crises. For energy and agricultural commodities, few significant temporary linkages are found. A more generalized interdependence was found among metals, but also in this case it seems more an occasional linkage than a structural relationship. In this respect, an interesting policy implication can be sketched. If we accept that, on the basis of this evidence, a single price shock should not motivate, by itself, a concern about a generalized rise in prices, we should also conclude that the role of the oil price (and, more in general, fossil energy) is probably overrated. On the contrary, more attention should be paid to the dynamics of agricultural commodities as possible triggers of a generalized price response.

Energy price is frequently considered a major driver of agricultural production and prices, but results of this paper seem to question this argument. This should not surprise since, after all, in some countries (e.g., the United States) fossil fuel prices contribute little to farm production costs. Actually, other recent studies (Adeosun et al., in press; Miljkovic & Vatsa, 2023) point to similar patterns, particularly on the lag relationship between oil and agricultural commodity prices. In general terms, the critical role of agricultural products in driving price interdependence among fossil fuels and metal seems to be often overlooked if not disregarded. It rather appears that, if an overall price driver has to be identified, agricultural commodities more than oil seem to be the best candidates. This clearly points to the need for a further careful investigation of the energy-food price linkage.

Some methodological considerations can be also drawn on the basis of the results presented here. The Granger causation emerging occasionally from the analysis may also be attributed to a weakness of the adopted approach in that it imposes a linear or log-linear relationship across commodity prices. Some recent works (Esposti, 2023) seem to rather show that price interdependence (or commonality) mostly, if not exclusively, emerges in periods of nonlinearity, of price booms, or fall. Consequently, other approaches more focused on modeling these nonlinearities and in consequent bubbles detection may be more appropriate or, in any case, can be helpful to confirm the evidence emerging from the time-varying Granger causation testing.

CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

AUTHOR CONTRIBUTIONS

CRediT authorship contribution statement Roberto Esposti: Conceptualization; data curation; formal analysis; investigation; methodology; validation; writing - original draft; writing - review & editing.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from IMF. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://www.imf.org/en/Research/commodity-prices with the permission of IMF.

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ENDNOTES

[1] Selected commodities are the most important worldwide (in terms of value) within the respective categories. In fact, nickel is the fifth in the list among metals after lead. But for this latter, a long enough series is not available.

[2] In practice, parameters express a relationship between price growth rates rather than price variations.

[3] As the interest here is on investigating the linkage across specific commodity prices (for instance, oil and wheat, or oil and copper), unlike some previous studies (Esposti, 2023; Shahzad et al., 2021), we do not consider the price indexes aggregated over groups of similar commodities (like energy, metals, agriculture) that are also released within the IMF data set.

[4] Very helpful suggestions are remarks by the editor and two anonymous reviewers on the recent empirical literature in the field are greatly acknowledged.

[5] This latter aspect mostly affects price volatility in local or national markets. As we consider here only global prices expressed in US$, this aspect should be less relevant in the present study.

[6] A detailed investigation on commodity price volatility and volatility transmission is outside the scope of the present study. However, for further evidence on the volatility clustering of these series over the time period under consideration, see Esposti (2023).

[7] Beside the presence of structural breaks, this kind of investigation has also to consider the nature of these breaks. For instance, in studying commodity price series, Esposti (2021) admits both a sudden change and a gradual shift in the mean of the series. Also, Enders and Jones (2016), instead of sharp breaks, consider more gradual changes in investigating the linkage between corn and oil prices.

[8] All tests, estimates, and calculations presented in this study have been performed with the software STATA 17.

[9] Therefore, the null hypothesis is that parameters $c_{js}(d_{is})$ are jointly not statistically different from zero.

[10] As well known (Morana, 2012), however, the number of parameters to be estimated within a multivariate VAR, thus the computational burden, amplifies with the increase of m.

