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A FAVAR APPROACH

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A FAVAR APPROACH [1]

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In 2010 all ECB publications feature a motif taken from the €500 banknote.

1 Without implicating, we thank an anonymous referee and participants at seminars at the Bank of England and the Bank of Canada for their useful suggestions. The views expressed are solely our own and do not necessarily reflect those of the European Central Bank or the ESCB.

2 All authors: European Central Bank, Kaiserstrasse 29, 60311 Frankfurt am Main, Germany, e-mail: marco.lombardi@ecb.int, chiara.osbat@ecb.int and bernd.schnatz@ecb.int

Address
Kaiserstrasse 29
60311 Frankfurt am Main, Germany

Postal address
Postfach 16 03 19
60066 Frankfurt am Main, Germany

Telephone
+49 69 1344 0

Internet
http://www.ecb.europa.eu

Fax
+49 69 1344 6000

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Abstract

In this paper we examine linkages across non-energy commodity price developments by means of a factor-augmented VAR model (FAVAR). From a set of non-energy commodity price series, we extract two factors, which we identify as common trends in metals and a food prices. These factors are included in a FAVAR model together with selected macroeconomic variables, which have been associated with developments in commodity prices. Impulse response functions confirm that exchange rates and of economic activity affect individual non-energy commodity prices, but we fail to find strong spillovers from oil to non-oil commodity prices or an impact of the interest rate. In addition, we find that individual commodity prices are affected by common trends captured by the food and metals factors.

JEL codes: E3, F3
Keywords: Oil price, Commodity prices, Exchange rates, Globalisation, FAVAR.

Non-technical summary

The broad-based surge in commodity prices in recent years was a major source of global inflationary pressures. A striking feature of the commodity price boom was that prices of different commodities rose jointly. Indeed, between the first quarter of 2003 and the third quarter of 2008, the prices of all major global commodities increased. This connection may have far-reaching monetary policy implications. If commodity prices move jointly, their overall inflationary impact can be very sizeable and persistent, although each individual commodity would contribute only marginally to domestic price pressures.

This paper examines the linkages across commodity markets, suggesting that commodity prices are driven by common macroeconomic shocks, commodity-related shocks and inter-linkages across markets. We first present evidence of significant comovements between different commodities. Then, from a set of non-energy commodity price series, we extract two factors, which we identify as common trends in metals and a food prices; the factors explain almost 90% of the total variance. The metals factor is mainly driven by developments in copper prices and to a smaller extent by trends in iron ore and nickel; the food factor is mainly linked to the evolution in maize, cocoa and wheat prices.

The factors are then included in a VAR model, together with selected macroeconomic variables, which have been associated with developments in commodity prices. Impulse responses allow us to study the interaction of non-energy commodity prices and their fundamentals. These suggest significant linkages across non-energy commodity markets while spillovers from oil to non-energy commodities are more difficult to discern. This is somehow surprising as there are theoretical reasons according to which non-energy commodities should react to oil price movements.

In addition, there is a strong and significant impact of the exchange rate on individual non-energy commodity prices. The impact of economic activity is estimated to have mostly the correct sign and is statistically relevant particularly for metals, while there does not appear to be a systematic impact of interest rate shocks on non-energy commodity prices.

1 Introduction

The broad-based surge in commodity prices in recent years was a major source of global inflationary pressures. A striking feature of the commodity price boom was that prices of different commodities rose jointly. Indeed, between the first quarter of 2003 and the third quarter of 2008, the prices of all major global commodities increased. This paper examines the linkages across commodity markets, suggesting that commodity prices are driven by common macroeconomic shocks, commodity-related shocks and interlinkages across markets.

From a theoretical standpoint, the literature has identified a set of common factors that should be driving commodity prices: firstly, prices of commodities that serve as input in the production process generally rise in periods of strong global economic activity. In particular booming emerging economies – above all China – have been frequently associated with the rise in commodity demand and higher prices. Secondly, as emphasised by Frankel (2006), commodity prices may also be influenced by short-term interest rates. Lower interest rates may diminish the incentive for extraction today rather than tomorrow, raise the incentive to carry inventories and encourage financial market participants to substitute into commodity assets. Thirdly, US dollar fluctuations have been suggested to drive commodity prices (Akram 2008, Breitenfellner and Crespo-Cuaresma 2008): as commodities are commonly invoiced in US dollars, exporters may wish to stabilise their purchasing power by raising prices in periods of US dollar weakness. On the demand side, a dollar depreciation also implies, c*eteris paribus*, a lower commodity price for importers whose currency has appreciated against the US dollar, who will then increase their demand for commodities, leading in turn to higher prices.[3]

In addition, complex interlinkages across commodities can lead to a co-movement of prices, some of which are more difficult to measure: Chaudhuri (2001) and Baffes (2007), for instance, suggest that a link between oil and non-energy commodity prices exists via transportation cost and fertiliser prices (the production of fertilisers is very energy-intensive).[4] Rising fertiliser prices increase marginal costs in food production and can lead to a simultaneous rise in food prices. Energy is also an input factor for the refining of metals (e.g. aluminium) and metals prices – particularly steel – account for a significant share of an oil project's cost.

A more indirect link between agricultural commodity prices arises in the context of biofuels production. As the incentives for planting maize (and sugarcane in Brazil) rise with increasing biofuels production, arable land is substituted away from other crops. This constrains the supply of competing crops such as wheat and soybeans used as feedstock and may raise agricultural commodities' prices simultaneously. As regards metals, while each has unique charac-

[3] Another factor occasionally mentioned in the context of rising food prices in recent years is the role of speculation. In particular, the rise of assets under management in index funds was blamed for rising food prices. The evidence on the role of speculation in driving commodity prices is rather mixed. Masters (2008) strongly argues in favour of speculative activity driving commodity prices, but empirical analyses found little evidence (see IMF, 2006). Redrado *et al.* (2009) as well as Reitz and Slopek (2008) examine this in an empirical framework which allows for chartists and fundamentalists and find that commodity prices may deviate from their fundamental level in the short term, but if the deviation becomes pronounced, the mean-reversion process becomes more powerful and brings prices back towards their long-term fundamental level. Looking at the issue from a slightly different perspective, Anzuini *et al.* (2009) found some evidence that commodity price increases may have been fuelled by loose monetary policy, whereas Caballero *et al.* (2008) argue that the commodity price surge was caused by global imbalances.

