On the long-term common movement of resource and commodity prices. A methodological proposal

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A methodological proposal

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Keywords: Resource Prices, State-space Representation, FAVAR Models, Price Volatility

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Abstract

This paper investigates the long-term common movement of resource and commodity prices. Beyond its unquestionable policy relevance, detecting such common behavior is empirically challenging. A novel methodological approach is proposed. It is based on a common latent factor hypothesis. This hypothesis is empirically investigated by specifying a FAVAR-MGARCH model combining the main univariate and multivariate stochastic features of these series. The two latent factors move around a zero-mean short-term level and a non-stationary long-run equilibrium level, respectively. Few heterogeneous and mostly unrelated resources and commodities are considered (crude oil, copper, wheat, beef, aluminium and corn). Using IMF monthly prices over the 1980:1-2019:12 period, a Kalman Filter ML estimation is performed. Results suggest that, besides the time-varying price volatility, the last 15 years have seen a slight rise of the long-term nominal prices corresponding to a stabilization of the respective long-term real prices after a period of regular decline. Policy implications seem relevant and deserve further investigation.

Keywords: Resource Prices, State-space Representation, FAVAR Models, Price Volatility.

1. Introduction: objectives of the paper

This paper proposes an empirically tractable approach to investigate the long-term dynamics of different Resource and Commodity Prices (RCP). In particular, the approach aims to assess whether a long-term common movement exists and to identify it. Designing such methodological approach is challenging. While the existence of seemingly common movements of RCP can be easily detected with descriptive statistics, their actual identification and estimation is problematic.

The literature on RCP stochastic properties and behavior is vast but most works tend to concentrate on one or few of these univariate or multivariate properties. The original contribution the present paper aims to provide within this literature is thus methodological. It presents an unifying framework where all these features are integrated within a single stochastic process that is suitable to identify and estimate the common price movement across heterogeneous commodities. Unlike most of the recent empirical literature on the topic, the proposed approach does not concentrate on market price interdependence and, therefore, on the causal relationships among prices (Baffes and

Haniotis, 2016). Here, the observed commonality actually comes from the fact that all prices depend on the same underlying drivers. These drivers can not be actually observed and behave as common latent factors.

Following this hypothesis, the common movement of prices is specified and investigated within a Factor Augmented VAR model with Multivariate GARCH effects (FAVAR-MGARCH model). For both price level and volatility, this model admits both interdependence and common movement. Although other approaches have been proposed in the recent empirical literature with a similar empirical motivation (Fousekis et al., 2016; Xu et al., 2019; Byrne et al., 2020), the novelty here consists in the identification of two different latent stochastics processes, respectively expressing the short and long-term common movement.

The extrapolation of this long-term common factors represents the main reason of practical interest of the proposed approach. The existence of a common long-term movement could signal that, besides common short-run shocks, these commodities also share long-term dynamics of the respective market fundamentals (demand, supply, storage). Therefore, the empirical approach here proposed can provide an helpful tool to periodically signal changes on the long-term cross-market fundamentals. This signal could deserve, at the same time, a political answer as well as further investigations on the possible underlying causes.

The paper is structured as follows. The relevant policy implications and the recent empirical literature about the main univariate and multivariate stochastic properties of RCP series are sketched in section 2. In section 3, the common latent factor hypothesis is implemented through a FAVAR-MGARCH model aiming to encompass all these stochastic features within an unifying framework. The presence of latent factors requires this model to be specified in the state-space form and the consequent ML estimation to be performed via Kalman Filter. Section 4 presents the data used concerning a small group of relevant but heterogeneous commodities and the adopted empirical specification. Section 5 illustrates the empirical results starting with a battery of tests to assess the common properties and behavior of the series. The FAVAR-MGARCH model estimation results are then presented and discussed. In the light of these results, section 6 outlines the main potentials and policy implications of the proposed approach and discusses some promising future improvements and research directions on the topic.

2. On why we should care about the common long-term price dynamics

2.1. Resource prices as signals of scarcity

In April 2011, Jeremy Grantham (one of the major investors and investment strategists worldwide) presented a detailed analysis of the 2007-2010 RCP bubble and eventually interpreted it as the macroscopic evidence of a major change in the long-term perspective on natural resource endowments (Grantham, 2011): mostly depending on the intense demand growth coming from emerging economies, the days of abundant resources are over and we are entering a new era of shortage and raising prices.[1] In October 2014 the Expo2015 Magazine[2] reported the following words of Lester Brown (one of the major world-wide experts on food security): "*The world is in transition from an era of food abundance to one of scarcity*".

But the Grantham and Brown (G-B) hypothesis is controversial. As recently pointed out by UNCTAD[3] (UNCTAD, 2017), "in real terms, commodity prices globally are at the levels of the late 1980s, albeit with major variations in the dynamics of the different groups. In particular, agricultural commodities are at one of their lowest levels since 2002". At the same time, UNCTAD concludes that the latest price movements actually signal a reversal of the RCP decline that began after the end of the boom in 2011 with all commodities that, in practice, had already recovered from that downturn. But serious doubts can be cast on whether this rebound is going to last and, above all, whether it contains some permanent change in the long-term prices.

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[1] Grantham designates this hypothesis as *the great paradigm shift* (Grantham, 2011, p. 5, 7, 8, 19).
[2] The quinquennial world exposition (EXPO2015) was held in Milan just on the topic of "Feeding the planet. Energy for life".
[3] United Nations Conference on Trade and Development.

The contradictory statements reported above highlights how the interpretation of the RCP dynamics can be challenging. This follows from two main reasons. The first reason concerns its policy implications. From a policy perspective, it seems critical to assess whether and to what extent a higher long-term equilibrium value of RCP is in fact occurring and, more importantly, to what extent it can be interpreted as the macroscopic evidence of a major change in the long-term perspective of these markets and the underlying natural resource endowment.[4] On the contrary, a downward trend would suggest that we are still in a period of abundance which occurred in the second half of the last century. In fact, a long-term declining or rising price trend might be a necessary condition but not a sufficient one for abundancy/scarcity. The key problem is that prices may be considered as an expression of market equilibrium and a change in their pattern as evidence of some imbalances. But prices are not, themselves, scarcity. For instance, commodity stocks are generally intended as the main market fundamental expressing scarcity or abundance at least from the agents' perspective. But the empirical evidence does not always support a strong negative correlation between stocks and prices.[5] Therefore, other aspects of price dynamics together with a deeper investigation on the respective market fundamentals should be considered to properly interpret these signals, and before drawing compelling policy conclusions.

In particular, according to several analysts, the common driver of all RCP actually is that set of macroeconomic variables (especially interest and inflation rates) eventually affecting the behaviour of agents operating on financial markets (Carter, 2002; Kim, 2015; Ohashi and Okimoto, 2016; Algieri et al., 2017; Bruno et al., 2017; Algieri and Leccadito, 2020).[6] The increasing financialization of the commodity markets makes them increasingly dependent on these

[4] "Were demand [for food] to being to outpace supply, the inevitable consequence would be an increase in [food] prices" (Godfray, 2015, p. 201).

[5] Considering three exemplary commodities (crude oil, natural gas, corn), for instance, a negative correlation is found between stocks and prices but it is relevant and statistically robust only for natural gas. It is worth reminding that the short price series available for natural gas prevents from considering it as a valid alternative to crude oil in the present study.

[6] Algieri and Leccadito (2020) distinguish the following different channels of cross-commodity price transmission: the "fundamental channel", mostly operating in the longer term, "that includes traditional factors linked to demand and supply"; two channels mostly operating in the shorter term, i.e., the "financial channel", linked to the stock market and a "sentiment channel" that "that comprises psychological factors including the economic policy uncertainty".

macroeconomic variables. As these latter may experience long-period jumps, this is eventually reflected in the common long-term mean price of most commodities (Arango et al. 2012). But this interpretation does not necessarily imply any long-term imbalance on the demand and/or supply sides as implied by the G-B hypothesis.

However, the major interest here concerns the second main challenge for the economic analysis. Even though we conclude that the long-term price dynamics is a meaningful signal of a commodity abundance/scarcity, the real problem is: can we identify it? Unfortunately, RCP dynamics is really and increasingly complex. Deducing some change in the long-term tendency is empirically challenging. The observed price dynamics might result an increase in market turbulence and short-term interdependence due to price levels and volatility transmission rather than (or in addition to) a change in some long-term tendency (Piot-Lepetit and M'Barek, 2011; Listorti and Esposti, 2012; Esposti and Listorti, 2013).

Eventually, in order to assess whether a change in the long-term RCP pattern actually occurred and whether it is common across markets, the price generation process must be properly identified. This requires a careful investigation of the price series stochastic properties to separate individual and common short-run movements from individual and common long-term components (Kim et al., 2003; Schleicher, 2003; Bai, 2013; Martin et al., 2013). These common long-term components actually behave as unobserved (i.e., latent) variables. In the present analysis, a proper methodological approach is proposed to identify and extract them from observed monthly price series.

2.2. *The stochastic properties of resource price series: an overview of recent empirical evidence*

In any empirical investigation on RCP dynamics, the first and often toughest challenge consists in the proper identification of the price series stochastic properties. Such properties emerge as some combination of short and long-run movements and of individual and common components (Kim et al., 2003; Schleicher, 2003; Bai, 2013; Martin et al., 2013). This combined effect may concern both the price levels and their variances (Piot-Lepetit and M'Barek, 2011; Listorti and Esposti, 2012; Esposti and Listorti, 2013; Algieri and Leccadito, 2020). The recent literature has focused on some critical aspects of this stochastic generation process.

One key property is that RCP are expected to behave like *mean-reverting series* (Bobenrieth et al., 2014; Valera and Lee, 2016). This comes from the fact that these markets depend on a stable and often inelastic demand while, on the supply side, they are strongly limited by natural constraints (i.e., some underlying natural resource stock). As a consequence, while in the short-term market prices may also significantly deviate, in the medium and long run they tend to revert back to the stable supply and demand market-clearing equilibrium. From the statistical point of view, the main consequence of this feature is that these price series are expected to be stationary, or integrated of order 0 (Schwartz, 1997; Routledge et al., 2000; Bobenrieth et al., 2014). Nonetheless, statistical tests performed on these series mostly suggest that RCP behave like I(1) (non-stationary) series (Cáceres- Hernández and Martín- Rodríguez, 2017).

This apparent contradiction may have three statistical explanations. On the one hand, RCP always show a strong serial correlation. The main implication is that price at a given time *t* is strongly influenced by its lagged values, thus temporary price shocks may persist for a long period of time (Wei and Leuthold, 1998; Esposti and Listorti, 2013).[7] A second possible explanation concerns the presence of structural breaks, that is shocks with permanent effects thus affecting the long-term mean value towards which the series tends to revert. It is well known that, if not properly considered, the presence of a structural breaks within a stationary series may lead to accept the presence of a unit root thus wrongly concluding the series is non-stationary (Glynn et al., 2007). A third possible explanation is a generalization of the second. It consists in the fact that the long-term equilibrium value towards which RCP tend to revert is not a constant value but it is itself a I(1) stochastic process (for instance, a random walk or a stochastic trend) as the consequence of

[7] This long memory is also called fractional integration and it may be the reasons why low power unit roots may tend to designate these prices as I(1) series.

successive permanent changes (or structural breaks) of the respective market fundamentals (Valera and Lee, 2016).

A further issue which emerged particularly in the last two decades, starting from 2007 (Piot-Lepetit and M'Barek, 2011; Chavas et al., 2014), is that this complex behaviour of RCP series does not only concern their levels but also their variances or *volatility*. Price volatility tends to remain quite stable over long periods then followed by shorter periods of rapid increase (*volatility clusters*). Also this increase often disappears in a few months but sometimes it may remain for longer periods or become permanent. Moreover, in some circumstances volatility tends to respond more to periods of price decrease than of price increase (the so-called *leverage effect*), thus making the volatility response not only time-varying but also asymmetric (Nelson, 1991).[8]

In general terms, the combination of these conflicting properties eventually motivate the recurrence of "*spikes, runs and bubbles*". At least part of these abrupt price changes could remain also in the longer-term, thus behaving as permanent *jumps* or *structural breaks* (Brooks and Prokopczuk, 2013; Xu et al., 2019; Gilbert and Kasidi Mugera, 2020) making it very problematic to disentangle the short-term (temporary) movements from the long-run dynamics (Gilbert, 1995).

The main focus of the present work, however, concerns a further property of these price dynamics. Despite their complex behaviour, they seem to move together (Brooks and Prokopczuk, 2013). This *common movement* is typically revealed by a positive correlation among price expected values (or means), and/or among the respective variances (i.e., volatility) (Chavas et al., 2014). The theoretical and empirical literature has suggested two different explanations of this common movement of RCP series.

The first explanation is that price levels are interdependent. There is some, possibly reciprocal, causation relationship due to some real or financial linkage. This interdependence takes the form of

[8] In the analysis of asset prices, the leverage effect refers to the observed tendency of an asset's volatility to be negatively correlated with the asset's returns. A number of empirical papers have confirmed that an unexpected fall in asset prices may increase volatility more than an unexpected increase of the same magnitude. Although such effect may be less relevant in the case of commodity prices, the increasing financialization of these markets suggest that asymmetric volatility should not be ruled out in the analysis.

price transmission, as the shocks experienced by one price in its level are transmitted to other prices. Consequently, price series are generated by interdependent stochastic processes and as such should be modelled within empirical analysis (Listorti and Esposti, 2012; Algieri and Leccadito, 2020).