[11] It is worth stressing that the objective here is not in separating the short- and long-term structural linkages occurring across commodity prices. The focus of the present study is on short-term interdependence,

regardless of the possible long-term structural relationship, as expressed by the Granger causality test. Recent papers in the field actually concentrated on this long-term linkage and this requires an appropriate structural VAR (SVAR) identification and estimation approach (Vatsa et al., 2023). It is worth reminding that the data here considered are expected to proxy sort of global commodity price levels, thus overlooking the possible spatial heterogeneity. This latter could be investigated within a panel data context. Any dynamic specification within a panel data context, however, poses a major endogeneity issue that requires an appropriate generalized method of moments (GMM) estimation approach (Chen et al., 2024). Consequently, also panel SVAR models demand this kind of estimation strategy (Roch, 2019). All these modeling and estimation alternatives are not considered here. However, extending nonlinear Granger causality testing in these directions may represent an interesting development for future research in the field (Aharon et al., 2023).

[12] Alternatively, whenever prices are found to be cointegrated, a VEC model could be estimated and a Granger causality test performed on these model parameter estimates. However, pretesting for co-integrating rank inevitably produces size distortions and Granger causality tests suffer from nuisance parameter dependencies and nonstandard limit theory (Toda & Phillips, 1994).

[13] The FE Granger causality test has been considered in Thoma (1994), but in the (unaugmented) original VAR model for systems containing integrated variables.

[14] The Wald statistic is not directly dependent on the sample size, but it contains the standard error of the estimated unrestricted parameter (or the variance–covariance matrix in a multivariate context), which, in turn, may depend on the sample size.

[15] The whole LA-VAR estimates are not reported here but are available upon request.

[16] Within the software STATA 17 used here, the optimal lag selection is performed with the varsoc routine.

[17] The adequacy of this lag selection is assessed by testing for serial correlation of estimated residual. All test results reject serial correlation. They are available upon request.

[18] For the sake of completeness and comparison, Section 4.3 and Appendix 3 also report the results obtained with the alternative lag specification $S = 4$ and $d = 2$, thus an LA-VAR $(4 + 2)$ model.

[19] Test results have been generated also for the logarithm of prices. They are reported in the Appendix and are largely concordant, though slightly statistically weaker, with what is obtained for price levels.

[20] Only results for the price levels are reported. Results for the logarithm of prices are largely concordant and available upon request.

[21] All other results (whole LA-VAR or VAR estimates, FE and RO tests, and the whole set of results for the logarithm of prices) are available upon request.

[22] This form of seasonal adjustment only considers a linear monthly effect. A multiplicative seasonality could be achieved by regressing the logarithm of prices on the monthly dummies.

[23] These estimates are available upon request. It is worth noting that for none of the three commodities the estimated coefficients associated with the monthly dummies are statistically different from 0 at the 5% confidence level. The only exception is June, which is statistically significant at the 10% significance level in the case of wheat. Also, for all commodities the *F*-test accepts the hypothesis of no seasonality at the 5% confidence level, while it rejects it only at the 10% confidence level in the case of wheat.

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APPENDIX 1: DESCRIPTION OF THE DATA USED IN THE ANALYSIS (*SOURCE*: IMF)

Oil: Crude Oil (petroleum), US$ per barrel, simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh.

Natural gas: Russian Natural Gas border price in Germany, US$ per million metric British Thermal Unit.

Coal: Australian thermal coal, 12,000 btu/pound, less than 1% sulfur, 14% ash, FOB Newcastle/Port Kembla, US$ per metric ton.

Aluminum: 99.5% minimum purity, LME spot price, CIF UK ports, US$ per metric ton.

Copper: Grade A cathode, LME spot price, CIF European ports, US$ per metric ton.

Zinc: high grade 98% pure, US$ per metric ton.

Nickel: Melting grade, LME spot price, CIF European ports, US$ per metric ton.

Wheat: No. 1 Hard Red Winter, ordinary protein, Kansas City, US$ per metric ton.

Corn: US No.2 Yellow, FOB Gulf of Mexico, US price, US$ per metric ton.

Soy: US soybeans, Chicago Soybean futures contract (first contract forward) No. 2 yellow and par, US$ per metric ton.

Beef: Australian and New Zealand 85% lean fores, CIF US import price, US cents/pound.

APPENDIX 2: PRICE SERIES IN LEVELS AND LOGARITHMS, AND RESULTS WITH THE PRICE LOGARITHMS

See Tables A1–A4.