[4] Gas is a critical input in nitrogen fertilizer production through the Haber-Bosch process, and accounts for 70 – 80 percent of the cost of fertilizer. The World Bank (2008) states that in the United States, fuel, fertilizers and chemicals accounted for 34% of maize production costs and for 27% of wheat production costs in 2007.

teristics, in certain applications they can be substituted, thereby limiting price divergence to some extent. Finally, the co-movement across commodities may also have emerged owing to other factors, which are more difficult to measure, such as the financialization of commodities (IMF 2008), changes in shipping or staffing costs. For instance, the average salary for an experienced geologist rose by almost 50% between 2005 and early 2008 (Financial Times, 12 January 2009).

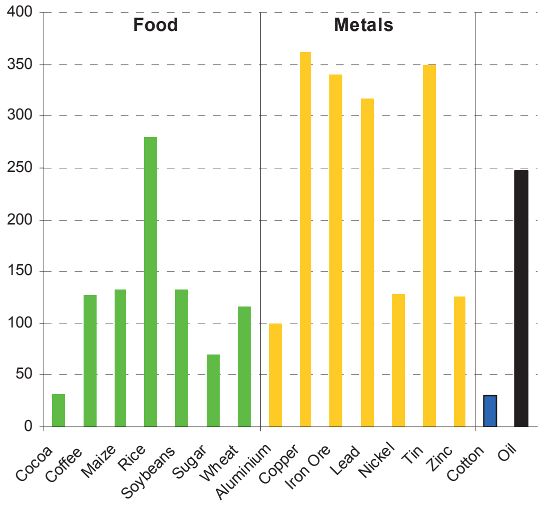
In this paper, we empirically examine all these effects and linkages: more specifically, we show that commodity prices are highly correlated and assess empirically the nature of such linkages. Our specification relates fifteen individual non-energy commodity prices to macroeconomic factors (global industrial production, US dollar effective exchange rate and US interest rate) and the price of oil. The impact of indirect substitution processes and other factors is more difficult to analyse. For instance, including all non-energy commodities in addition to the macroeconomic determinants into a single model in order to study the linkages across the commodity spectrum would be technically infeasible, at least in a frequentist framework.

Therefore, we use factor-augmented VAR models which allow to account for movements in all prices in a way that reduces the dimensionality problem. Given that the variables included in the VAR are all integrated, as indicated by unit root tests, we also test for cointegration, to see if using a FAVECM (Banerjee and Marcellino 2008) or a FAVAR in first differences (Bernanke *et al.* 2005) is the most appropriate procedure. We extract two common factors and see that their loadings are clustered in such a way that the first factor appears to be a "metals" factor and the second one, a predominantly "food" factor. In the second step, we estimate a FAVECM model (Banerjee and Marcellino 2008) for each non-energy commodity price, including the fundamentals and the common factors and test for cointegration. As we find no evidence of cointegration in this model, we conduct the analysis with a FAVAR specified in growth rates. Impulse response functions allow us to study the interaction of non-energy commodity prices and their fundamentals. These suggest significant linkages across non-energy commodity markets while spillovers from oil to non-energy commodities are more difficult to discern. In addition, there is a strong and significant impact of the exchange rate on individual non-energy commodity prices. The impact of economic activity is estimated to have mostly the correct sign and is statistically relevant particularly for metals, while there does not appear to be a systematic impact of interest rate shocks on non-energy commodity prices.

2 Stylised Facts

A striking feature of the most recent commodity price boom is that between the first quarter of 2003 and the third quarter of 2008 the prices of all major commodities – seven metals, seven commodities in the category food and tropical beverages and cotton – increased. The rise in metals prices was particularly pronounced, with prices of copper, lead, iron ore and zinc rising more than fourfold while aluminium prices which rose the least in the category, doubled (cf. Figure 1). Compared with metals prices, food commodity prices increased less strongly but prices of coffee, maize, soybeans and wheat more than doubled. Over the same period, WTI crude oil prices rose by more than 250% before dropping sharply in the second half of 2008 (cf. Figure 2).

Figure 1: Price developments in commodity markets, 2003Q1 and 2008Q3
(percent change)



Source: IMF, authors' calculations.

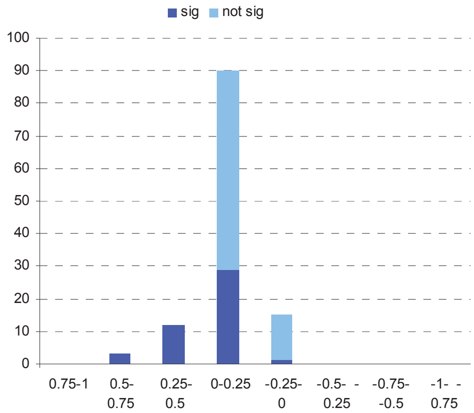
Figure 2: WTI oil price developments
(USD per barrel, monthly data)

A correlation analysis can provide additional insights into the co-movement of commodity prices (Pindyck and Rotemberg 1990). In order to purge the series from a co-movement of US dollar prices owing to the underlying trends in US monetary policy and inflation, all commodity prices have been transformed into real prices by dividing them by the US producer price index. Although most of the real commodity price series do not show a clear upward or downward trend over the sample period, augmented Dickey-Fuller tests indicate that the series are non-stationary, with the possible exception of cotton and sugar prices, for which the ADF tests reject the null hypothesis of a unit root (see Table 2).

In levels, there is a high degree of correlation among the 15 main non-energy commodity prices as well as oil prices over the period 1975 to 2008 (for details, see Table A in the appendix). However, this needs to be interpreted very cautiously, given that the time series are found to be non-stationary (cf. Table 1). In growth rates, the correlation coefficients of the price series are also mostly positive (105 out of 120). Notably, we also find many significant correlations between metals and food commodities. At the same time, changes in the oil price appear to be often negatively correlated with developments in food commodities, in particular, which stands in some contrast with the argument developed earlier. Most of the correlations are between 0 and 0.25 and a sizeable fraction of the correlations is statistically significant (cf. Figure 3). These initial simple observations suggest that there are important linkages among non-energy commodity prices and implies that they may be determined by common trends.