The second explanation excludes a relevant causation relationship among prices. In fact, they actually are independent stochastic processes. After all, real linkages can hardly be argued when very different and apparently unrelated commodities are under investigation, like beef and copper, for instance. Nonetheless, they may share some common exogenous drivers and whenever these drivers experience a shock, this is transmitted to all prices (Baffes and Haniotis, 2016). Some of these common factors are expression of generalized market fundamentals (e.g., long-term demand/supply growth forces) and behave as unobserved factors (Gilbert, 1995).[9] Others might actually be observable at the global level (for instance, interest rate, population and income growth, etc.) but not necessarily at the same (usually higher) frequency at which prices are observed and investigated. For these reasons, these common drivers can hardly be entered as observable variables in the empirical analysis and have to be regarded as the underlyings of one or more common latent factors.

There is a further major feature of the RCP common movement that have been highlighted by recent several empirical studies: the common movement occurs not only in the price levels but also in the price variances or volatilities (Algieri and Leccadito, 2020). This implies that also price volatilities can be transmitted (*volatility spillovers*). Consequently, if asymmetric response of volatility is observed in one market, volatility transmission itself can be asymmetric (Koutmos and Booth, 1995; Jane and Ding, 2009).[10]

[9] A detailed review of these possible underlying common market fundamentals is well beyond the scope of the present study. Algieri and Leccadito (2020) provides a short list of common macroeconomic variables driving commodity prices.

[10] Also for volatility transmission, a common factor hypothesis can be formulated, that is, the presence of latent factors affecting all price volatilities thus generating a common volatility behaviour (Cortazar et al., 2017). This circumstance is not considered here as it would lead to an empirically unidentifiable model specification. Nonetheless, this may represent a major challenge for future research in this field.

Eventually, the recent empirical literature clearly suggests that the actual RCP dynamics is generated by complex stochastic processes resulting from some combination of these univariate and multivariate short-run and longer-term properties. Representing such processes is a major methodological challenge in terms of empirical specification, identification and estimation. The empirical literature separately investigating these aspects is vast, including recent studies exploring the possible role of common latent factors (Byrne et al., 2020). But none of these studies is able to incorporate all the aforementioned data generating mechanisms. The present paper aims to fill this methodological gap.

3. Modelling approach: state-space representation and the FAVAR-MGARCH model

3.1. Modelling the price interdependence

From the discussion above it follows that the empirical investigation of the common movement of prices necessarily concerns a balanced panel dataset where *N* price series are observed over *T* periods (months in the present case). Firstly assume that the generic i-th price observed at the generic time *t* ($p_{i,t}$) follows an autoregressive (AR) process:

$$(1) \qquad p_{i,t} = \alpha_i + \sum_{s=1}^{s=S<T} \alpha_s p_{i,t-s} + \varepsilon_{it}, \qquad \forall i \in N; \forall t, s \in T$$

where α_i is a constant term (drift), α_s are autocorrelation coefficients and ε_{it} is a disturbance term assumed to be i.i.d. Once these AR processes are estimated, usual tests can be performed in order to assess the underlying stochastic processes and, in particular, their order of integration and the presence of conditional heteroskedatisticy (ARCH).

If there is some common movement across prices, however, this representation of the underlying stochastic process is incomplete. In this case, a correlation across estimated error terms, that is, $E(\varepsilon_{it,}\varepsilon_{jt}) \neq 0, \forall i, j \in N, \forall t \in T$, must be admitted (Chen et al., 2014). Cross-price correlation can be the consequence of price interdependence (or price transmission) with the stochastic process generating any single price represented as:

$$(2) \qquad p_{i,t} = \alpha_i + \sum_{s=1}^{s=S<T} \sum_{i,j=1}^{N} \alpha_{js} p_{j,t-s} + \varepsilon_{it}, \qquad \forall i,j \in N; \forall t,s \in T$$

As prices are reciprocally interdependent, the actual stochastic process generating price series has to be represented in a vector form, i.e., as a VAR process:

$$(3) \qquad \mathbf{p}_t = \Phi(L)\mathbf{p}_{t-1} + \boldsymbol{\varepsilon}_t$$

where $\mathbf{p}_t$ is the Nx1 vector of prices and $\boldsymbol{\varepsilon}_t$ the Nx1 vector of the i.i.d. disturbance terms.

Cross-price correlation, however, can also originate from common drivers. They behave as exogenous possibly lagged variables affecting all prices' dynamics. With *M* common drivers, the single price formation process (2) becomes:

$$(4) \qquad p_{i,t} = \alpha_i + \sum_{i,j=1}^{N} \sum_{s=1}^{s=S<T} \alpha_{js} p_{j,t-s} + \sum_{k=1}^{M} \sum_{s=0}^{s=S<T} \delta_{iks} z_{kt-s} + \varepsilon_{it}, \qquad \forall i,j \in N; \forall t,s \in T; \forall k \in M$$

where z_{kt} indicates the value of the k-th generic common driver at time *t* and δ_{iks} are coefficients expressing the direct effect of z_k on p_i (also called *factor loadings*). In a more compact matrix form, (4) can be written as a VAR model with exogenous variables (VARX):

$$(5) \qquad \mathbf{p}_t = \Phi(L)\mathbf{p}_{t-1} + \Theta(L)\mathbf{z}_t + \boldsymbol{\varepsilon}_t$$

where $\mathbf{z}$ indicates the Mx1 vector of common factors. Two main issues arise when an estimable specification of (5) has be chosen to properly represent this multivariate stochastic generation process. One concerns $\mathbf{z}$, the other concerns the error term $\boldsymbol{\varepsilon}_t$.

3.2. Modelling the common latent factors

Common drivers $\mathbf{z}$ might be unobservable thus behaving as common latent factors. This occurs not only for the lack of data (at least at the same frequency at which prices are observed), but also because these factors may actually be the outcome of complex and multiple phenomena barely expressed by single observed variables (Gilbert, 1995). If unobserved, the stochastic process of $\mathbf{z}$ is also unknown and must be somehow assumed *ex ante*.

Following previous works, here we consider two latent state variables expressing two complementary market fundamentals or market imbalances (Gilbert, 1995): z_1 represents the long-term equilibrium level towards which prices tend to revert; z_2 represents the short-run deviations from this equilibrium. Here we assume that z_1 follows a Brownian motion process and, in particular, a random walk, while z_2 follows a zero-mean Ornstein-Uhlenbeck process, i.e., a stationary AR process without a drift (Schwartz and Smith 2000; Sørensen 2002). According to this representation, beyond short-run deviations, prices tend to revert to their long-term mean which is, however, not constant but behaves like an I(1) process due to persistent shocks in the underlying market fundamentals (i.e., supply and demand).

This specification of latent factor z_1 is of major relevance as it makes two aforementioned features of commodity prices explicit. In particular, it implies that z_1 is a process whose exogenous shocks retains, at least partially, a permanent effect. Once transmitted to prices according to (5), it may explain both non-stationarity and the presence of structural breaks in RCP series. On the former aspect, it can be concluded that, as one of their drivers is a random walk, prices themselves eventually behave as I(1) (Valera and Lee, 2016). On the latter aspect, a non-stationary latent factors as z_1 may be the generator of exogenous structural breaks in RCP series due to the non-mean reverting permanent shocks. After all, as mentioned, I(1) processes and structural breaks can be confounded in testing resource price properties and this is perfectly logic here as they come from the same underlying stochastic process.

Though unobservable, one possible way to empirically deal with latent factors is to treat them as state variables within a state-space representation of the stochastic process expressing price formation (Schwartz, 1997). The state-space representation of (5) consists, as usual, by a *transition* (or *state*) *equation* and a *measurement* (or *observation*) *equation.* The transition equation describes the stochastic dynamics of the (unobserved) state variables. (Schwartz and Smith, 2000; Sørensen, 2002). The measurement equation relates observables (i.e. prices) among them and to the state variables according to (5). In compact matrix notation, the state-space representation of (5) is thus the following:

(6) $$\mathbf{Z}_t = \mathbf{A}\mathbf{Z}_{t-1} + \mathbf{C}\boldsymbol{\nu}_t$$

$$\mathbf{Y}_t = \sum_s \mathbf{B}_s \mathbf{Y}_{t-s} + \mathbf{D}\mathbf{Z}_t + \boldsymbol{\epsilon}_t$$

where **A**, **C**, $\mathbf{B}_S$ and **D** are matrices of unknown coefficients to be estimated while $\boldsymbol{\epsilon}_t = \mathbf{G}_t^{1/2}\boldsymbol{\varepsilon}_t$. $\mathbf{G}_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix $\boldsymbol{G}_t$ (see section 3.3). For the presence of autoregressive unobserved factors, this kind of model is also called Dynamic-Factor (DF) model and, whenever the observation equation takes on an autoregressive form (VAR) as in (6), it is designated as a Factor Augmeneted VAR (FAVAR) model (Bernanke et al, 2005).[11]

3.3. *Modelling the conditional volatility and volatility transmission*

In (6) the NxN $\mathbf{G}_t$ matrix can be specified to admit time-varying volatility thus the presence of volatility clusters (i.e., periods characterized by higher/lower price variances). Moreover, a proper specification $\mathbf{G}_t$ can admit that correlation also occurs across variances, that is, price volatility is transmitted across markets (volatility spillovers) (Algieri and Leccadito, 2020). To achieve this, $\mathbf{G}_t$ can be specified as a MGARCH[12] structure. A DCC[13]-MGARCH (1,1) specification (Engle and Sheppard, 2001; Engle, 2002) is here adopted to admit both volatility clusters and transmission.[14]

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[11] With respect to DF models, the FAVAR specification better resembles some typical features of macroeconomic series as well as of resource and commodity prices. In particular, FAVAR specification not only admits that (some of the) observable variables (commodity prices in the present case) follow an autoregressive stochastic process but also that they are dynamically interdependent, that is, they behave like factors by hitting (some of) the other prices directly. This specification thus seems appropriate here as both priced interdependence and the presence of exogenous common drivers are admitted as possible determinants of the common movement of prices (see sections 1 and 2). See Stock and Watson (2016; 2017) for a discussion on the relation between DF models and FAVAR models.

[12] Multivariate Generalized AutoRegressive Conditional Heteroskedasticity.

[13] Dynamic Conditional Correlation.

[14] The price transmission process in both level and volatility could suggest more complex structures of the conditional variability. In particular, in order to account for the search of the best compromise between returns and risk by investors, the possibility of a linkage between the risk (conditional volatility) and the conditional mean of a price could be included in the adopted framework. This would admit an effect on price levels of changes in market volatility. In asset price modelling this effect is sometime explicitly considered

This specification can be expressed as $\mathbf{G}_t = \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2}$ where $\mathbf{D}_t$ is a diagonal matrix of conditional variances σ_t^2 evolving according to a univariate GARCH(1,1) model, and $\mathbf{R}_t$ is a matrix of conditional quasicorrelations defined as $\mathbf{R}_t = \mathrm{diag}(\mathbf{Q}_t)^{-1/2}\mathbf{Q}_t\mathrm{diag}(\mathbf{Q}_t)^{-1/2}$ with $\mathbf{Q}_t = (1-\lambda_1-\lambda_2)\bar{\mathbf{Q}}+\lambda_1\tilde{\boldsymbol{\epsilon}}_{t-1}\tilde{\boldsymbol{\epsilon}}'_{t-1}+\lambda_2\mathbf{Q}_{t-1}$. $\tilde{\boldsymbol{\epsilon}}_{t-1}$ is a (4x1) vector of standardized residuals, $\tilde{\boldsymbol{\epsilon}}_t= \mathbf{D}_t^{1/2}\boldsymbol{\epsilon}_t$. Matrix $\bar{\mathbf{Q}}$ is the unconditional covariance matrix of the standardized errors $\tilde{\boldsymbol{\epsilon}}_t$. λ_1 and λ_2 are non-negative adjustment parameters with $0 \leq (\lambda_1+\lambda_2) < 1$ that govern the dynamics of conditional quasicorrelations (thus also called adjustment parameters). Eventually, the DCC-MGARCH (1,1) model returns estimates of two adjustment parameters and of N(N-1)/2 (quasi)correlation terms.

Finally, this specification can be augmented to admit asymmetric volatility transmission whenever case an asymmetric response of volatility (or leverage effect) is observed in at least one commodity market. An asymmetric GARCH model can be obtained via two alternative strategies (Chen et al., 2019). One is the Exponential GARCH (EGARCH) model (Nelson, 1991) where asymmetry is admitted simply through a parameter whose statistical significance, sign and magnitude indicates whether and to what extent negative or positive innovations in the market have a greater impact on its volatility. EGARCH modelling is are very helpful to investigate asymmetry in univariate analysis (and it is adopted here for this purpose), but its extension to the multivariate case (Koutmos and Booth, 1995; Jane and Ding, 2009) can be particularly challenging when N≥4, as in the present case, due to the large number of parameters to be estimated. Moreover, the loglinear specification implied by EGARCH modelling would be inconsistent here with the linear conditional variance equation to be integrated in the state-space specification (6).

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with the so-called GARCH‑M (GARCH-in-Mean) models (Beirne et al., 2010). Such a circumstance, however, seems unlikely in the case of commodity markets. Moreover, this solution, as well as other alternative and richer specifications, is unfeasible in the present study as the adopted state-space specification and estimation approach make it underidentified or prevent the Kalman Filter MLE procedure to achieve convergence. Nonetheless, future research in this direction may definitely represent an interesting field of study.