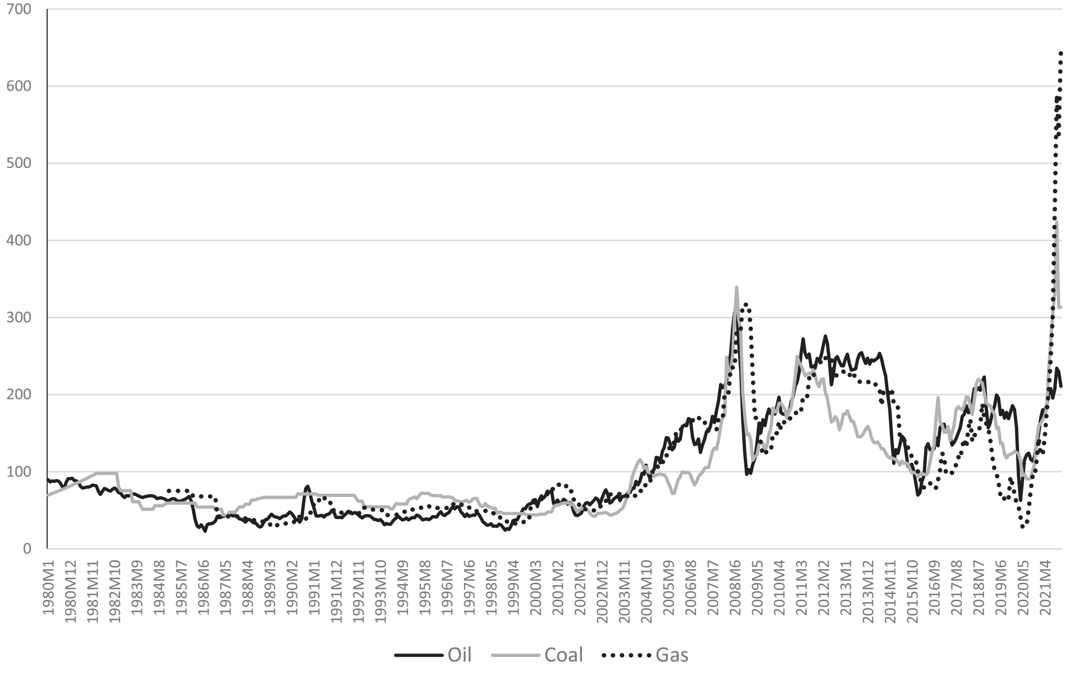

FIGURE A1 Energy commodities price series, 1980M1–2021M12 (2005M1 = 100).