In the following, we assess the linkages across commodities in more details and control for common macroeconomic shocks. We use commodity prices as provided by the IFS Statistics. As regards the macroeconomic fundamentals, we employ the broad US dollar real effective exchange rate, a one-year US Treasury notes and bond yield deflated by the US consumer price index; the real oil price reflects the WTI crude oil price relative to the US producer price index; finally, global industrial production is an index including the OECD countries plus six major non-OECD countries such as Brazil, Russia, China and India.[5]

Figure 3: Frequency distribution of correlation coefficients across commodities (in growth rates)



Source: ECB staff.
Note: Correlation coefficient using quarterly data across 16 commodities. Dark contributions of the columns refer to correlations significantly different from zero at the 10% level of significance.

3 Econometric framework and estimation

A joint econometric analysis of the linkages across all non-energy commodity price series is unfeasible in a frequentist framework: a VAR model comprising a sufficiently representative set of commodities as well some macroeconomic variables representing common macroeconomic shocks would be far too large to be estimated using classical methods. As a means of reducing the dimensionality of the problem, we employ factor analysis using a factor-augmented VAR (FAVAR) as proposed by Bernanke et al. (2005).[6]

Our goal is to analyse the impact on a single commodity of a set of macroeconomic variables and other commodity prices. We denote the vector containing macroeconomic variables and the complete set of commodity log-prices as X_t. Assuming I(1) prices, we will examine the ΔX_t. Since we work with a large set of commodities, the size *N* of X_t will be considerable, which would imply estimation difficulties for the VAR

$$\Delta X_t = \Phi(L)\Delta X_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0,\Omega). \tag{1}$$

Let us then concentrate on one commodity at time, and collect the commodity under scrutiny and the macroeconomic variables in a vector Y_t of size *M*. Since only one commodity appears in Y_t, *M* will be much smaller than *N*. To summarize developments in other commodity

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[5] Data on interest rates and exchange rates are from the BIS, US CPI and global industrial production are from the OECD and oil and commodity prices are from the IFS.

[6] We remark, however, that using a Bayesian approach would overcome the dimensionality problem, as the lack of curvature of the likelihood function is compensated by the use of informative prior distributions. A recent approach that has been found to be effective especially for forecasting purposes is the so-called Bayesian shrinkage (De Mol *et al.* 2006, Banbura *et al.* 2008).

prices that can indeed be relevant, we employ a synthetic measure, namely a set of *K* unobservable factors F_t.

We therefore estimate the VAR

$$\begin{bmatrix} \Delta Y_t \\ F_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \Delta Y_{t-1} \\ F_{t-1} \end{bmatrix} + u_t, \quad u_t \sim N(0, Q), \tag{2}$$

where $\Phi(L)$ is a finite-order polynomial in the lag operator. Of course, if the terms of $\Phi(L)$ relating ΔY_t to F_{t-1} are zero, the system is a standard VAR in ΔY_t. If this is not true, however, omitting F_t from the system will result in biased estimates.

Equation (2) cannot be estimated directly as the factors F_t are not observed. In our case however, as we have anticipated, the idea is to use them to summarise the information on the developments in other commodity prices, which we have excluded from vector Y_t. Therefore, the factors will represent the common pattern to other commodities, which could be useful to explain the behaviour of the commodity under scrutiny (for instance, we would estimate a model for aluminium prices, which includes a set of macroeconomic fundamentals and a set of factors based on all commodity prices except aluminium). So, it is possible to construct factors beforehand, by using any factor extraction scheme, and then just plug them into (1) as if they were observable variables. As noted by Stock and Watson (2002), this two-step procedure provides consistent estimators of the factors, the only caveat being that it is necessary to bootstrap confidence intervals for the estimates of the coefficients of interest, to take into account the uncertainty in the factor estimation (Kilian, 1998). Furthermore Bai and Ng (2006) have also shown that, under suitable conditions about the relative rate of convergence of *T* and *N*, using estimates of the factors does not generate a significant amount of additional uncertainty.

This factor-augmented approach has been extended to cointegrated systems by Banerjee and Marcellino (2008). If we assume that the elements of vector X_t are I(1), we could express the model (1) in error-correction form as

$$\Delta X_t = \alpha \beta' X_{t-1} + v_t, \tag{3}$$

or in common trends specification as

$$X_t = \Psi F_t + w_t, \tag{4}$$

where F_t is the dynamic common factor.

If, as was done before, we extract a subvector of X_t containing only one commodity, we can express (4) as

$$X_t = \begin{bmatrix} Y_t \\ Z_t \end{bmatrix} = \begin{bmatrix} \Psi_Y \\ \Psi_Z \end{bmatrix} F_t + w_t, \tag{5}$$

from which it appears clearly that Y_t and F_t are cointegrated. We can therefore represent their joint behaviour with an error-correction specification

$$\begin{bmatrix} \Delta Y_t \\ \Delta F_t \end{bmatrix} = \begin{bmatrix} \gamma_Y \\ \gamma_F \end{bmatrix} \delta' \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + e_t; \tag{6}$$

where γ and δ play the same role as α and β in (3) and in which further lags can be added in order to purge e_t from autocorrelation.

As for the FAVAR, also the FAVECM (6) can be easily estimated in two steps: factors are extracted via any standard technique (e.g. principal components) and then plugged into the error correction model.

4 Empirical results

4.1. FAVAR or FAVEC

The decision on the most appropriate econometric technique – i.e. employing a FAVEC following Banerjee and Marcellino (2008) or, if we cannot find cointegration, using a FAVAR along the lines of Bernanke et al. (2005) – hinges crucially on the presence of cointegration among the variables.

In the first step, we extract factors employing principal component analysis. As discussed in Banerjee and Marcellino (2008), the principal components extracted from the 15 commodity price series are a consistent estimator of the factors. Using a minimum eigenvalue of 1 as a threshold, we find that two common factors explain a large share of the movements of non-energy commodity prices.[7] As an alternative, the minimum-average partial method would suggest four common factors. As the first two factors explain almost 90% of the total variance, we choose to use two common factors, as this also keeps the FAVAR estimated in the next section more parsimonious. The loadings indicate that – with the exception of cotton and tin prices – food prices load mainly on the second factor. The communality and uniqueness estimates show that for each commodity, the two common factors account for more than 50% of the correlation. For eight of the fifteen commodities, even more than 80% of the correlations are accounted for by the two common factors.