An alternative strategy to admit asymmetry is represented by the Threshold GARCH (TGARCH) model originally proposed by Glosten et al. (1993) (thus also known as GJR-GARCH model). In this case, the conditional variance equation is simply augmented by introducing indicator variables (that is, a set of dummies) taking value 1 when the price variation is negative (price declines) and zero otherwise (price increases). Due to its estimation feasibility and consistency with the specification (6), this solution is here adopted to admit asymmetry within the MGARCH model.

Therefore, for any of the N prices a full first-order EGARCH specification is firstly adopted to assess whether asymmetry occurs in individual series (see section 5.2). Then, for those N^* series (with $N^* \leq N$) for which asymmetry is statistically confirmed, if any, the conditional variance equation of the MGARCH model is augmented by introducing the (N^*xT) matrix $\mathbf{\Gamma}$ containing the aforementioned N^* dummies. To this matrix of dummies, a (N^*xN^*) matrix of unknown parameters $\mathbf{F}$ is associated. Once estimated, the diagonal elements of $\mathbf{F}$ (f_{ii}, $\forall i \in N^*$) are expected to confirm the asymmetry within the individual markets, while the off-diagonal elements (f_{ij}, $\forall i,j \in N^*$, $i \neq j$) indicate whether and to what extent asymmetry is also transmitted across markets (i.e., asymmetric volatility spillovers).

4. Empirical analysis

4.1. Selected commodities and data

The present application uses the monthly prices (in US$) from January 1980 to December 2019 (therefore, 480 observations for any price series) as reported in the IMF Primary Commodity Price Database. Although more than 50 different prices are available in the database, the model is here applied to only 4 commodities. This reduces the computational complexity implied by the adopted estimation approach and also facilitates the interpretation of results.[15] Nonetheless, as the objective of the present exercise pertains the generalised price dynamics of natural and agricultural

[15] Given the state-space specification of the model, the adopted estimation approach based on the Kalman filter and ML estimation is unable to achieve convergence for more than four commodities. Further developments could reduce this limitation in future applications thus allowing the estimation of the model on a larger set of commodities.

commodities, this relatively small number may represent a limitation. To cope with this issue, two empirical strategies are adopted here.

First of all, the four cases are selected to still represent the whole set of different production processes and uses, i.e. the wide heterogeneity across commodities. Therefore, a relevant case for any group of commodities (energy, metal, crop and livestock) is selected: crude oil, copper, wheat, beef. Wheat and beef are agricultural commodities but with quite different production processes, supply chains and uses. Though very different in their supply chains, uses and market fundamentals, these four commodities may still show interdependence since the price increase of one commodity (e.g., crude oil or wheat) may cause an increase of production costs of another commodity (e.g., copper and beef).

Secondly, model estimation is performed twice: first, on the four aforementioned commodities; then, replacing two of these four cases with other commodities belonging to same group. In particular, copper is replaced with aluminium and wheat with corn. This allows assessing whether the empirical evidence is robust with respect to the composition of the commodity set under analysis.

A further relevant issue is whether to use the actually observed nominal prices (as available in the IMF dataset) or nominal prices adjusted for inflation (*real prices*). The use of real prices seems a natural choice for a robust estimation and interpretation, whenever the extraction of the price long-term pattern is aimed to indicate possible real imbalances in underlying market fundamentals. In fact, for this reason, most of the previous empirical studies in this field use deflated (i.e. real) prices. At the same time, however, nominal price deflation is always an artefact (Peterson and Tomek, 2000). Not only the proper deflator should be detected. More importantly, deflating may significantly change the stochastic properties of price series eventually influencing the whole modelling and estimation strategy.

Therefore, in the present study the empirical analysis is carried out using both nominal and real prices in parallel in order to assess whether and to what extent price deflation meaningfully alters the empirical results. Real prices are obtained, for all price series, by using as deflator the monthly US Consumer Price Index (CPI) reported by the IMF Macroeconomic & Financial Data.

4.2. Empirical specification and estimation approach

According to the discussion above, model (6) takes the following extensive form:

Transition/State equation:

$$(7a)\quad \begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} c_L \\ 0 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & \delta_1 \end{pmatrix} \begin{pmatrix} z_{1t-1} \\ z_{2t-1} \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & \delta_2 \end{pmatrix} \begin{pmatrix} z_{1t-2} \\ z_{2t-2} \end{pmatrix} + \underset{(2x2)}{\boldsymbol{I}} \begin{pmatrix} \nu_{1t} \\ \nu_{12} \end{pmatrix}$$

Measurement/Observation equation:

$$(7b)\quad \begin{pmatrix} cr_t \\ cp_t \\ wh_t \\ be_t \end{pmatrix} = \begin{pmatrix} c_{cr} \\ c_{cp} \\ c_{wh} \\ c_{be} \end{pmatrix} + \begin{pmatrix} \gamma_{1cr} & \gamma_{2cr} \\ \gamma_{1cp} & \gamma_{2cp} \\ \gamma_{1wh} & \gamma_{2wh} \\ \gamma_{1be} & \gamma_{2be} \end{pmatrix} \begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{pmatrix} \begin{pmatrix} cr_{t-1} \\ cp_{t-1} \\ wh_{t-1} \\ be_{t-1} \end{pmatrix}$$

$$+ \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{pmatrix} \begin{pmatrix} cr_{t-2} \\ cp_{t-2} \\ wh_{t-2} \\ be_{t-2} \end{pmatrix} + \underset{(4x4)}{\mathbf{G}_t^{1/2}} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{pmatrix}$$

where cr_t, cp_t, wh_t and be_t indicate crude oil, copper, wheat and beef prices, respectively. Then, cr_t is replaced by al_t (aluminium) and wh_t by co_t (corn). $c_{.}$, $\delta_{..}$, $\gamma_{..}$, $\alpha_{..}$ and $\beta_{..}$ are unknown parameters to be estimated. I.i.d. normal distribution is assumed for both ν_{kt} and ε_{it}. Specifying $\mathbf{G}_t$ as a MGARCH process possibly with asymmetry (thus, with the additional $f_{..}$ parameters), finally designates (7a)-(7b) as a FAVAR-MGARCH model.[16] This specification admits transmission in both price levels and volatility (asymmetry included) and admits common latent factors for price levels. So, it seems suitable to capture most of the complex common movements across prices.

The consistent estimation of a combination of VAR and MGARCH processes is challenging (Carnero and Eratalay, 2014; Maekawa and Setiawan, 2014; Ohashi and Okimoto, 2016) and is

[16] It is worth noticing that the Choleski factorization implied by this MGARCH structure assumes that volatility transmission follows a commodity ordering that starts from cr_t and ends with be_t.

even more problematic when latent factors are included in the VAR structure. In principle, due to the distributional assumptions on ν_{kt} and ε_{it}, model (7a)-(7b) could be estimated with Maximum Likelihood Estimation (MLE) using the diffused Kalman Filter to obtain the prediction error form of the log-likelihood function (Harvey, 1989). In practice, however, this Kalman Filter MLE estimation is unfeasible both for the non-linearity implied by the MGARCH structure and for the highly computational complexity involved.

To overcome this estimation issue, a two-step estimation procedure is followed here. Firstly, a consistent estimation of $\mathbf{G}$ ($\hat{\boldsymbol{G}}$) is obtained with a conventional DCC-MGARCH model ML estimation (Engle and Sheppard, 2001; Engle, 2002) possibly admitting asymmetry according to the respective tests on the individual series. Then, $\hat{\boldsymbol{G}}$ is entered within model (7a)-(7b) to perform the Kalman Filter ML estimation.

5. Results

The empirical investigation starts with some descriptive evidence and with the univariate analysis aiming to identify the stochastic properties of the price series and their common features. The multivariate analysis is then presented by firstly estimating conventional models expressing price interdependence in levels and volatility (VAR/VECM[17] and MGARCH models). Finally, the FAVAR-MAGARCH model is estimated with the consequent latent factor extraction.

5.1. Main regularities of resource price dynamics: some descriptive evidence

Figure 1 juxtaposes the monthly price dynamics of the 4 different commodities over the period under consideration.[18] Both nominal and real prices are displayed (Figures 1a and 1b, respectively).

[17] Vector Error Correction Model.

[18] For the sake of space limitations, the other two commodities considered in the present empirical analysis (aluminium and corn in replacement of copper and wheat, respectively) are not included in Figure 1. Their dynamics is substantially analogous with the commodities they replace. Respective figures are available upon request.

Sample averages and standard deviations are computed for four sub-periods (1980-1994, 1995-2004, 2005-2013, 2014-2019).[19]

For all commodities the average nominal price observed in the 2005-2013 period is significantly higher (more than 50%) than previous periods when it remained quite stable. The observed average price in this sub-period exceeds the upper 95% confidence bound computed by adding up twice the standard deviation to the average of the previous periods. On the contrary, the following sub-period (2014-2019) shows, for three commodities, a sort of reversion towards the values observed in the 1980-1994 and 1995-2004 periods. In general terms, however, price levels observed in this last time segment seem to be closer to the values of the post-2005 period suggesting that part of the price spikes observed during the 2005-2013 period actually persisted in the longer-term.

These regularities seem to hold true not only for price levels but also for price volatility. Figure 1a,b clearly shows that in the 2005-2013 decade also the standard deviation grew sharply for all commodities. Even in this case, the last five years (2014-2019) partially reabsorb the spike of the previous decade but, as for the levels, most of the volatility growth actually remains and suggests a sort of permanent effect. In general terms, all commodities approximately behave in the same way and with the same timing. Such apparently common dynamics of price levels and volatilities would also suggest a multivariate stochastic generation process.

A further interesting evidence concerns the difference between nominal and real prices. Not surprisingly, moving from nominal to real values substantially downsizes the price dynamics both in terms of levels and volatility. However, real prices show less homogeneous patterns across commodities. Therefore, the presence of common movement, with the consequent multivariate

[19] These four subperiods are arbitrary and considered here only for descriptive purposes as they are not considered further in the specification of the empirical model and in the consequent estimation procedure. Obviously, alternative sub-periods other than the four here adopted could be considered. The choice is made on the basis of a pure visual inspection of price series that suggests a small price jump (at least for wheat and beef) around 1995 and a major jump for all commodities starting around 2005. These discontinuities are also confirmed by the ZV and CMR unit-root tests reported in Table 1. An analogous identification of sub-periods (or structural breaks) can be found in previous works on similar commodity sets (Grantham, 2011; Fan and Xu, 2011; Esposti and Listorti, 2013; Chen et al., 2014).

conditionality, seems more questionable for both real price level and volatility.[20] For wheat and beef the 1980-1995 period shows the highest values in both price level and volatility. In the following sub-periods, prices seem to stabilize and the post-2005 price spike seems almost negligible. For the two non-agricultural cases (crude oil and copper) the existence itself of a long-term price trend is questionable. In these cases, however, volatility clusters are more evident with higher volatility observed in the first (1980-1994) and the third (2005-2013) subperiods. The key point is that the properties of the stochastic process eventually generating the real and the nominal price series might be substantially different. This makes the adoption of an econometric approach admitting but not imposing these stochastic properties particularly appropriate.

5.2. Univariate analysis

Table 1 reports a battery of diagnostic statistical tests performed on nominal and real prices of the six commodities under study. They are, in sequence: the Augmented Dickey Fuller (ADF) unit-root test; the Lagrange Multiplier (LM) test for the presence of conditional heteroskedasticity (ARCH effects); the t-test on the term expressing the asymmetric response of volatility within a full first-order EGARCH model; the test of fractional integration (Phillips 1999a,b) assessing persistence (or long memory); the Zivot-Andrews (ZV) unit-root test admitting one endogenous structural break; the Clemente-Montanes-Reyes (CMR) unit-root test admitting two endogenous breaks in the AO (Additive Outlier) and IO (Innovational Outlier) alternative specifications.[21]

It emerges that all prices show very similar stochastic features. Once the proper specification has been selected (number of lags, and of the presence of drift and deterministic trend), all price series show a unit root.[22] No significant difference emerges between nominal and real prices, the only

[20] The main changes that can be observed moving from nominal to real prices could be evidently attributed to periods of rising/declining inflation. As inflation homogenously affects all prices, however, the differences observed in real prices among commodities express actual differences in the respective short and long-term dynamics.

[21] For more details on the ZV and CMR tests, see Zivot and Andrews (2002), Clement et al. (1998) and Baum (2005).

[22] The ADF test is reported in Table 1. Also the Kwiatkowski-Phillips-Schmidt-Shin (KPPS) and Phillips–Perron (PP) tests are performed. The former assumes stationarity as the null hypothesis while the latter is expected to be more robust

difference being that real prices show a unit root with no deterministic trend, arguably taking into account the common underlying inflation rate in the case of nominal prices.

However, the ADF test can lose power thus providing misleading evidence under two circumstances. The first concerns the presence of long memory or fractional cointegration. Fractional integration implies that price series, though not behaving as random walks, still keep the memory of a shock for a long period.[23] In this respect Table 1 suggests that all price series are neither I(0) nor I(1) but rather I(d) processes, with $0<d<1$ (Wei and Leuthold, 1998). Test results indicate that stationarity can be excluded in all cases while the I(1) hypothesis actually show quite low p-values with three commodities (wheat, aluminium and corn) for which it is lower than 10%. All series, both nominal and real, thus show a dynamics that is very close to being either an I(1) process or a mean-reverting series where the effects of one-time shock take a very long time to vanish.