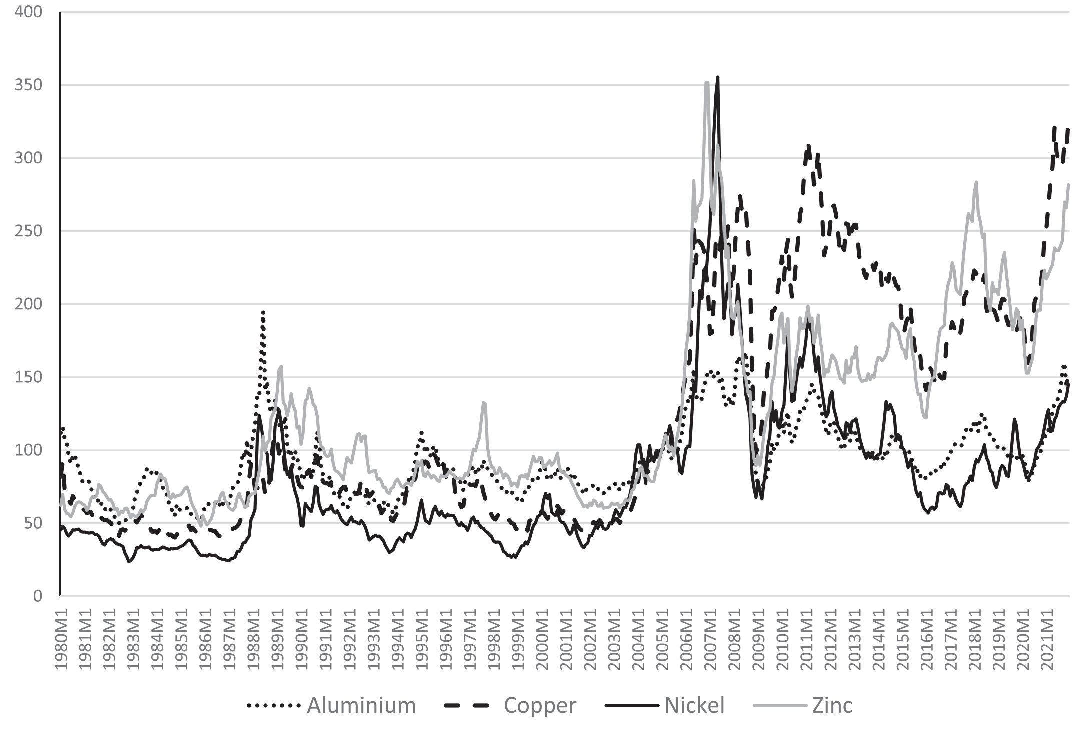

FIGURE A2 Metals price series, 1980M1–2021M12 (2005M1 = 100).

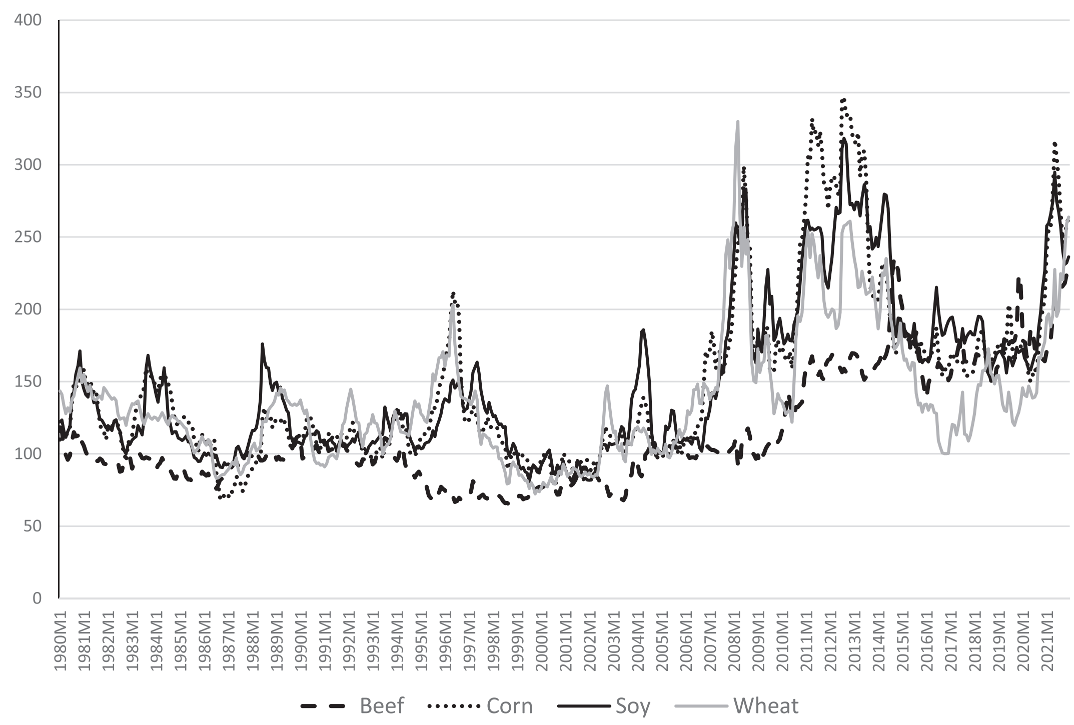

FIGURE A3 Agricultural commodities price series, 1980M1–2021M12 (2005M1 = 100).