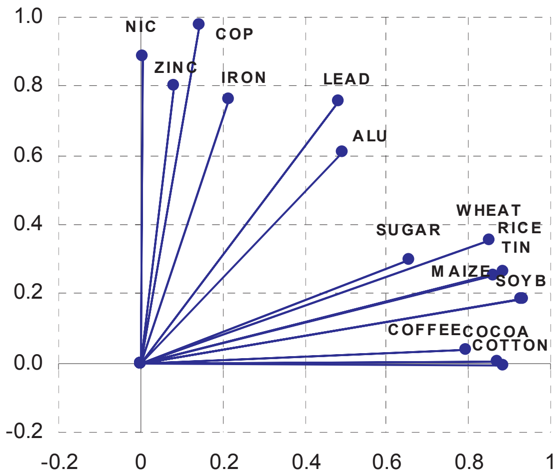
Table 1: Common factor analysis

	Rotated Factor loadings		Score coefficients			
	F1 (metals)	F2 (food)	F1 (metals)	F2 (food)	Communality	Uniqueness
Aluminium	0.609	0.495	0.062	0.025	0.616	0.092
Copper	0.978	0.142	0.731	-0.172	0.978	0.016
Iron Ore	0.761	0.215	0.108	-0.014	0.625	0.082
Lead	0.754	0.482	0.061	0.012	0.801	0.124
Nickel	0.885	0.007	0.096	-0.032	0.783	0.117
Tin	0.253	0.863	-0.006	0.095	0.809	0.079
Zinc	0.802	0.082	0.041	-0.011	0.650	0.245
Cocoa	0.006	0.871	-0.069	0.162	0.759	0.053
Coffee	0.039	0.793	-0.019	0.049	0.631	0.158
Maize	0.185	0.934	-0.066	0.336	0.907	0.025
Rice	0.264	0.886	-0.006	0.098	0.854	0.078
Soybeans	0.184	0.929	-0.022	0.111	0.896	0.076
Sugar	0.300	0.656	0.008	0.039	0.520	0.133
Wheat	0.354	0.854	0.017	0.140	0.854	0.050
Cotton	-0.009	0.884	-0.045	0.100	0.782	0.088

[7] See also Labys (2006) for an analysis of common factors in metals prices. Following the methodology of Kose *et al.* (2003), Vansteenkiste (2008) estimates a dynamic factor model using more commodities and a longer estimation sample and tests which fundamentals can account for these common trends.

The rotated loadings to the two common factors are displayed in Figure 4, showing that non-energy commodities appear to naturally cluster in two groups: The loadings of the food commodities are clustered in the lower-right corner of the graph while the loadings of metals are concentrated in the upper-left (except for tin). Accordingly, we label the first common factor the "metals factor" and the second common factor the "food factor". The score coefficients in Table 2 indicate that the metals factor is mainly driven by developments in copper prices and to a smaller extent by trends in iron ore and nickel. The food factor is mainly linked to the evolution in maize, cocoa and wheat prices.

Figure 4: Rotated loadings



Source: ECB staff.
Note: The rotated factors are computed based on GLS estimates.

Moving to the implementation of the FAVAR, we extract, for each individual commodity, the two factors underlying the fourteen remaining commodity prices. We add them to a vector autoregression (VAR) containing four fundamentals representing common macroeconomic shocks: real WTI crude oil prices (deflated by the US PPI), the real effective exchange rate of the US dollar, real US interest rates, and world industrial production. All variables are in logarithms (except the interest rate). The estimation sample goes from the first quarter of 1976 to the third quarter of 2008 and includes several cycles in commodity markets and in real economic activity, such as the oil price shocks of the seventies and the eighties, the 1981 recession and the subsequent 'great moderation' phase. However, we had to include an exogenous dummy variable to account for extreme observations in the oil price, i.e. the collapse of OPEC in the first quarter of 1986 and the first Iraq war following the Kuwait invasion in the third quarter of 1990. Although information criteria indicate rather a low lag order, we consistently use four lags in the estimation in order to account for residual autocorrelation.

In each of these 15 VARs, we conduct cointegration tests, using Bartlett-corrected critical values (Johansen 2000). These tests univocally indicate that there is no evidence of cointegration among the variables (cf. Table 2). Hence we analyse the response of common commodity trends and the dynamics in individual non-energy commodity prices to their fundamentals in a FAVAR framework.

Table 2: Unit root and cointegration tests: p-values

Metals	ALU	COP	IRO	LEA	NIC	TIN	ZIN	
ADF-tests	0.03	0.33	0.97	0.35	0.030	0.61	0.015	
Trace statistic p-value	0.43	0.89	0.19	0.75	0.22	0.67	0.50	
Food and others	**COC**	**COF**	**MAI**	**RIC**	**SOY**	**SUG**	**WHE**	**COT**
ADF test	0.38	0.24	0.12	0.38	0.30	0.016	0.06	0.31
Trace statistic p-value	0.20	0.57	0.21	0.53	0.63	0.71	0.46	0.36

Note: ADF with drift and Johansen Trace test employing Bartlett finite-sample correction factor. Both tests employ four lags.