The second possible confounding factor concerns the presence of structural breaks that, within a stationary series, may lead to wrongly accept the presence of a unit root (Fan and Xu, 2011; Chen et al., 2014; Al-Maadid et al., 2017; Dogan and Ozturk, 2017; Hickam et al., 2018; Omojou et al., 2020).[24] The two unit-root tests admitting endogenous structural breaks (ZV and CMR tests) are concordant in confirming that all prices are non-stationary in both nominal and real terms regardless the presence of structural breaks. In this respect, the ZV test suggests that no statistical structural break is found for real term prices, while only for nominal crude oil and copper prices a statistically significant structural break occurred in mid-2005. Even though the CMR test allows for two

under heteroskedasticity. Results of these tests fully correspond with those obtained with ADF tests and are available upon request.

[23] Fractional integration is here tested following the approach originally proposed by Geweke and Porter-Hudak (1983) and then modified by Phillips (1999a,b). This test is based on a particular representation of the stochastic process generating the price series called ARFIMA(p,d,q) (Autoregressive Fractionally Integrated Moving Average) model, where p and q express, as usual, the orders of auto-regressive and the moving-average parts, respectively, and d the order of (fractional) integration. The procedure proposed by Phillips (1999a,b), and here adopted, tests the value of parameter d thus distinguishing stationary, unit-root and fractionally integrated processes. This procedure produces two test statistics, one for the null d=0 and one for d=1. If d=0 is accepted the series is stationary; if d=1 is accepted the series has a unit root. If both are rejected (namely, $0<d<1$), then fractional integration (long memory) is accepted.

[24] We would like to thank an anonymous referee for helpful suggestions on this aspect.

structural breaks, it substantially confirms the ZV test results: no statistical structural break for real prices; only one significant break for crude oil and copper nominal prices. In such case, when innovational outliers are considered (the IO model, allowing for a gradual shift in the mean of the series) the break is dated in early 2005, while under additive outliers (the AO model, which captures a sudden change in the series) the break is dated almost one year later, as expected.[25] In any case, what matters here is that the possible presence of structural breaks does not eliminate the clear evidence in favor of a generalized non-stationarity of the series considered.

Finally, the ARCH test indicates that for no price series the presence of conditional heteroskedasticity can be excluded thus suggesting the generalized presence of volatility clusters. Also in this case, the conclusion holds true without significant differences between nominal and real prices. In addition, the positive sign of the respective coefficient within the EGARCH models suggests the presence of a leverage effect, that is, negative innovations (unanticipated price decrease) increases volatility more than positive innovations. However, the asymmetry in the volatility response is found significant only for crude oil, copper and aluminum (both nominal and real prices). Moreover, even when statistical significant this asymmetric effects is not particularly strong as it is substantially lower than the symmetric effect.[26] As anticipated in section 3.3, these statistically significant asymmetric responses are properly taken into account by augmenting the MGARCH modelling approach with the respective dummies.[27]

Eventually, the adopted battery of tests suggest that all 6 price series, both in nominal and real terms, show similar stochastic processes, with only some minor differences. This does not necessarily mean, however, that they share some common movement. To provide initial evidence supporting this hypothesis, Table 1 also reports the pair-wise correlation coefficients of estimated

[25] Even though not statistically significant, it is still worth noticing that the second break is dated between 2014 and 2015. More generally, and regardless statistical significance, the breaks identified across all series tend to confirm the sub-periods adopted in Figure 1a,b.
[26] For the sake of space limitations, the whole set of EGARCH model estimates are not reported here. They are available upon request.
[27] We are grateful to an anonymous referee for helpful comments on the possible presence of asymmetries.

residuals of the 6 ADF unit-root test equations. For almost all pairs of prices (in both nominal and real terms) we observe a significant and positive correlation coefficient for. This positive correlation suggests that whenever the individual autoregressive stochastic processes are taken into account, there remains a residual part of price dynamics that shows some commonality across series. Correlation is quite strong for pairs of commodities belonging to the same group, that is, copper and aluminum, wheat and corn. This provides further justification for using these couples as alternatives in the 4-case model estimation.

5.3. Multivariate analysis

5.3.1. Cointegration and volatility spillover

Table 2 reports results concerning the cointegration analysis for both nominal and real prices of the four commodities under study. Results for the alternative group of commodities are reported in the Annex (Table A1). The trace cointegration test indicates that these prices are cointegrated but, in fact, they may move along two different cointegration vectors. The same result is obtained with aluminium and corn replacing copper and wheat. Consequently, cointegration by itself does not guarantee a univocal economic interpretation of price linkages. Even if we consider only the first extracted cointegration relationship, the VECM estimation confirms that, although a long-run relationship among prices can be identified, its interpretation is not straightforward and, somehow, counterintuitive.

The cointegration vector coefficient of copper is not statistically different from 0, thus its counterintuitive (i.e., negative) sign is not qualitatively meaningful. A similar result is obtained with aluminium instead of copper but with a statistically significant parameter, suggesting that aluminium moves in the opposite direction compared to other commodities while they are expected to move in the same direction. According to the adjustment parameters, no price behaves as an exogenous driver of all the others. All prices respond to the others and this is not easily interpretable especially when crude oil, the main candidate being the driving price, is considered. The Granger causality tests make the picture emerging from this VECM estimation even more puzzling. Crude oil and wheat prices are caused by all other prices, while copper price is independent from beef price (as could be expected) and beef price only depends on wheat price.

Although Johansen et al. (2000) generalize the standard cointegration framework by proposing a VECM with a structural break in the deterministic terms, here the univariate analysis does not support the occurrence of a common structural breaks. Therefore, this variant of the VECM is not adopted here. Nonetheless, in order to take the evidence emerging from test on individual series properly into account, the crude oil and copper price equations of the VECM with nominal prices are augmented with a dummy variable taking value 1 from mid-2005 onwards. Then, following Esposti and Listorti (2018), an ex-post cointegration testing is performed through an ADF test on residuals of the long-run cointegration relationship. In this respect, Table 2 and Table A1 indicate that the estimated parameters associated to the structural break ($d_{2005,cr}$ and $d_{2005,cp}$) are not statistically significant thus rejecting the presence of a structural break within the relationship expressing price interdependence. Furthermore, all ADF tests on the residuals of the estimated VECM long-run relation clearly indicate they are stationary thus confirming the correctness of the cointegrating relationship.

Table 3 and Table A2 report the DCC-MGARCH model estimates on the two alternative groups of prices. Results suggest that price volatility varies over time for all series as indicated by the adjustment parameters, thus confirming the ARCH effects emerging in Table 1. This evidence apparently supports the existence of volatility clusters that are synchronous across the commodities as visually suggested by Figure 1. The DCC-MGARCH model collapses to the CCC-MGARCH model when $\lambda_1 = \lambda_2 = 0$. Both these two estimated coefficients are positive (as expected) but are substantially different in magnitude with only λ_2 statistically different from 0. So the CCC[28] specification can be evidently excluded with the implication that not only conditional variances are

[28] Constant Conditional Correlation.

correlated but that this correlation is also time-variant. On the other hand, however, the conditional (quasi)correlation between the standardized residuals is statistically significant only between crude oil and copper (or aluminium). In all other cases, quasicorrelation is poor (always lower than 0.1) and not statistically different from 0. Therefore, the DCC-MGARCH estimation does not confirm the existence of generalised volatility spillovers. The only clear evidence is the volatility of the crude oil price that is positively transmitted to the volatility of copper and aluminium.

A similar conclusion can be drawn with respect to asymmetric volatility response. The coefficients associated to the respective dummies confirm that asymmetry occurs for crude oil, copper and aluminum nominal and real prices (terms $f_{cr,cr}$, $f_{cp,cp}$ and $f_{al,al}$). But, unlike asset markets where it is often observed, here results indicate that the cross-market transmission of this asymmetry is excluded as the respective terms ($f_{cr,cp}$,$f_{cp,cr}$ and $f_{cr,al}$, $f_{al,cr}$) are not statistically different from 0.

A final remark about this multivariate analysis concerns the comparison between nominal and real prices. As for the univariate analysis, no significant differences emerge, with the only difference of the lack of a deterministic trend and of possible structural break outside the cointegration relationship. Cointegration is observed also for real prices with quite similar cointegration relationships and comparable adjustment parameters. The same conclusion holds for the DCC-MGARCH estimates and the possible asymmetry of the volatility response. They are largely comparable between nominal and real prices with asymmetric response of volatility limited to the crude oil price and some evidence of volatility transmission (or spillover) from crude oil to copper and aluminium but not generalizable to agricultural commodities.

5.3.2. Latent factors estimates

The FAVAR-MGARCH model (7a)-(7b) estimation is reported in Table 4 (and in Table A3 for the alternative group of commodities). Estimates confirm that all prices are significantly driven by the long-term latent factor (z_1) and the sign confirms the expectation as all prices move in concordance with the variations of the factor. This occurs without any significant difference for both real and nominal prices and is confirmed also on the alternative group commodities.

For the short-term latent factor (z_2), on the contrary, only some prices show a significant relationship. This is the case of crude oil and copper for both real and nominal prices and of real aluminium and beef price in the alternative group. Moreover, significant parameters are either positive or negative, thus do not indicate a univocal response to variations of this latent factor. This behaviour of parameters associated to factor z_2 seems fully consistent with the fact that the autoregressive structure of the model should already take short-term responses into account and z_2 is expected to capture only the unexplained part of this variation.

Through the autoregressive terms the VAR structure also takes the possible interdependence across price into account. In fact, only some of the estimated parameters associated to these terms are statistically significant. This occurs for most of the own lags and for the linkage emerging between mineral prices (copper and aluminium) and crude oil and between agricultural prices (wheat and corn) and beef prices, while wheat/corn and beef prices show only some significant positive coefficients in response to crude oil prices. Also in this respect, no major difference emerges between real and nominal prices.

The most interesting outcome of the proposed approach, however, is the estimation of the latent factors themselves as their extraction is expected to reveal presence and behaviour of the common drivers of prices. They are displayed in Figure 2a for the nominal price and in Figure 2b for the real prices.[29] In both cases, it emerges that the estimated patterns are fully consistent with latent variable construction in equation (7a). z_2 behaves as a zero-mean stationary autoregressive process. Nonetheless, particularly the 2005-2015 decade signals larger deviations from the mean value reasonably as consequence of the increased price volatility. z_1 is consistent with a random walk with

[29] Figure reports estimates starting from 1981:1 as the first 12 observations (months) are used to initialize and stabilize the Kalman Filter estimation of the latent factors.

drift and it is able to capture what can be intended as the varying long-term equilibrium price with the respective jumps (or structural breaks).

As expected, however, for z_1 substantial differences occur between nominal and real prices. In the former case, this long-term price shows a slight regular increase until late eighties then it remains substantially stable over the nineties and in the early '00s. Starting about in 2004/2005 this long-term equilibrium price jumped to a significantly higher value maintained for almost a decade. Then, it drops again to finally stabilize at a value that seems significantly higher (between 5% and 10%) than the pre-2004/2005 stable level. In the case of real prices, the long-term dynamics is essentially different though with a substantial correspondence of the years and periods of deviations, jumps or structural breaks. In this case, factor z_1 does not provide any evidence of a generalized rising level over time. On the contrary, a slight decline emerges over the first 25 years though more regular in the eighties than in the nineties and early '00s. Then, after 2007 this decline stops showing a small jump in the 2007-2011 period and then, a stabilization until the end of the period under study. This stabilization level is about 15% lower than the initial z_1 value.

Eventually, this seems to be the main empirical result of the present study in the light of the underlying research question. Comparing the estimated long-term latent factor, z_1, for nominal and real prices, it emerges that the supposed increase in the long-term equilibrium values, possibly as a consequence of an increasing scarcity, tends to disappear when the inflation rate is properly taken into account. It remains true, however, that the last two decades seem to mark the end of the previous long period of declining prices in real terms and of stable nominal prices, but also a significant increase of volatility.

If compared to the two latent factors extracted for the first group of four commodities, the factors obtained replacing copper with aluminium and wheat with corn are qualitatively and statistically similar (Figure A2). Of the two latent factors, z_2 seems less volatile, especially in the last decades, for this alternative group of commodities. Also factor z_1 seems more stable but its overall pattern largely confirms, for both nominal and real prices, what was observed on the original group.

Beside the interpretation of specific results, however, the major evidence emerging from the proposed approach is the confirmation that it is able to provide an alternative representation, that of common latent factors, of the common movement of resource prices compared to the conventional multivariate analysis. In fact, it integrates and expand the usual multivariate models. Results suggest that price interdependence, thus price transmission, in both level and volatility can not be ruled out but it is weak and often concerns sub-set of commodities. At the same time, the estimated latent common factors seem able to explain large part of the common movement of different commodities. Extracting the latent factor expressing the non-stationary long-term equilibrium price (factor z_1) suggests that, apart from the increased price volatility, no indisputable evidence of a long-term generalised price rise actually emerges. On the one hand, only a slight significant and permanent rise occurs in the last fifteen years in nominal prices. On the other hand, when looking at real prices this long-term dynamics seems rather to indicate a stabilization after a long period of decline.

6. Concluding remarks and further research developments

This paper focuses on the common movement of resource and commodity prices and its underlying drivers. The policy implications of this common movement are remarkable as it might signal long-term changes of market fundamentals eventually indicating periods of abundance/scarcity. The present work has a methodological motivation, that is, to develop an unifying framework able to empirically capture all the common stochastic properties of these price series, and their common long-term movement in particular, but still incorporating possible price interdependence in both levels and volatility.