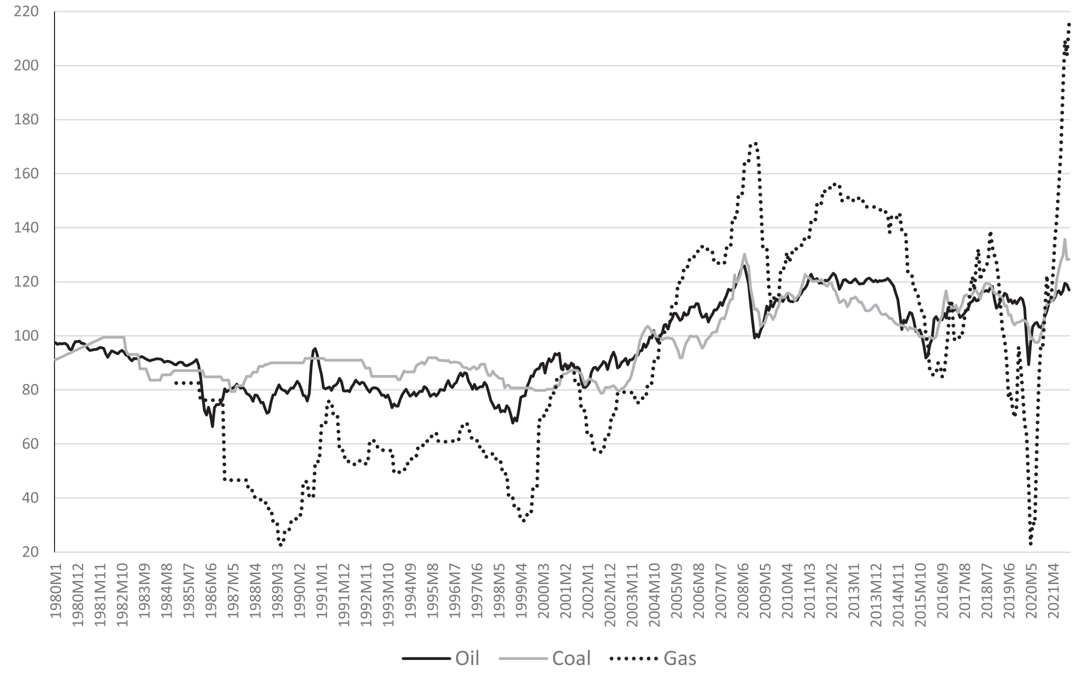

FIGURE A4 Logarithms of the energy commodities prices, 1980M1–2021M12 (2005M1 = 100).