4.2. Commodity fundamentals and common trends in a FAVAR

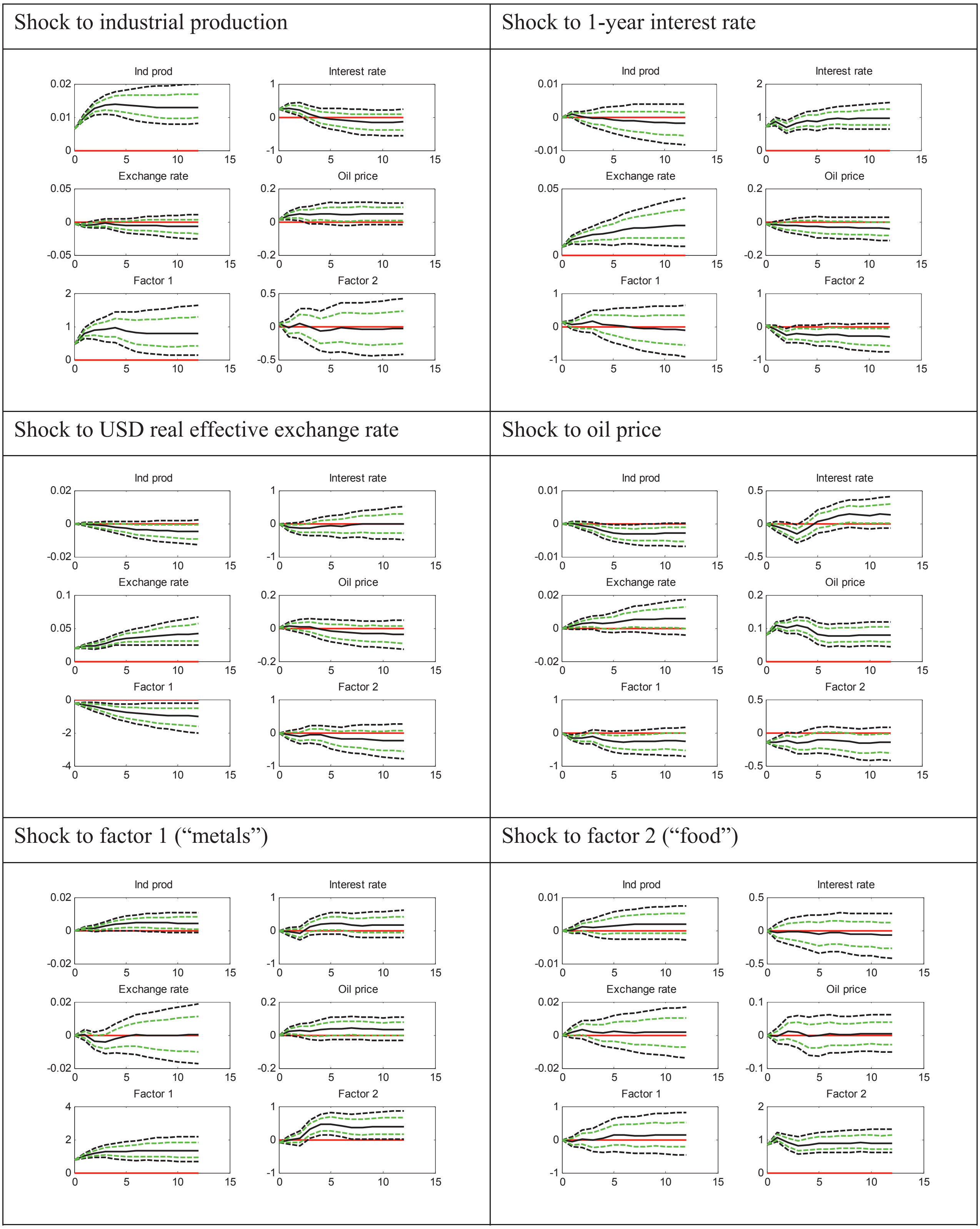
As the FAVARs require the employment of stationary time series, we conduct the following exercise with data in first differences. In the first step, we show the interrelations between common factors and macroeconomic fundamentals based on a 6-variable FAVAR, in which no individual commodities are present. In the second step, we estimate the 15 different FAVAR models, with each model comprising 7 variables: four (real) macroeconomic variables (global industrial production, interest rate, US effective exchange rate and oil prices), two common commodity factors and the (real) commodity price under investigation.

We mostly base our analysis on impulse-response functions based on a triangular identification scheme, which is sensitive to the ordering of the variables in the VAR. We place non-energy commodity price series last, based on the sensible assumption that commodity market shocks have no contemporaneous effects on macroeconomic variables. Industrial production is placed first, followed by the interest rate, the exchange rate, oil price, and the two factors. This assumes that demand shocks affect instantaneously all equations in the system, which appears reasonable if we consider that exchange rates and interest rates are highly responsive to macroeconomic conditions. This "slow-to-fast" ordering (suggested by Bernanke *et al.* 2005) ensures that the estimated impact on the last variable, which is the one we focus on, is netted out of the joint impact of other macroeconomic variables. We compute the impulse responses to one-standard-deviation shocks on each variable on each non-energy commodity price index. We derive 90% and 68% standard error bands using the procedure proposed by Kilian (1998), who shows that his proposed bootstrap method, which adjusts for bias and skewness in the small-sample distribution of the impulse responses, has better properties than traditional estimators of impulse response error bands.

The shapes of the estimated impulse response functions (cf. Figure 5) are in line with basic economic theory:

- A shock to global economic activity (as proxied by world industrial production) leads to an increase in the price of oil, confirming the importance of demand shocks for oil prices (Kilian, 2008). We find a temporary upward reaction of US interest rates to higher industrial production. A very strong and permanent effect can also be identified on the common metals factor, suggesting that a global economic boom also raises the prices of metals significantly, which is in line with Vansteenkiste (2008) and the common knowledge that industrial commodity price cycles closely follow global economic activity. By contrast, we find less evidence of an impact of activity on the food factor, suggesting that food consumption responds less elastically to activity shocks. This appears rather plausible, as people do not linearly increase their food consumption with rising wealth. To a certain extent, it also refutes the popular argument that the rapid economic development of China was the culprit of surging food prices in recent years.