Results here presented confirm that the proposed approach is capable of achieving this purpose and, therefore, it may represent a significant original contribution in this field. In particular, extracting the common latent factors represents a significant addition to the toolkit available to market analysts and decision makers. This new tool might allow a sort of periodical surveillance mechanism on the common long-term perspective of the resource markets and, thus, may constitute a significant new support to appropriate policy decision making in this field.

Nonetheless, the empirical exercise here presented also leaves room for significant improvements within the proposed methodology. Three aspects, in particular, are worth noticing. First of all, caution is needed in deriving conclusions on general validity on the long-term price dynamics and, in particular, about a global end of abundance and a new era of scarcity with the consequent considerable policy implications. In fact, results here presented actually convey inconclusive information on whether there is a monotonic rising or declining trend in the long run. This does not only require additional information in terms of longer time series but, more importantly, an extension of the analysis to a wider set of heterogenous resources and commodities. Unfortunately, such an extension is problematic within the adopted approach due to the computational limitations it arises whenever the number of series under analysis exceeds four.

Secondly, an economics of the price latent factors, therefore a deeper latent factor interpretation, is still lacking. The proposed modelling strategy is not explicit on the major economic drivers underlying these factors but it is flexible enough to be developed in this direction. Therefore, interesting future directions of research in this field may consist in integrating the approach here presented with additional modelling and data about the market fundamentals underlying the extracted latent factors, thus reconnecting the modelling strategy with the vast literature produced in this respect.

There is another limitation of the adopted approach. The proposed model disregards the possible univariate and multivariate interdependence between price level and price volatility. Even though this seems more likely in asset markets than in resource and commodity markets, this interdependence could be a major determinant of the change of the long-term common dynamics observed since the early '00s. Results here obtained actually suggest the need for a deeper investigation of this level-volatility linkage. In principle, the structure of the model here proposed admits some improvements in this respect: However, the adopted specification and estimation solutions, and the consequent computational burden, seriously question their empirical feasibility. Future research could significantly contribute in this direction.

References

Al-Maadid, A., Caporale, G.M., Spagnolo, F. and Spagnolo, N. (2017). Spillovers between food and energy prices and structural breaks. *International Economics* 150, 1–18.

Algieri, B., Kalkuhl, M. and Koch, N. (2017) A tale of two tails: Explaining extreme events in financialized agricultural markets. *Food Policy* 69, 256-269.

Algieri, B., Leccadito, A. (2020). Extreme price moves: an INGARCH approach to model coexceedances in commodity markets. *European Review of Agricultural Economics* (in press). Doi.org/10.1093/erae/jbaa030.

Arango, L.E., Arias, F. and Florez, A. (2012). Determinants of commodity prices. *Applied Economics* 44(2), 135-145.

Baffes, J. and Haniotis, T. (2016). What explains agricultural price movements? *Journal of Agricultural Economics* 67(3), 706–721.

Bai, J. (2013). Panel Data Model and Factor Analysis. In D. Acemoglu, M. Arellano and D. Eddie (eds.), *Advances in Economics and Econometrics. Volume III: Econometrics*. Cambridge University Press, New York, 437-484.

Baum, C.F. (2005). Stata: The Language of Choice for Time-Series Analysis? *The Stata Journal* 5(1), 46-63.

Beirne, J., Caporale, G.M., Schulze-Ghattas, M. and Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review* 11(3), 250-260.

Bernake, B.S., Boivin, J. and Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics* 120(1), 387-422.

Bobenrieth, E. S. A., Bobenrieth, R. A. and Wright, B. D. (2014). Bubble Troubles? Rational Storage, Mean Reversion, and Runs in Commodity Prices. In: J-P. Chavas, D. Hummels, B.D. Wright (eds.), *The Economics of Food Price Volatility*. University of Chicago Press, Chicago.

Brooks, C. and Prokopczuk, M. (2013). The Dynamics of Commodity Prices. *Quantitative Finance* 13(4), 527-542.

Bruno, V.G., Büyükşahin, B. and Robe, M. A. (2017). The Financialization of Food? *American Journal of Agricultural Economics* 99(1): 243-264.

Byrne, J.P., Sakemoto, R. and Xu, B. (2020). Commodity price co-movement: heterogeneity and the time-varying impact of fundamentals. *European Review of Agricultural Economics* 47(2). 499-528.

Cáceres- Hernández, J.J. and Martín- Rodríguez, G. (2017). Evolving splines and seasonal unit roots in weekly agricultural prices. *Australian Journal of Agricultural and Resource Economics* 61(2), 304-323.

Carnero, M.A. and Eratalay, M.H. (2014). Estimating VAR-MGARCH models in multiple steps. *Studies in Nonlinear Dynamics & Econometrics* 18(3), 339-365.

Carter, C. (2002). Commodity futures markets: a survey. *Australian Journal of Agricultural and Resource Economics* 43(2), 209-247.

Chavas, J-P., Hummels, D. and Wright B.D. (eds.) (2014). *The Economics of Food Price Volatility*. University of Chicago Press, Chicago.

Chen, P., Chien-Chiang, L. and Zeng, J. (2014). The relationship between spot and futures oil prices: do structural breaks matter? *Energy Economics* 43, 206–217.

Chen, S-L., Jackson, J.D., Kim, H. and Resiandini, P. (2014). What Drives Commodity Prices. *American Journal of Agricultural Economics* 96(5), 1455-1468.

Chen, H., Zhang, J., Tao, Y. and Tan, F. (2019). Asymmetric GARCH type models for asymmetric volatility characteristics analysis and wind power forecasting. *Protection and Control of Modern Power Systems* 4(29), 1-11.

Clemente, J., Montañés, A. and Reyes, M. (1998). Testing for a unit root in variables with a double change in the mean. *Economics Letters* 59(2), 175-182.

Cortazar, G., Lopez, M. and Naranjo, L. (2017). A multifactor stochastic volatility model of commodity prices. *Energy Economics* 67, 182–201.

Dogan, E. and Ozturk, I. (2017). The influence of renewable and non-renewable energy consumption and real income on CO_2 emissions in the USA: evidence from structural break tests. *Environmental Science and Pollution Research* 24, 10846–10854.

Engle, R.F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics* 20, 339–350.

Engle, R.F. and Sheppard, K. (2001). Theoretical and Empirical properties of Dynamic Conditional Correlation Multivariate GARCH. *NBER Working Papers, No. 8554*, National Bureau of Economic Research , Cambridge Mass.

Esposti, R. and Listorti, G. (2013). Agricultural price transmission across space and commodities during price bubbles. *Agricultural Economics* 44, 125–139.

Esposti, R. and Listorti, G. (2018). Price Transmission in the Swiss Wheat Market: Does Sophisticated Border Protection Make the Difference? The International Trade Journal 32(2), 209-238.

Fan, Y. and Xu, J. (2011). What has driven oil prices since 2000? A structural change perspective. *Energy Economics* 33 (6), 1082–1094.

Fousekis, P., Emmanouilides, C. and Grigoriadis, V. (2016). Prices linkages in the international skim milk powder market: empirical evidence from nonparametric and time varying copulas. *Australian Journal of Agricultural and Resource Economics* 61(1), 135–153.

Geweke, J. and Porter-Hudak, S. (1983). The Estimation and Application of Long Memory Time Series Models, *Journal of Time Series Analysis* 4(4), 221-238.

Gilbert, C.L. (1995). Modelling market fundamentals: a model of aluminium market. *Journal of Applied Econometrics* 10, 385-410.

Gilbert, C.L. and Kasidi Mugera, H. (2020). Competitive Storage, Biofuels and the Corn Price. *Journal of Agricultural Economics* 71(2): 384-411.

Glynn, J,, Perera, N. and Verma, R. (2007). Unit-root tests and structural breaks: a survey with applications. *Journal of Quantitative Methods for Economics and Business Administration* 3(1): 63-79.

Glosten, L.R., Jagannathan, R. and Runkle, D.E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance* 48(5), 1779-1801.

Godfray, H.C.J. (2015). The debate over sustainable intensification. *Food Security* 7, 199-208.

Grantham, J. (2011). Time to Wake Up: Days of Abundant Resources and Falling Prices Are Over Forever. GMO Quarterly Letter, April, Boston.

Hansen, P.R., Huang, Z. (2016). Exponential GARCH Modeling With Realized Measures of Volatility. *Journal of Business & Economic Statistics* 34(2), 269-287

Hicham, A. (2018). Poverty Reduction, Financial Development and Economic Growth in Algeria: A Gregory Hansen Co-Integration Regime Shift Analysis. *The Economic Research Guardian* 8(2), 40-52.

Jane, T-D. and Ding, C.G. (2009). On the multivariate EGARCH model. *Applied Economics Letters* 16(17): 1757-1761.

Johansen, S., Mosconi, R. and Nielsen, B. (2000). Cointegration Analysis in the Presence of Structural Breaks in the Deterministic Trend. *Econometrics Journal* 3(1), 216–49.

Kim, A. (2015). Does Futures Speculation Destabilize Commodity Market? *Journal of Futures Markets* 35(8), 696-714.

Kim, T-H., Pfaffenzeller, S., Rayner, T. and Newbold, P. (2003). Testing for linear trend with application to relative primary commodity prices. *Journal of Time Series Analysis* 24(5), 539-551.

Koutmos, G. and Booth, G.G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance* 14(6): 747–62.

Le Mouël, C., Forslund, A. (2017). How can we feed the world in 2050? A review of the responses from global scenario studies. *European Review of Agricultural Economics* 44(4): 541–591.

Listorti, G. and Esposti, R. (2012). Horizontal price transmission in agricultural markets: fundamental concepts and open empirical issues. *Bio-based and Applied Economics* 1(1), 81-108.

Maekawa, K. and Setiawan, K. (2014). Estimation of Vector Error Correction Model with GARCH Errors: Monte Carlo Simulation and Application. Paper Presented at the International Conference on Economic Modelling – ECOMOD 2014, July 16-18, Bali.

Martin, V., Hurn, S. and Harris, D. (2013). *Latent Factor Models*. Econometric Modelling with Time Series. Cambridge University Press, New York.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica* 59(2), 347-370.

Ohashi, K. and Okimoto, T. (2016). Increasing Trends in the Excess Comovement of Commodity Prices. CAMA Working Paper 9/2016, Crawford School of Public Policy, Australian National University, Acton.

Omoju, O.E., Li J., Zhang J., Rauf A. and Sosoo V.E. (2020). Implications of shocks in energy consumption for energy policy in sub-Saharan Africa. *Energy & Environment* 31(6),1077-1097.

Peterson, H.H. and Tomek, W.G. (2000). Implications Of Deflating Commodity Prices For Time-Series Analysis. NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Chicago, April 17-18.

Phillips, P.C.B. (1999a). Discrete Fourier Transforms of Fractional Processes. Cowles Foundation for Research in Economics, Discussion Paper No. 1243, Yale University.

Phillips, P.C.B. (1999b). Unit Root Log Periodogram Regression. Cowles Foundation for Research in Economics, Discussion Paper No. 1244, Yale University.

Piot-Lepetit I. and M'Barek, R. (eds.) (2011). *Methods to Analyse Agricultural Commodity Price Volatility*. Springer Verlag, Berlin.

Routledge, B.R., Seppi, D.J. and Spatt, C.S. (2000). Equilibrium Forward Curves for Commodities. *The Journal of Finance* 55(3), 1297-1338.

Schleicher, C. (2003). Structural Time Series Models with Common Trends and Common Cycles. Computing in Economics and Finance n. 108, Society for Computational Economics.

Schwartz, E.S. (1997). The Stochastic Behavior of Commodity Prices: Implications for Valuation and Hedging. *The Journal of Finance* 52(3), 923-973.

Schwartz, E.S. and Smith, J.E. (2000). Short-Term Variations and Long-Term Dynamics in Commodity Prices. *Management Science* 46(7), 893-911.

Sørensen, C. (2002). Modelling Seasonality in Agricultural Commodity Futures. *Journal of Future Markets* 22(5), 393-426.

Stock, J.H. and Watson, M.W. (2016). Dynamic Factor Models, Factor-Augmented Autoregressions, and Structural Vector Autoregressions in Macroeconomics. In J.B. Taylor and H. Uhlig (eds), *Handbook of Macroeconomics. Vol. 2*. Elsevier, Amsterdam, 415-526.

Stock, J.H. and Watson, M.W. (2017). Twenty Years of Time Series Econometrics in Ten Pictures. *Journal of Economic Perspectives* 31(2), 59-86.

UNCTAD (2017). *Trade and Development Report 2017. Beyond austerity: towards a global new deal*. United Nations publication, Sales No. E.16.II.D3, New York and Geneva.

Valera, H.G.A. and Lee, J. (2016). Do rice prices follow a random walk? Evidence from Markov switching unit-root tests for Asian markets. *Agricultural Economics* 47, 683-695.

Wei A. and Leuthold, R.M. (1998). Long Agricultural Future Prices: ARCH, Long Memory or Chaos Processes? OFOR Paper n. 98-03, Department of Agricultural Economics, University of Illinois at Urbana-Champaign.

Xu, Y., Pan, F., Wang, C. and Li, J. (2019). Dynamic Price Discovery Process of Chinese Agricultural Futures Markets: An Empirical Study Based on the Rolling Window Approach. *Journal of Agricultural and Applied Economics* 51, 664–681.

Zivot, E. and Andrews, D.W.K. (2002.) Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis, *Journal of Business & Economic Statistics* 20(1), 25-44.