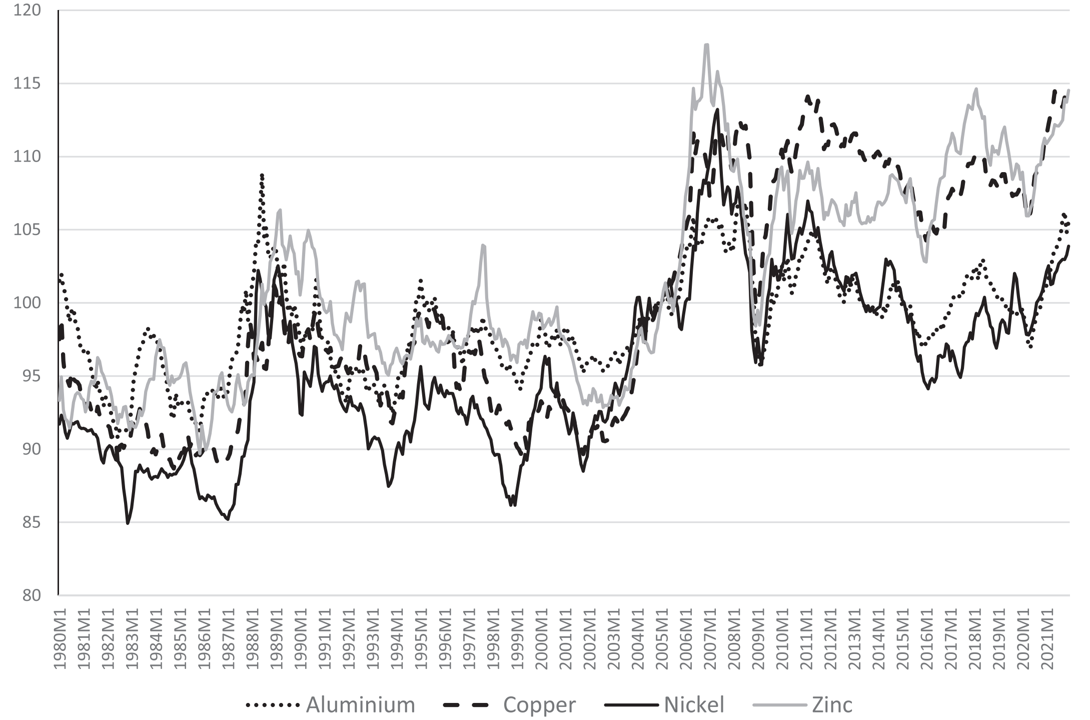

FIGURE A5 Logarithms of the metals prices, 1980M1–2021M12 (2005M1 = 100).

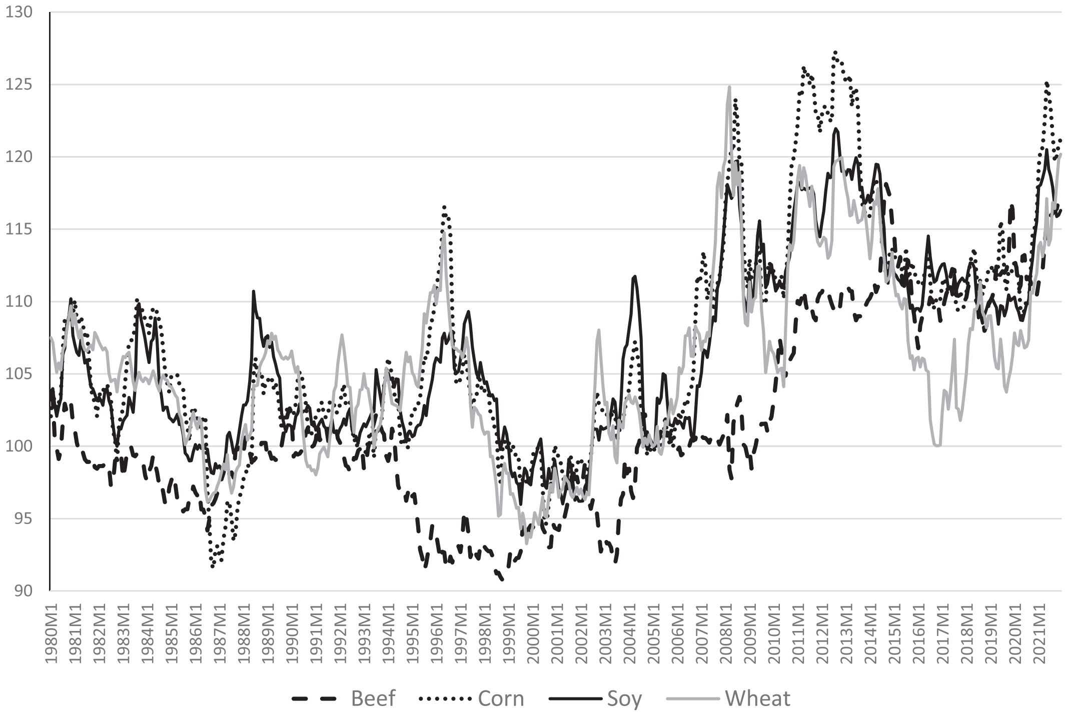

FIGURE A6 Logarithms of the agricultural commodities prices, 1980M1–2021M12 (2005M1 = 100).

TABLE A1 Time-varying Granger causality tests for the logarithm of energy commodities prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Oil G-caused by			
Coal	10.489	15.739	16.573
	(21.816)	(20.280)	(23.549)
	[33.028]	[28.588]	[34.416]
Natural gas[a]	5.364	19.168	19.168
	(20.949)	(22.852)	(23.516)
	[27.586]	[30.148]	[30.944]
Coal G-caused by			
Oil	15.446	12.344	17.945
	(23.061)	(21.439)	(23.226)
	[32.853]	[30.268]	[32.853]
Natural gas[a]	8.176	18.182*	20.227*
	(14.984)	(15.395)	(15.878)
	[25.637]	[26.409]	[26.633]
Natural gas G-caused by			
Oil	19.498	15.114	27.912
	(28.418)	(30.433)	(31.165)
	[33.960]	[34.249]	[36.187]
Coal	4.041	15.791	16.143
	(18.563)	(18.143)	(18.789)
	[21.900]	[23.824]	[24.341]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

[a]1985M1–2021M12.