Figure 5: Impulse response functions



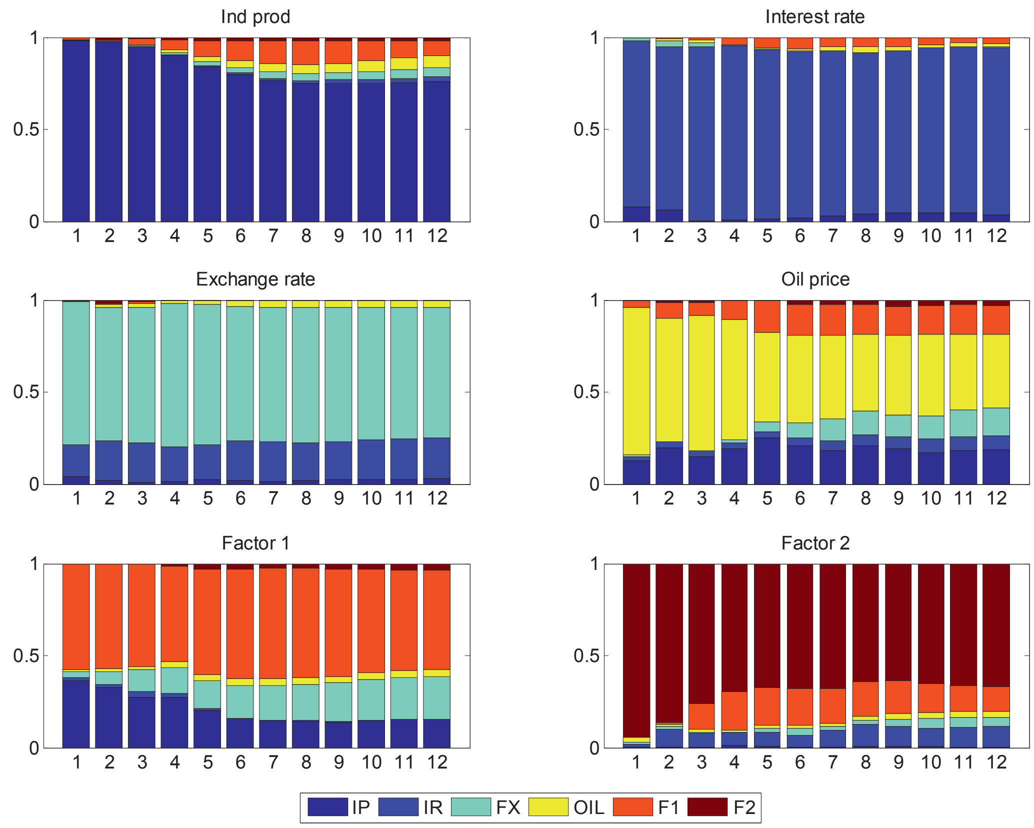
- A rise in the US real effective exchange rate has little effect on the interest rate and the food common factor. In contrast to Akram (2008) and Crespo Cuarema and Breitenfellner (2008), we also fail to identify a strong response of oil prices to US dollar shocks. However, we find a negative reaction of the metals factor and of global activity to changes in the dollar rate. This is not surprising, given that metals are priced in US dollars on international markets, and a USD depreciation may induce producers to require higher prices in order to stabilize their purchasing power.
- Oil price shocks have the expected adverse effects on global industrial production (cf, also Anzuini *et al.* 2008) and lead to a temporary reduction in US interest rates. Contrary to Baffes (2007) and Vansteenkiste (2008), however, we cannot find evidence for a positive impact on the common factors for non-energy commodity prices – if anything the reaction appears to be negative. This is somehow surprising as there are theoretical reasons according to which non-energy commodities should react to oil price movements: the production of metals (aluminium overall) is heavily energy-intensive, and in the case of food commodities there are also substitution effects due to the higher viability of biofuels under high oil prices; finally, higher oil prices increase transportation costs. This issue will be analysed in more detail for individual commodities in the next section.
- Shocks to the common metals and food factors have little impacts on the fundamentals, except for global activity, which seems to respond positively to higher metals prices. In addition, it seems that food prices respond to changes in metals prices, while this is not the case *vice versa*.

4.3. Variance decomposition

To assess the contributions of each shock to the total variability of the observed series at different horizons, we performed a forecast error variance decomposition (Figure 6). As one would expect, for each variable the foremost contributor is the own shock, yet some peculiar features can be identified.

More specifically, we observe that, at longer horizons, part of the variance in industrial production is explained by the first factor, i.e. that related to industrial metals. The exchange rate is partly explained by interest rate shocks, which is in line with the theory. The oil price is partially determined, especially at longer horizons, by industrial production and the first factor, and also, to a smaller extent, by the exchange rate. Industrial production also affects, even at short horizons, the 'metals' factor, but not the 'food' one.

Figure 6: Forecast Error Variance Decomposition



4.4. Commodity fundamentals, common factors and individual commodity prices

These relationships are broadly confirmed when looking in more detail at responses of individual commodities. Figure 6 shows for the six different shocks the median response of the 15 individual non-energy commodities at the one-year horizon (black diamond) as well as the one- and the two-standard-deviation error bands (black and red marks, respectively). As factors are placed before individual commodities in the Choleski ordering, the impulse responses measure the idiosyncratic reaction of every commodity to shocks after common effects are taken into account.

Non-energy commodity prices show a positive response to a rise in global industrial production in 13 out of 15 cases. In the majority of cases, the response is stronger than one standard deviation and in almost half of the cases it is significant at the two-standard-error level. Only in two cases – maize and soybeans – the response is negative, albeit very close to zero. All metals prices react markedly to changes in economic activity. This also might explain the surge in metals prices in periods of strong global growth, particularly in commodity-intensive China. Particularly nickel and copper appear to react very strongly to global industrial production shocks.

Non-energy commodity prices also react strongly to exchange rate shocks. Only for coffee and cocoa, we find the opposite-than-expected sign. Again, metals prices – particularly copper, lead and nickel – appear to be more sensitive to changes in the exchange rate,[8] but also some food commodities such as rice, soybeans and wheat show a strong responsiveness to exchange rate shocks. The majority of non-energy commodities also react as anticipated to interest rate shocks. Contrary to our priors, only zinc prices show a 90% significant positive response. Eleven commodities show indeed a positive response, but only half of them a significant at the 68% level. Somewhat surprisingly, we find that food commodities – particularly rice, soybeans and sugar – react more forcefully to interest rate shocks than metals prices, for which the Hotelling rule principles would apply more evidently.

The responses of individual non-energy commodity prices to shocks in the oil price are in line with the effects recorded on the common commodity trends, but they are still rather puzzling. We find a significant and positive response to an oil price shock only for iron ore and for sugar. The reaction of sugar could be due to price interdependencies owing to biofuel production, which is established since a longer period than for maize. However, we would have expected a more significant link between oil prices and other metals prices, because their production (such as that of aluminium) is highly energy-intensive.

The linkages across commodities become most visible in the two bottom charts, which corroborate the evidence that commodity prices move in tandem with other commodities in the same class. In each case, the common factors have been computed excluding the commodity under consideration. The 'metals' factor has a positive effect on each individual commodity and a strong and generally significant effect on all individual metals prices (except for iron ore). In addition, there appear to be spillovers from rising metals prices to food prices with the exception of cocoa prices. The latter impulse response functions are generally above the one standard-deviation threshold. The 'food' factor has generally positive spillovers to individual food prices. Only for sugar, there is no discernable effect and the error bands are very wide. The effect on other commodities is also somewhat mixed. In line with the factor loading presented above, we find significant interlinkages between food and tin prices. The response is also positive for lead and nickel, while it is negative for aluminium.

5 Conclusions

Using a Factor-Augmented VAR approach, we have investigated interlinkages between a set of commodity prices and macroeconomic variables. Impulse response analysis has confirmed that exchange rates and industrial production affect individual non-energy commodity prices. In contrast, no robust spillovers from oil to non-oil commodity prices or an impact of the interest rate have been found.

In this paper we have focused on spillovers in the levels of the series (i.e. returns on commodity prices, since we work with first differences). Another interesting approach could be to look at volatility spillovers; this could be accomplished, for example, in a multivariate GARCH framework.