Table 1 – Univariate analysis on the 6 commodity nominal and real prices.

Nominal prices

	ADF[a]	ARCH[b]	EGARCH[c]	Fractional integration[d]		ZV (break month)[e]	CMR (break months)[f]	
				t (H_0: d=0)	z (H_0: d=1)		IO	AO
Crude oil	-2.584	83.076*	0.194*	0.000	0.112	-4.876* (2005m5*)	-5.753* (2005m1*, 2014m6)	-5.992* (2005m12*, 2015m3)
Copper	-2.355	91.203*	0.193*	0.000	0.124	-5.325* (2005m7*)	-5.927* (2005m3*, 2014m7)	-5.668* (2006m3*, 2015m4)
Wheat	-2.913	37.168*	0.046	0.000	0.088	-5.073*	6.662*	-5.729*
Beef	-1.998	27.716*	0.118	0.000	0.184	-4.934*	-5.496*	-5.938*
Aluminium	-3.164	98.195*	0.160*	0.000	0.066	-5.058*	-5.765*	-5.494*
Corn	-2.806	30.299*	0.090	0.000	0.074	-5.251*	-5.872*	-5.745*

Correlation coefficient of estimated residuals of ADF unit-root test equations

	Crude oil	Copper	Wheat	Beef	Aluminium	Corn
Crude oil	1.000					
Copper	0.313*	1.000				
Wheat	0.166*	0.179*	1.000			
Beef	0.167*	0.197*	0.193*	1.000		
Aluminium	0.278*	0.532*	0.149*	0.085	1.000	
Corn	0.187*	0.181*	0.507*	0.169*	0.154*	1.000

Real prices

	ADF[a]	ARCH[b]	EGARCH[c]	Fractional integration[d]		ZV (break month)[e]	CMR (break months)[f]	
				t (H_0: d=0)	z (H_0: d=1)		IO	AO
Crude oil	-2.828	79.442*	0.185*	0.000	0.106	-4.835*	-5.609*	-5.664*
Copper	-2.633	79.914*	0.165*	0.000	0.117	-5.749*	-5.554*	-5.547*
Wheat	-3.120	25.727*	-0.038	0.000	0.067	-4.966*	-5.642*	-5.030*
Beef	-2.324	25.462*	0.102	0.000	0.155	-4.803*	-5.765*	-5.579*
Aluminium	-3.341	94.489*	0.146*	0.000	0.055	-4.939*	-6.643*	-5.590*
Corn	-3.278	28.983*	0.078	0.000	0.060	-4.831*	-5.547*	-5.658*

Correlation coefficient of estimated residuals of ADF unit-root test equations

	Crude oil	Copper	Wheat	Beef	Aluminium	Corn
Crude oil	1.000					
Copper	0.292*	1.000				
Wheat	0.144*	0.174*	1.000			
Beef	0.108*	0.109*	0.153*	1.000		
Aluminium	0.255*	0.527*	0.118*	0.080	1.000	
Corn	0.126*	0.119*	0.506*	0.120*	0.139*	1.000

[a] *Augmented Dickey Fuller (ADF) unit-root test with 12 lags and deterministic trend*
[b] *Lagrange Multiplier (LM) test performed on the residuals of the ADF unit-root test equations and 12 lags*
[c] *Term expressing the asymmetric response within a full first-order EGARCH model (Nelson, 1991)*
[d] *Test of fractional integration according to Phillips (1999a,b); p-values are reported*
[e] *Zivot Andrews (ZV) unit-root test with one endogenous structural break in the intercept, lags selected with AIC and deterministic trend; only statistically significant breaks are reported*
[f] *Clemente, Montanes and Reyes (CMR) unit-root test with two endogenous breaks, lags selected with AIC and deterministic trend; AO (Additive Outlier), IO (Innovational Outlier) ; only statistically significant breaks are reported*
**Statistically significant at 5% level*

Table 2 – Cointegration analysis on the 4 commodity nominal and real prices: cointegration rank, VECM estimates [a] and causality test (results with Aluminium and Corn are reported in the Annex).

Nominal prices

Rank	Trace statistic		Vector	Adjustment	Short-run Granger causality test ($\chi 2$)
0	70.89*	Crude oil	1	-0.022*	Copper: 16.09* Wheat: 20.98* Beef: 15.10*
1	38.31	Copper	1.005*	-0.027*	Crude oil: 17.06* Wheat: 24.54* Beef: 4.90
2	13.92	Wheat	-4.246*	-0.025*	Crude oil: 7.28 Copper: 22.17* Beef: 12.45*
		Beef	-0.912*	-0.012*	Crude oil: 5.15 Copper: 9.86 Wheat: 19.33*

Structural break dummies: $d_{2005,cr}$: 0.994; $d_{2005,cp}$: 2.085

Real prices

Rank	Trace statistic		Vector	Adjustment	Short-run Granger causality test ($\chi 2$)
0	67.23*	Crude oil	1	-0.051*	Copper: 12.97* Wheat: 16.01* Beef: 14.49*
1	35.10	Copper	0.821*	-0.019*	Crude oil: 11.51* Wheat: 11.92* Beef: 4.21
2	13.81	Wheat	-3.921*	-0.027*	Crude oil: 5.04 Copper: 16.52* Beef: 11.45*
		Beef	-0.743*	-0.018*	Crude oil: 2.05 Copper: 5.82 Wheat: 15.60*

[a] The VECM model is estimated on the first cointegration vector extracted with 6 lags. In the case of nominal prices, a deterministic trend is also included within the cointegration vector.
**Statistically significant at 5% level*

Table 3 – DCC-MGARCH (1,1) model estimates on the 4 commodity nominal and real prices (results with Aluminium and Corn are reported in the Annex).

Nominal prices	
Correlation parameters	Adjustment parameters
Crude oil and Copper: 0.321* Crude oil and Wheat: -0.009 Crude oil and Beef: 0.075	$\lambda_1 = 0.013$ $\lambda_2 = 0.944$*
Copper and Wheat: 0.138 Copper and Beef: 0.060	p-value ($\lambda_1 = \lambda_2 = 0$) = 0.000[a]
Wheat and Beef: 0.032	
Asymmetry parameters $f_{cr,cr}$: 0.129* ; $f_{cr,cp}$: 0.051 ; $f_{cp,cp}$: 0.094*; $f_{cp,cr}$: 0.025	
Real prices	
Correlation parameters	Adjustment parameters
Crude oil and Copper: 0.305* Crude oil and Wheat: -0.016 Crude oil and Beef: 0.040	$\lambda_1 = 0.012$
Copper and Wheat: 0.125 Copper and Beef: 0.026	$\lambda_2 = 0.924$* p-value ($\lambda_1 = \lambda_2 = 0$) = 0.000[a]
Wheat and Beef: 0.019	
Asymmetry parameters $f_{cr,cr}$: 0.107* ; $f_{cr,cp}$: 0.040 ; $f_{cp,cp}$: 0.091*; $f_{cp,cr}$: 0.022	

[a] Wald test

**Statistically significant at 5% level*

Table 4 – FAVAR model (7a)-(7b) estimates on nominal and real prices (estimated standard error in parenthesis).

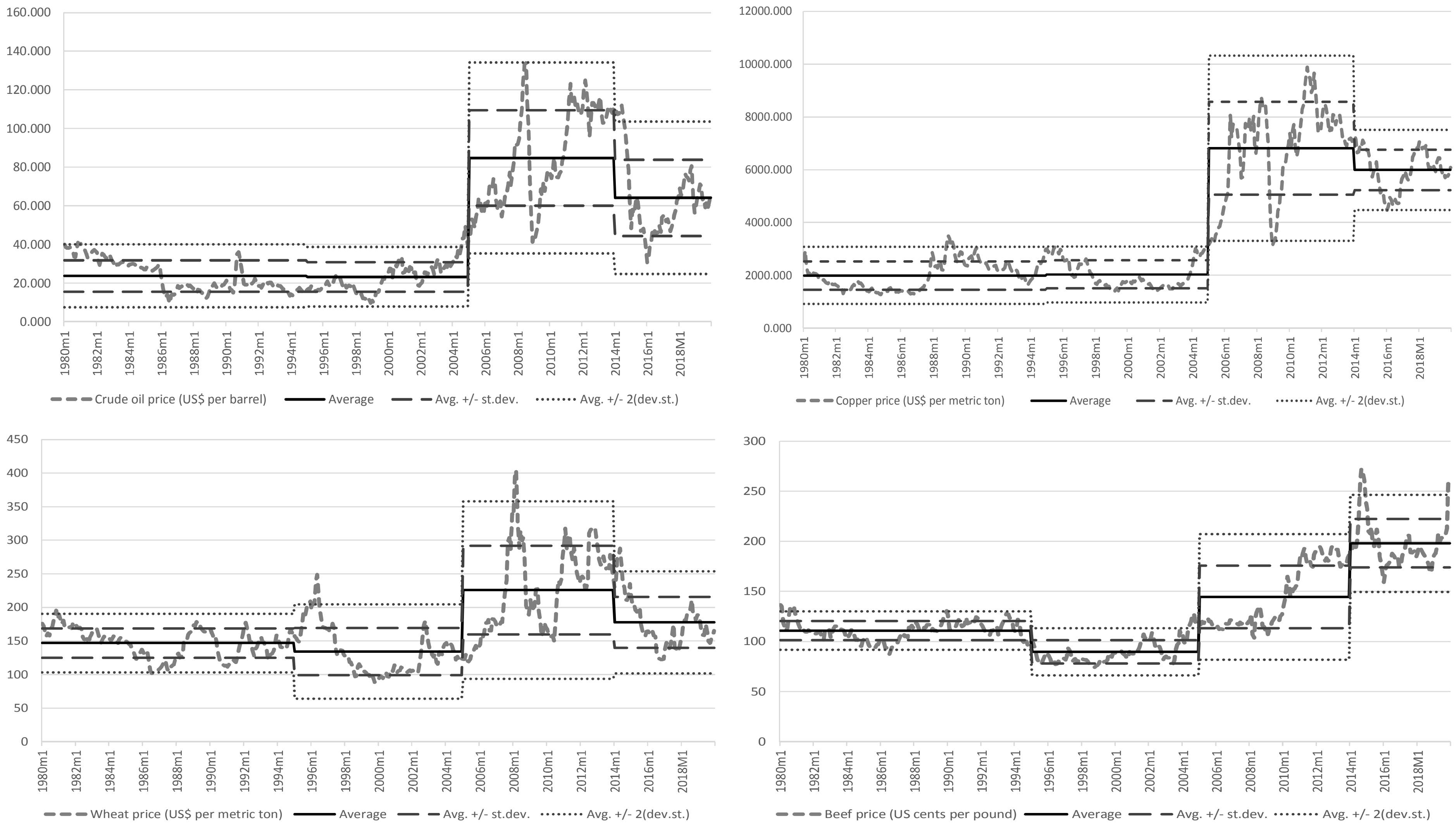
Equation *Coefficient*	*Estimate*		*Equation* *Coefficient*	*Estimate*	
		Nominal Prices			
Factor 1 (z_1)			*Wheat (wh)*		
Constant (c_L)	1.855*	(0.254)	Constant (c_{wh})	38.0*	(12.08)
Factor 2 (z_2)			z_{1t} (γ_{1wh})	2.97*	(0.522)
z_{2t-1} (δ_1)	0.647*	(0.189)	z_{2t} (γ_{2wh})	0.799	(0.659)
z_{2t-1} (δ_2)	0.325	(0.189)	cr_{t-1} (α_{31})	0.557*	(0.244)
Crude oil (cr)			cr_{t-2} (β_{31})	0.096	(0.183)
Constant (c_{cr})	6.01*	(2.95)	cp_{t-1} (α_{32})	0.001	(0.002)
$d_{2005,cr}$	1.521	(0.907)	cp_{t-2} (β_{32})	0.003	(0.003)
z_{1t} (γ_{1cr})	1.74*	(0.231)	wh_{t-1} (α_{33})	0.922*	(0.051)
z_{2t} (γ_{2cr})	-1.43*	(0.227)	wh_{t-2} (β_{33})	-0.017	(0.050)
cr_{t-1} (α_{11})	0.833*	(0.168)	be_{t-1} (α_{34})	0.209*	(0.104)
cr_{t-2} (β_{11})	-0.150*	(0.069)	be_{t-2} (β_{34})	-0.400*	(0.104)
cp_{t-1} (α_{12})	-0.001	(0.001)	*Beef (be)*		
cp_{t-2} (β_{12})	-0.001	(0.001)	Constant (c_{be})	16.6	(5.93)
wh_{t-1} (α_{13})	0.010	(0.017)	z_{1t} (γ_{1be})	0.941*	(0.248
wh_{t-2} (β_{13})	0.013	(0.017)	z_{2t} (γ_{2be})	-0.281	(0.278)
be_{t-1} (α_{14})	0.031	(0.032)	cr_{t-1} (α_{41})	-0.053	(0.092)
be_{t-2} (β_{14})	-0.062	(0.032)	cr_{t-2} (β_{41})	-0.069	(0.072)
Copper (cp)			cp_{t-1} (α_{42})	0.004*	(0.001)
Constant (c_{cp})	351.4*	(135.4)	cp_{t-2} (β_{42})	-0.001	(0.002)
$d_{2005,cp}$	5.773	(4.896)	wh_{t-1} (α_{43})	-0.120*	(0.022)
z_{1t} (γ_{1cp})	66.0*	(20.8)	wh_{t-2} (β_{43})	0.077*	(0.020)
z_{2t} (γ_{2cp})	158.2*	(22.1)	be_{t-1} (α_{44})	1.12*	(0.046)
cr_{t-1} (α_{21})	-4.99*	(2.41)	be_{t-2} (β_{44})	-0.221*	(0.047)
cr_{t-2} (β_{21})	-1.77	(6.23)			
cp_{t-1} (α_{22})	0.786*	(0.110)			
cp_{t-2} (β_{22})	-0.110*	(0.497)			
wh_{t-1} (α_{23})	2.88	(2.23)			
wh_{t-2} (β_{23})	-0.398	(0.877)			
be_{t-1} (α_{24})	4.56	(3.15)			
be_{t-2} (β_{24})	-1.23	(2.39)			