*,**Statistically significant at 5% and 1% confidence level, respectively.

TABLE A2 Time-varying Granger causality tests for the logarithm of metals prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Alum G-caused by:			
Copper	12.895*	14.977*	22.339**
	(11.963)	(12.575)	(13.018)
	[15.865]	[15.294]	[15.865]
Zinc	10.939*	11.935*	17.390*
	(10.544)	(10.351)	(11.685)
	[15.799]	[16.300]	[17.809]
Nickel	18.345	21.829*	22.916*
	(19.091)	(19.735)	(20.865)
	[27.554]	[28.131]	[28.406]
Copper G-caused by			
Alum	9.794	16.142*	16.589*
	(14.812)	(14.876)	(15.665)
	[17.589]	[18.077]	[19.569]
Zinc	6.702	17.228*	19.100*
	(16.372)	(16.611)	(18.164)
	[22.872]	[22.601]	[24.755]
Nickel	4.767	10.874	12.270
	(19.005)	(17.811)	(19.005)
	[26.993]	[26.373]	[26.993]
Zinc G-caused by			
Alum	7.014	14.668*	17.304**
	(11.028)	(11.985)	(12.368)
	[14.971]	[14.706]	[15.095]
Copper	5.242	13.083	13.768
	(18.627)	(17.582)	(20.592)
	[25.520]	[22.897]	[26.609]
Nickel	10.145	9.432	11.901
	(17.673)	(18.546)	(18.979)
	[23.425]	[25.248]	[25.878]
Nickel G-caused by			
Alum	16.378	14.829	16.378
	(19.508)	(20.036)	(20.629)
	[23.856]	[25.885]	[28.586]
Copper	34.346**	27.525**	34.346**
	(17.897)	(17.677)	(19.290)
	[23.643]	[23.512]	[23.643]
Zinc	4.064	15.803*	15.803
	(15.113)	(14.660)	(16.296)
	[21.361]	[19.006]	[21.407]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

*,**Statistically significant at 5% and 1% confidence level, respectively.

TABLE A3 Time-varying Granger causality tests for the logarithm of agricultural commodities prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Wheat G-caused by			
Corn	6.421	16.354	21.021*
	(16.512)	(16.472)	(15.181)
	[22.106]	[21.817]	[28.956]
Soy	5.039	27.375**	27.375*
	(14.815)	(14.027)	(15.181)
	[26.170]	[27.306]	[28.956]
Beef	16.842**	15.795**	19.534**
	(9.303)	(8.910)	(9.362)
	[14.287]	[12.531]	[14.379]
Corn G-caused by			
Wheat	21.031	21.444	21.876
	(27.297)	(28.216)	(29.554)
	[37.413]	[38.468]	[40.103]
Soy	6.003	21.134*	22.687*
	(20.142)	(20.109)	(21.134)
	[29.357]	[29.500]	[30.645]
Beef	6.418	10.444	10.444
	(10.194)	(11.261)	(12.384)
	[15.883]	[15.513]	[16.868]
Soy G-caused by			
Wheat	7.531	15.404	17.678
	(19.861)	(19.762)	(21.584)
	[24.944]	[27.995]	[29.959]
Corn	5.792	9.694	21.926*
	(19.740)	(19.585)	(20.459)
	[29.633]	[27.240]	[29.987]
Beef	12.574	14.734	16.407
	(13.906)	(15.159)	(16.850)
	[17.324]	[17.837]	[18.237]
Beef G-caused by			
Wheat	14.239*	26.162**	27.462**
	(8.642)	(9.440)	(10.015)
	[15.565]	[15.747]	[16.086]
Corn	5.191	9.999*	10.430
	(10.812)	(9.896)	(10.863)
	[13.439]	[14.972]	[15.197]
Soy	6.846	14.029*	11.029
	(11.713)	(11.379)	(12.919)
	[16.535]	[14.396]	[16.859]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

*,**Statistically significant at 5% and 1% confidence level, respectively.