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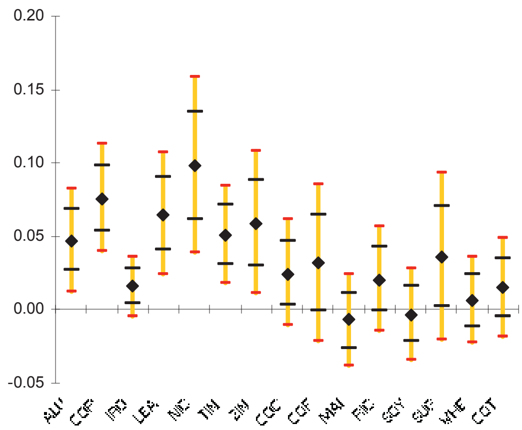
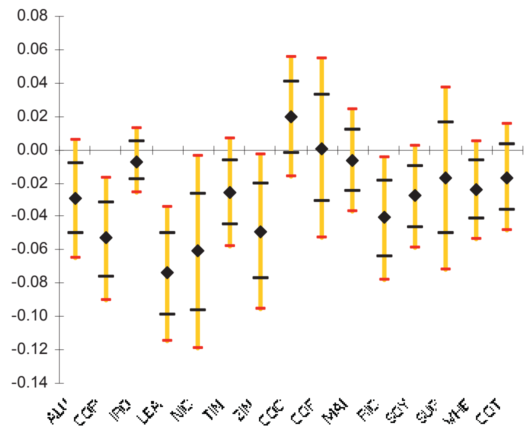
[8] Boschi and Pieroni (2008) also find for aluminum a significant effect of the real exchange rate on aluminum prices while the effect of the interest rate is small.

Chart 6: Impulse responses of non-energy commodity prices to shocks on …

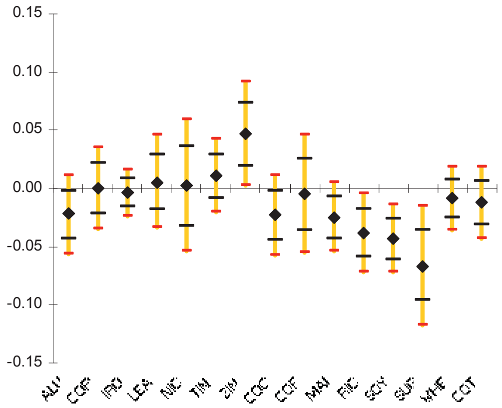
a: … industrial production



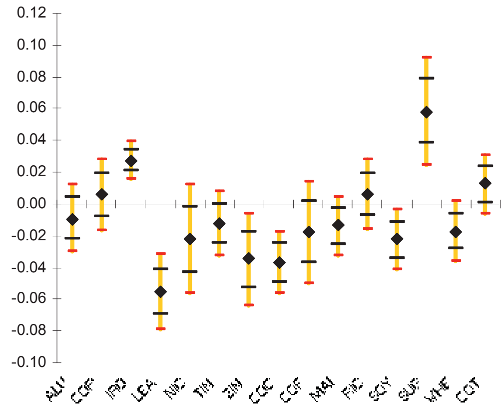
b: … exchange rate



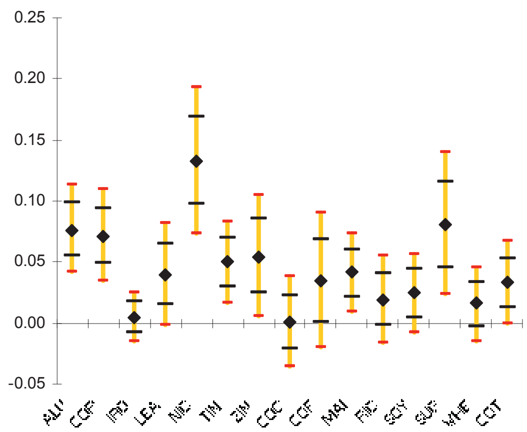
c: … interest rate



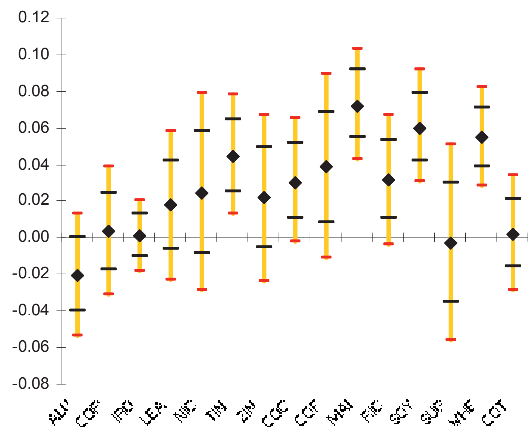
d: … oil prices



e: … first common factor (metals)



f: … second common factor (food)



Source: ECB staff.
Note: The black diamond shows the median response at the one-year horizon. The black/red marks show the one- and the two-standard-deviation error bands.

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Table A: Correlations across commodities in levels (upper right triangular of the matrix) and in first differences (lower-left triangular of the matrix)