Table 4 (continued)

Equation *Coefficient*	*Estimate*		*Equation* *Coefficient*	*Estimate*	
	Real Prices				
Factor 1 (z_1)			*Wheat (wh)*		
Constant (c_L)	2.128*	(0.305)	Constant (c_{wh})	79.1	(53.0)
Factor 2 (z_2)			z_{1t} (γ_{1wh})	11.0*	(3.01)
z_{2t-1} (δ_1)	1.16*	(0.187)	z_{2t} (γ_{2wh})	3.88	(3.03)
z_{2t-1} (δ_2)	-0.175	(0.189)	cr_{t-1} (α_{31})	-0.053	(0.344)
Crude oil (cr)			cr_{t-2} (β_{31})	0.003	(0.187)
Constant (c_{cr})	3.00	(3.98)	cp_{t-1} (α_{32})	-0.004	(0.004)
z_{1t} (γ_{1cr})	0.495*	(0.225)	cp_{t-2} (β_{32})	0.003	(0.003)
z_{2t} (γ_{2cr})	-0.823*	(0.332)	wh_{t-1} (α_{33})	0.194*	(0.022)
cr_{t-1} (α_{11})	1.02*	(0.054)	wh_{t-2} (β_{33})	-0.075	(0.168)
cr_{t-2} (β_{11})	-0.108*	(0.046)	be_{t-1} (α_{34})	0.189*	(0.072)
cp_{t-1} (α_{12})	0.002*	(0.001)	be_{t-2} (β_{34})	-0.156	(0.113)
cp_{t-2} (β_{12})	-0.001	(0.001)	*Beef (be)*		
wh_{t-1} (α_{13})	0.018	(0.055)	Constant (c_{be})	57.75	(58.73)
wh_{t-2} (β_{13})	0.001	(0.014)	z_{1t} (γ_{1be})	0.256*	(0.119)
be_{t-1} (α_{14})	0.013	(0.027)	z_{2t} (γ_{2be})	-0.630	(0.345)
be_{t-2} (β_{14})	-0.022	(0.027)	cr_{t-1} (α_{41})	0.318*	(0.099)
Copper (cp)			cr_{t-2} (β_{41})	0.212	(0.134)
Constant (c_{cp})	992.1*	(322.7)	cp_{t-1} (α_{42})	0.002	(0.002)
z_{1t} (γ_{1cp})	104.6*	(12.0)	cp_{t-2} (β_{42})	0.001	(0.002)
z_{2t} (γ_{2cp})	-160.5*	(45.6)	wh_{t-1} (α_{43})	0.110*	(0.051)
cr_{t-1} (α_{21})	2.44	(1.64)	wh_{t-2} (β_{43})	-0.084	(0.089)
cr_{t-2} (β_{21})	-0.778	(3.21)	be_{t-1} (α_{44})	0.089*	(0.037)
cp_{t-1} (α_{22})	0.554*	(0.087)	be_{t-2} (β_{44})	0.168	(0.146)
cp_{t-2} (β_{22})	-0.053	(0.055)			
wh_{t-1} (α_{23})	-0.602	(4.11)			
wh_{t-2} (β_{23})	-0.211	(2.40)			
be_{t-1} (α_{24})	-0.987	(2.53)			
be_{t-2} (β_{24})	-0.509	(2.66)			

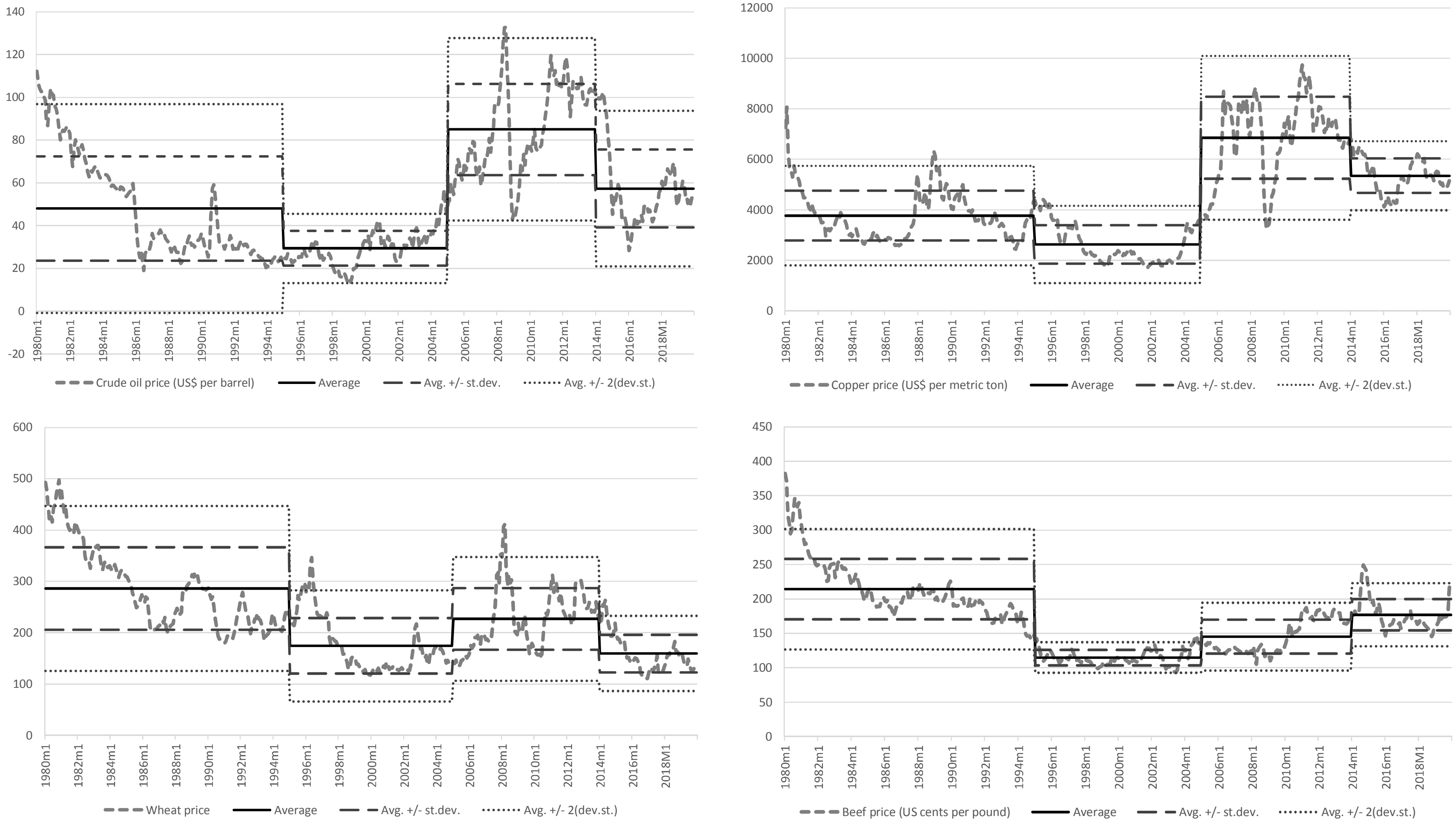
**Statistically significant at 5% level*

Figure 1a – Monthly international nominal prices of the 4 commodities (in US$) from January 1980 (1980m1) to December 2019 (2019m12): sub-period statistics (1980m1-1994m12; 1995m1-2004m12; 2005m1-2013m12; 2014m1-2019m12).



Source: IMF

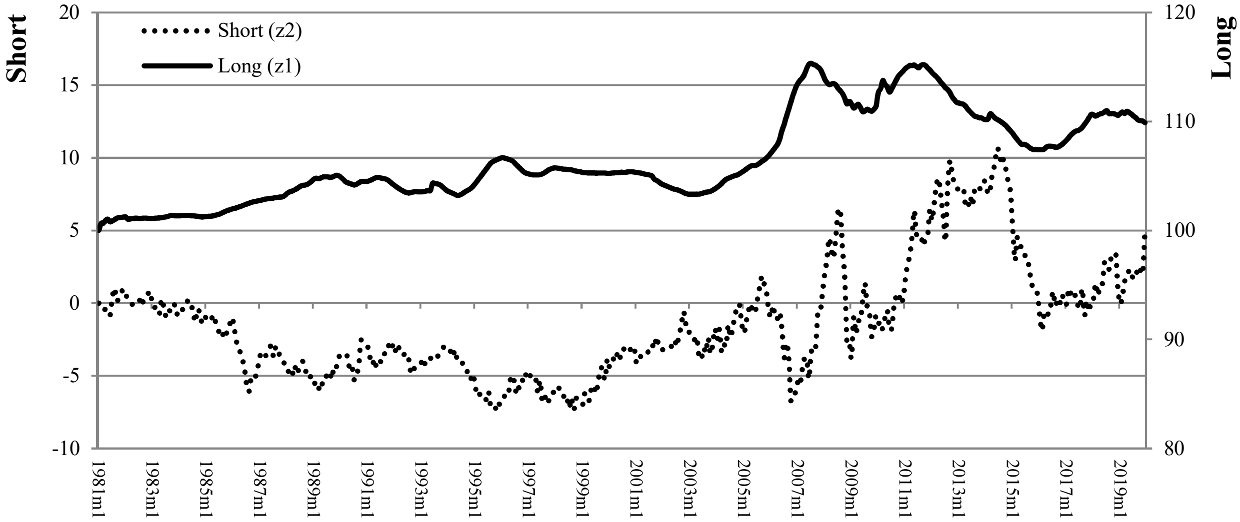
Figure 1b – Monthly international real prices (US CPI used as deflator) of the 4 commodities (in US$) from January 1980 (1980m1) to December 2019 (2019m12): sub-period statistics (1980m1-1994m12; 1995m1-2004m12; 2005m1-2013m12; 2014m1-2019m12).



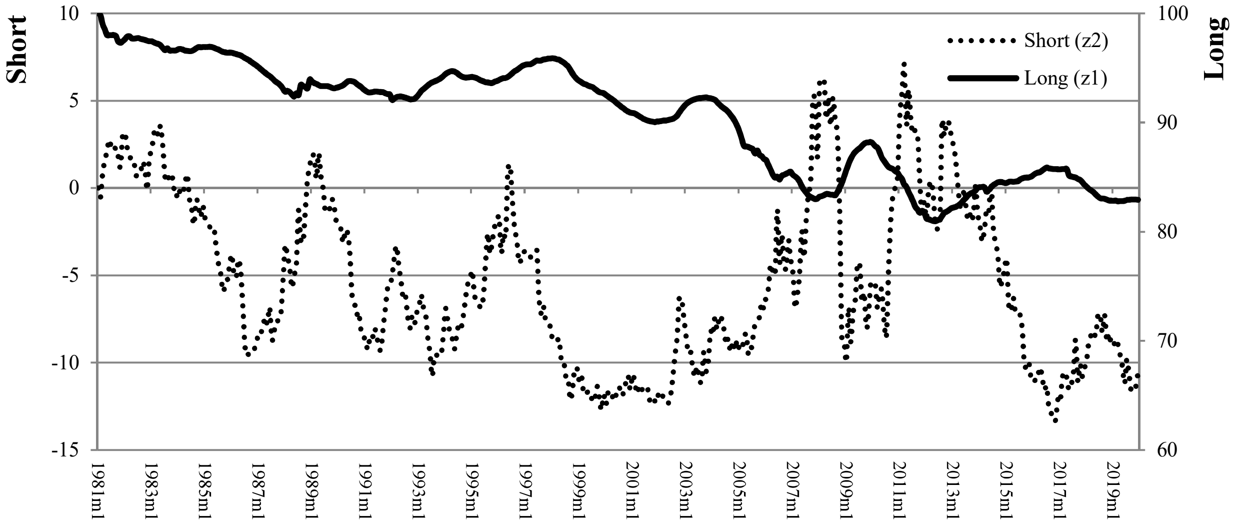
Source: IMF

Figure 2 – Estimated Long (z_1) (1981m1=100) and Short-term (z_2) (1981m1=0) dynamic latent factors: nominal (a) and real (b) prices.

a)



b)



ANNEX

Table A1 – Cointegration analysis on the nominal and real prices of the alternative group of 4 commodities (with aluminium and corn replacing copper and wheat): cointegration rank, VECM estimates [a] and causality test.