TABLE A4 Time-varying Granger causality tests for the logarithm of a mixed set of commodity prices (1980M1–2021M12).

	Max Wald FE	Max Wald RO	Max Wald RE
Oil G-caused by			
Copper	13.090	10.027	20.104
	(18.065)	(19.406)	(21.480)
	[25.115]	[25.389]	[28.881]
Wheat	8.606	24.392**	24.392**
	(13.663)	(10.769)	(13.663)
	[19.126]	[16.000]	[19.326]
Copper G-caused by			
Oil	4.112	10.726	13.449
	(17.839)	(19.626)	(20.044)
	[24.406]	[23.820]	[27.047]
Wheat	6.036	12.847	17.303*
	(13.651)	(16.827)	(17.127)
	[21.140]	[22.739]	[23.867]
Wheat G-caused by			
Oil	4.177	10.312	11.312
	(11.200)	(10.434)	(11.925)
	[12.827]	[11.973]	[13.149]
Copper	7.876	9.862	9.862
	(14.469)	(17.765)	(18.657)
	[21.955]	[24.116]	[24.116]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: FE, forward expanding window; RE, recursive evolving; RO, rolling window.

*,**Statistically significant at 5% and 1% confidence level, respectively.

APPENDIX 3: ROBUSTNESS CHECKS

See Table A5.

TABLE A5 Time-varying RE Granger causality tests (Max Wald RE) for the price level of a mixed set of commodities prices (1980M1–2021M12) under alternative data treatments[a,b] and model specifications.[c,d]

	Deflated prices[a]	Seasonally adjusted prices[b]	First-differenced series[c]	VAR($S+d$) with $S=4$, $d=2$[d]
Oil G-caused by				
Copper	17.934	15.601	16.823	24.215
	(25.478)	(31.526)	(31.367)	(29.842)
	[26.930]	[34.756]	[36.602]	[36.821]
Wheat	20.988**	15.296**	21.948*	40.979**
	(11.821)	(8.874)	(20.841)	(17.882)
	[15.479]	[13.017]	[26.804]	[27.644]
Copper G-caused by				
Oil	12.935	13.541	14.798	26.431
	(21.819)	(30.095)	(15.830)	(29.616)
	[23.906]	[34.182]	[27.805]	[39.467]
Wheat	19.154**	26.937**	25.197*	34.367**
	(9.464)	(20.168)	(22.854)	(17.755)
	[14.609]	[26.824]	[37.736]	[23.565]
Wheat G-caused by				
Oil	8.741	11.990	11.076	15.680*
	(11.113)	(12.463)	(11.472)	(15.693)
	[16.156]	[15.753]	[15.771]	[20.795]
Copper	16.121**	14.164*	13.720*	29.105*
	(11.943)	(11.248)	(13.342)	(21.499)
	[15.565]	[15.270]	[17.336]	[36.905]

Note: The 95th and 99th percentiles of the empirical distribution of the bootstrap test statistics are shown in parentheses and brackets, respectively.

Abbreviations: CPI, Consumer Price Index; RE, recursive evolving.

*,**Statistically significant at 5% and 1% confidence level, respectively.

[a]Deflated prices: Deflated (i.e., real) prices are obtained, for all price series, by using as deflator the monthly US CPI reported by the IMF Macroeconomic & Financial Data (see also Esposti, 2021).

[b]Seasonally -adjusted prices: The seasonal adjustment of the three commodity prices is performed following Pedace (2013) by regressing the original price series on their two lags, a constant and a trend, and a set of 11 monthly dummies (January is excluded). The estimated residuals are then added to the mean.

[c]First-differenced series: A VAR(2) model in the first differences of the series is estimated instead of an LA-VAR(2 + 1) model.

[d]$S=4$, $d=2$: A LA-VAR(4 + 2) model is estimated instead of an LA-VAR(2 + 1) model.