	ALU	COP	IRO	LEA	NIC	TIN	ZIN	COC	COF	MAI	RIC	SOY	SUG	WHE	COT	OILW
ALU	1.000	0.667	0.385	0.739	0.620	0.597	0.525	0.531	0.539	0.492	0.585	0.598	0.553	0.538	0.506	0.316
t-Statistic	-----	10.327	4.810	12.636	9.119	8.571	7.121	7.224	7.388	6.525	8.314	8.609	7.653	7.360	6.757	3.838
Probability	-----	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
COP	0.463	1.000	0.755	0.799	0.852	0.358	0.798	0.123	0.165	0.311	0.386	0.312	0.398	0.468	0.139	0.523
t-Statistic	5.999	-----	13.281	15.300	18.740	4.421	15.264	1.425	1.926	3.779	4.820	3.788	4.998	6.107	1.623	7.074
Probability	0.000	-----	0.000	0.000	0.000	0.000	0.000	0.157	0.056	0.000	0.000	0.000	0.000	0.000	0.107	0.000
IRO	0.041	0.107	1.000	0.717	0.633	0.476	0.574	0.277	0.192	0.348	0.389	0.320	0.223	0.448	0.057	0.739
t-Statistic	0.471	1.240	-----	11.855	9.431	6.237	8.075	3.319	2.260	4.280	4.876	3.900	2.637	5.772	0.658	12.665
Probability	0.638	0.217	-----	0.000	0.000	0.000	0.000	0.001	0.025	0.000	0.000	0.000	0.009	0.000	0.512	0.000
LEA	0.218	0.353	0.042	1.000	0.672	0.666	0.585	0.515	0.435	0.534	0.631	0.589	0.496	0.655	0.401	0.578
t-Statistic	2.563	4.329	0.487	-----	10.477	10.304	8.309	6.925	5.575	7.275	9.376	8.411	6.593	9.993	5.053	8.162
Probability	0.012	0.000	0.627	-----	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NIC	0.521	0.401	0.033	0.172	1.000	0.228	0.745	0.012	-0.002	0.193	0.198	0.206	0.220	0.308	-0.032	0.500
t-Statistic	7.019	5.030	0.384	2.010	-----	2.700	12.880	0.138	-0.023	2.272	2.331	2.427	2.597	3.727	-0.375	6.654
Probability	0.000	0.000	0.701	0.046	-----	0.008	0.000	0.891	0.982	0.025	0.021	0.017	0.011	0.000	0.709	0.000
TIN	0.232	0.245	0.029	0.311	0.224	1.000	0.242	0.842	0.748	0.805	0.824	0.826	0.523	0.799	0.738	0.533
t-Statistic	2.745	2.899	0.336	3.761	2.646	-----	2.877	18.004	13.000	15.670	16.766	16.875	7.071	15.299	12.631	7.270
Probability	0.007	0.004	0.738	0.000	0.009	-----	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ZIN	0.359	0.535	0.100	0.383	0.443	0.128	1.000	0.001	0.102	0.269	0.277	0.220	0.346	0.342	0.096	0.276
t-Statistic	4.424	7.277	1.158	4.769	5.675	1.482	-----	0.008	1.186	3.220	3.329	2.604	4.257	4.195	1.118	3.317
Probability	0.000	0.000	0.249	0.000	0.000	0.141	-----	0.994	0.238	0.002	0.001	0.010	0.000	0.000	0.266	0.001
COC	0.147	0.136	0.175	0.227	0.058	0.197	0.081	1.000	0.843	0.729	0.725	0.822	0.433	0.665	0.755	0.246
t-Statistic	1.709	1.581	2.043	2.675	0.662	2.309	0.934	-----	18.083	12.287	12.138	16.618	5.546	10.273	13.283	2.921
Probability	0.090	0.116	0.043	0.008	0.509	0.023	0.352	-----	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004
COF	0.168	0.141	0.193	0.069	0.117	-0.016	0.025	0.246	1.000	0.661	0.688	0.752	0.451	0.583	0.767	0.092
t-Statistic	1.954	1.636	2.257	0.790	1.348	-0.179	0.291	2.920	-----	10.149	10.945	13.154	5.822	8.281	13.802	1.064
Probability	0.053	0.104	0.026	0.431	0.180	0.858	0.771	0.004	-----	0.000	0.000	0.000	0.000	0.000	0.000	0.289
MAI	0.129	0.053	0.130	0.102	0.211	0.140	0.109	0.007	0.080	1.000	0.872	0.907	0.668	0.913	0.791	0.259
t-Statistic	1.496	0.614	1.505	1.178	2.483	1.628	1.259	0.075	0.916	-----	20.549	24.833	10.365	25.843	14.905	3.098
Probability	0.137	0.540	0.135	0.241	0.014	0.106	0.210	0.940	0.361	-----	0.000	0.000	0.000	0.000	0.000	0.002
RIC	0.136	0.095	0.116	-0.035	0.096	0.232	-0.060	0.071	-0.045	0.321	1.000	0.856	0.773	0.845	0.795	0.265
t-Statistic	1.583	1.100	1.348	-0.401	1.111	2.736	-0.688	0.822	-0.516	3.899	-----	19.077	14.070	18.219	15.107	3.165
Probability	0.116	0.273	0.180	0.689	0.269	0.007	0.492	0.413	0.606	0.000	-----	0.000	0.000	0.000	0.000	0.002
SOY	0.152	0.123	0.137	0.156	0.195	0.129	0.141	0.098	0.222	0.653	0.138	1.000	0.630	0.834	0.832	0.216
t-Statistic	1.766	1.419	1.591	1.820	2.280	1.495	1.641	1.137	2.618	9.915	1.597	-----	9.347	17.421	17.324	2.554
Probability	0.080	0.158	0.114	0.071	0.024	0.137	0.103	0.258	0.010	0.000	0.113	-----	0.000	0.000	0.000	0.012
SUG	0.213	0.141	0.134	0.107	-0.047	0.076	0.111	0.034	-0.015	0.171	0.046	0.095	1.000	0.703	0.674	0.126
t-Statistic	2.500	1.641	1.558	1.238	-0.536	0.874	1.285	0.388	-0.168	1.999	0.533	1.102	-----	11.395	10.528	1.468
Probability	0.014	0.103	0.122	0.218	0.593	0.384	0.201	0.699	0.867	0.048	0.595	0.273	-----	0.000	0.000	0.145
WHE	-0.007	0.160	0.029	0.183	0.035	0.108	0.099	0.019	0.085	0.476	0.098	0.257	0.214	1.000	0.699	0.379
t-Statistic	-0.077	1.859	0.328	2.144	0.402	1.251	1.146	0.215	0.981	6.217	1.133	3.057	2.521	-----	11.277	4.719
Probability	0.938	0.065	0.743	0.034	0.689	0.213	0.254	0.830	0.328	0.000	0.259	0.003	0.013	-----	0.000	0.000
COT	0.217	0.201	0.086	0.160	0.119	0.157	0.108	0.076	-0.015	0.209	0.049	0.324	0.116	0.014	1.000	0.045
t-Statistic	2.557	2.353	0.988	1.860	1.383	1.832	1.243	0.875	-0.174	2.455	0.559	3.936	1.337	0.157	-----	0.523
Probability	0.012	0.020	0.325	0.065	0.169	0.069	0.216	0.383	0.862	0.015	0.577	0.000	0.184	0.876	-----	0.602
OILW	0.104	0.145	0.040	0.055	0.093	0.279	-0.100	-0.038	-0.059	-0.164	-0.020	-0.072	0.029	-0.086	0.087	1.000
t-Statistic	1.198	1.688	0.455	0.633	1.077	3.337	-1.152	-0.432	-0.680	-1.911	-0.231	-0.830	0.328	-0.995	0.999	-----
Probability	0.233	0.094	0.650	0.528	0.284	0.001	0.251	0.667	0.498	0.058	0.818	0.408	0.743	0.322	0.320	-----