Nominal prices

Rank	Trace statistic		Vector	Adjustment	Short-run Granger causality test
		Crude oil	1	-0.030*	Aluminium: 18.55* Corn: 11.98* Beef: 19.02*
0	69.07*	Aluminium	0.801	-0.025*	Crude oil: 13.74* Corn: 17.58* Beef: 4.03
1	32.21				
2	10.34	Corn	-1.426*	-0.010*	Crude oil: 15.35* Aluminium: 4.17 Beef: 14.36*
		Beef	-0.780*	-0.012*	Crude oil: 6.96 Aluminium: 4.11 Corn: 12.70*

Structural break dummy: $d_{2005,cr}$: 0.906

Real prices

Rank	Trace statistic		Vector	Adjustment	Short-run Granger causality test
		Crude oil	1	-0.021*	Aluminium: 16.39* Corn: 18.06* Beef: 14.58*
0	57.77*	Aluminium	0.914*	-0.032*	Crude oil: 11.86* Corn: 11.07* Beef: 5.00
1	20.41				
2	8.83	Corn	-1.717*	-0.019*	Crude oil: 16.13* Aluminium: 6.12 Beef: 12.01*
		Beef	-0.655*	-0.020*	Crude oil: 2.95 Aluminium: 2.56 Corn: 11.64*

[a] The VECM model is estimated on the first cointegration vector extracted with 6 lags. In the case of nominal prices, a deterministic trend is also included within the cointegration vector.
**Statistically significant at 5% level*

Table A2 – DCC-MGARCH (1,1) model estimates on the nominal and real prices of the alternative group of 4 commodities (with aluminium and corn replacing copper and wheat).

Nominal prices	
Correlation parameters	Adjustment parameters
Crude oil and Aluminium: 0.350* Crude oil and Corn: -0.039 Crude oil and Beef: 0.061	$\lambda_1 = 0.021$* $\lambda_2 = 0.938$*
Aluminium and Corn: 0.092 Aluminium and Beef: 0.024	p-value (λ_1=λ_2=0) = 0.000[a]
Corn and Beef: 0.006	
Asymmetry parameters $f_{cr,cr}$: 0.118* ; $f_{cr,al}$: 0.039 ; $f_{al,al}$: 0.102*; $f_{al,cr}$: 0.025	
Real prices	
Correlation parameters	Adjustment parameters
Crude oil and Aluminium: 0.291* Crude oil and Corn: -0.062 Crude oil and Beef: 0.059	$\lambda_1 = 0.030$* $\lambda_2 = 0.911$*
Aluminium and Corn: 0.095 Aluminium and Beef: 0.024	p-value (λ_1=λ_2=0) = 0.000[a]
Corn and Beef: 0.005	
Asymmetry parameters $f_{cr,cr}$: 0.116* ; $f_{cr,al}$: 0.044 ; $f_{al,al}$: 0.096*; $f_{al,cr}$: 0.023	

[a] *Wald test*
**Statistically significant at 5% level*

Table A3 – FAVAR model (7a)-(7b) estimates on the alternative group of 4 commodity nominal and real prices (estimated standard error in parenthesis).

Equation *Coefficient*	*Estimate*		*Equation* *Coefficient*	*Estimate*	
Nominal Prices					
Factor 1 (z_1)			*Corn (co)*		
Constant (c_L)	1.278*	(0.557)	Constant (c_{co})	150.2*	(59.3)
Factor 2 (z_2)			z_{1t} (γ_{1co})	4.64*	(0.573)
z_{2t-1} (δ_1)	1.419*	(0.578)	z_{2t} (γ_{2co})	0.425	(0.347)
z_{2t-1} (δ_2)	-0.424	(0.249)	cr_{t-1} (α_{31})	0.688*	(0.156)
Crude oil (cr)			cr_{t-2} (β_{31})	0.006	(0.017)
Constant (c_{cr})	8.36*	(4.07)	al_{t-1} (α_{32})	-0.019	(0.016)
$d_{2005,cr}$	1.440	(0.839)	al_{t-2} (β_{32})	-0.015	(0.009)
z_{1t} (γ_{1cr})	0.113*	(0.040)	co_{t-1} (α_{33})	0.673*	(0.080)
z_{2t} (γ_{2cr})	0.268	(0.221)	co_{t-2} (β_{33})	0.002	(0.058)
cr_{t-1} (α_{11})	0.903*	(0.057)	be_{t-1} (α_{34})	0.458*	(0.159)
cr_{t-2} (β_{11})	-0.190*	(0.058)	be_{t-2} (β_{34})	0.198	(0.111)
al_{t-1} (α_{12})	-0.004*	(0.002)	*Beef (be)*		
al_{t-2} (β_{12})	-0.001	(0.003)	Constant (c_{be})	44.5	(22.8)
co_{t-1} (α_{13})	0.091*	(0.026)	z_{1t} (γ_{1be})	1.61*	(0.407)
co_{t-2} (β_{13})	-0.010	(0.020)	z_{2t} (γ_{2be})	-2.05	(1.88)
be_{t-1} (α_{14})	0.137	(0.143)	cr_{t-1} (α_{41})	-0.047	(0.260)
be_{t-2} (β_{14})	-0.006	(0.035)	cr_{t-2} (β_{41})	0.503	(0.291)
Aluminium (al)			al_{t-1} (α_{42})	-0.044	(0.025)
Constant (c_{al})	1593.0*	(323.5)	al_{t-2} (β_{42})	0.036	(0.018)
z_{1t} (γ_{1al})	50.1*	(7.30)	co_{t-1} (α_{43})	0.074*	(0.033)
z_{2t} (γ_{2al})	47.7	(37.9)	co_{t-2} (β_{43})	-0.073	(0.070)
cr_{t-1} (α_{21})	6.22*	(1.87)	be_{t-1} (α_{44})	0.087*	(0.015)
cr_{t-2} (β_{21})	-3.29	(1.69)	be_{t-2} (β_{44})	0.015	(0.198)
al_{t-1} (α_{22})	0.351*	(0.082)			
al_{t-2} (β_{22})	0.098	(0.064)			
co_{t-1} (α_{23})	-1.57	(0.802)			
co_{t-2} (β_{23})	0.435	(0.677)			
be_{t-1} (α_{24})	1.60	(1.32)			
be_{t-2} (β_{24})	-1.95	(1.23)			

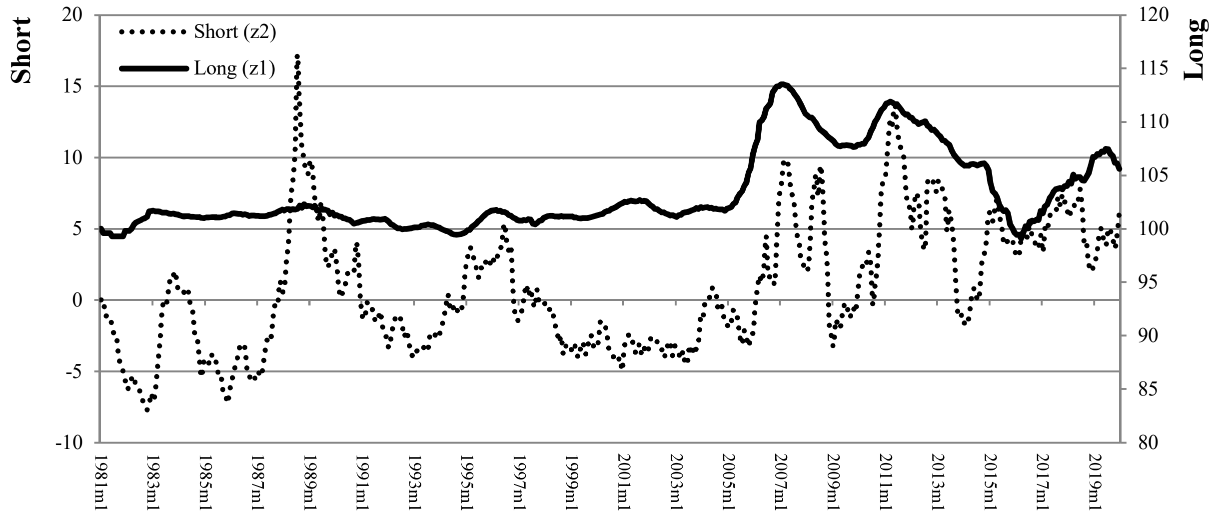
Table A3 (continued)

Equation *Coefficient*	*Estimate*		*Equation* *Coefficient*	*Estimate*	
		Real Prices			
Factor 1 (z_1)			*Corn (co)*		
Constant (c_L)	1.639*	(0.346)	Constant (c_{co})	7.41*	(3.45)
Factor 2 (z_2)			z_{1t} (γ_{1co})	5.09*	(1.67)
z_{2t-1} (δ_1)	0.778*	(0.062)	z_{2t} (γ_{2co})	-3.14	(2.26)
z_{2t-1} (δ_2)	0.214	(0.063)	cr_{t-1} (α_{31})	0.271*	(0.120)
Crude oil (cr)			cr_{t-2} (β_{31})	-0.137	(0.277)
Constant (c_{cr})	4.40*	(1.21)	al_{t-1} (α_{32})	0.021*	(0.004)
z_{1t} (γ_{1cr})	0.225*	(0.074)	al_{t-2} (β_{32})	0.003	(0.004)
z_{2t} (γ_{2cr})	0.253	(0.554)	co_{t-1} (α_{33})	0.529*	(0.118)
cr_{t-1} (α_{11})	1.05*	(0.048)	co_{t-2} (β_{33})	0.018	(0.073)
cr_{t-2} (β_{11})	-0.119*	(0.048)	be_{t-1} (α_{34})	0.086	(0.207)
al_{t-1} (α_{12})	-0.001	(0.002)	be_{t-2} (β_{34})	0.022	(0.107)
al_{t-2} (β_{12})	0.001	(0.001)	*Beef (be)*		
co_{t-1} (α_{13})	0.015	(0.054)	Constant (c_{be})	26.6*	(10.4)
co_{t-2} (β_{13})	-0.006	(0.018)	z_{1t} (γ_{1be})	2.51*	(1.15)
be_{t-1} (α_{14})	0.037	(0.038)	z_{2t} (γ_{2be})	-3.76*	(0.976)
be_{t-2} (β_{14})	-0.014	(0.029)	cr_{t-1} (α_{41})	0.141	(0.083)
Aluminium (al)			cr_{t-2} (β_{41})	-0.027	(0.072)
Constant (c_{al})	49.7*	(12.0)	al_{t-1} (α_{42})	-0.001	(0.002)
z_{1t} (γ_{1al})	59.6*	(19.9)	al_{t-2} (β_{42})	0.001	(0.002)
z_{2t} (γ_{2al})	50.0*	(17.0)	co_{t-1} (α_{43})	0.122*	(0.050)
cr_{t-1} (α_{21})	5.09*	(2.09)	co_{t-2} (β_{43})	-0.014	(0.032)
cr_{t-2} (β_{21})	-6.15	(3.45)	be_{t-1} (α_{44})	0.688*	(0.078)
al_{t-1} (α_{22})	0.433*	(0.103)	be_{t-2} (β_{44})	-0.184	(0.061)
al_{t-2} (β_{22})	0.213*	(0.064)			
co_{t-1} (α_{23})	2.20*	(0.931)			
co_{t-2} (β_{23})	2.04	(1.40)			
be_{t-1} (α_{24})	0.674	(2.879)			
be_{t-2} (β_{24})	-0.187	(1.94)			

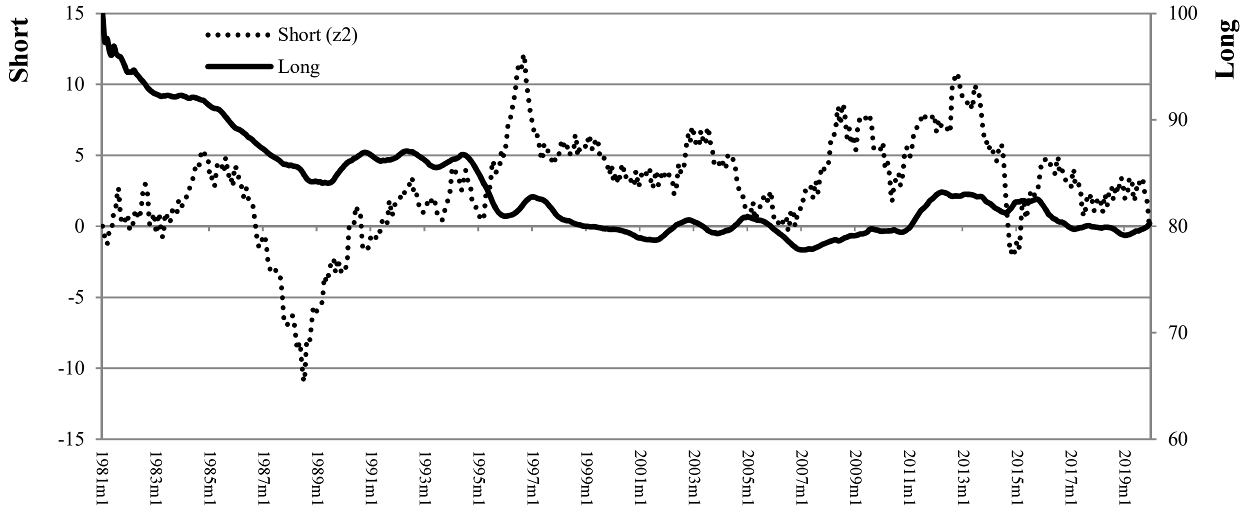
**Statistically significant at 5% level*

Figure A2 – Estimated Long (z_1) (1981m1=100) and Short-term (z_2) (1981m1=0) dynamic latent factors on the alternative group of 4 prices: nominal (a) and real (b) prices

a)



b)



Author Statement

All contents of the manuscript are the sole responsibility of the author.
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