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COMMODITY MARKET STRUCTURE AND RISK FACTOR ANALYSIS IN BULGARIA

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Abstract

Analyzing the Bulgarian raw material, crude oil and natural gas markets is an important step in setting up an early warning system (EWS). The Comprehensive Price Index is based on the weighting of imports from the energy and non-energy sectors, including the crude oil sector. The explanatory variables that describe the crisis index are analyzed and predicted by the ordered Probit model. The EWS system developed in this study takes into account the most important measurable variables that affect the raw material market, and based on this understanding, we focus on which variables can represent risk.

Key words: raw material market, oil and natural gas market, early warning system, probit model

JEL: C53, Q31, Q32

Introduction

The raw materials are very homogeneous products and are used as the main input in the production of various products. Therefore, their price volatility is an important source of uncertainty for economic operators. Motivated by previous theoretical and empirical discoveries, we will empirically investigate the impact of raw material price uncertainty on Bulgaria's economic activity. As far as we know, there is limited empirical literature on the impact of commodity price uncertainty on macroeconomic fluctuations. Early empirical studies have identified the well-known macroeconomic fact where rising oil market prices and volatility lead to investment restraint, lower GDP growth, and recession.

Bulgaria does not have enough natural resources, so most of them need to be imported. Due to its small and very open economy, sudden rises in the prices of such raw materials can have a serious impact on the domestic economy, both in terms of imports and exports. Therefore, the early warning system "EWS" that monitors price trends in the raw material market is of utmost importance.

Since Bulgaria is a pricing maker, authorities cannot influence these changes, so models that predict significant price fluctuations should be considered purely

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exogenous. However, if further analysis confirms that price fluctuations are likely to be permanent, authorities will need to respond accordingly. The advantage of a well-designed early warning system is that it provides both authorities and the private sector with useful tools to prepare for emergencies and mitigate adverse effects (as much as possible).

The concept of EMS for monitoring commodity markets needs to be adapted to best reflect the structure and details of foreign trade. The model should focus on the energy sector (oil, gas, electricity). Therefore, the leading indicators here should be available oil inventories, oil production, economic variables, and net positions in crude oil futures contracts. Given the importance of some commodities to Bulgarian exports, it is necessary to build a similar model for other commodities such as iron, copper, steel and chemicals. In practice, the predictive power of such models is shown to be limited, as raw material prices are also determined by non-economic factors such as politics, natural disasters, non-trade barriers and geopolitical interests. Thus, qualitative monitoring also needs to be emphasized.

Factors Behind the Dynamics of the Commodities Market

When analyzing raw materials (Kowalski, 2021), it is necessary to identify all the important technical factors that are putting pressure on prices, acknowledging that every product has its own unique tendency. However, there are some factors that need to be considered. Each commodity has its own supply and is in contact with the tendency to ultimately determine the least price pursuit, and inflationary pressures are likely to be exerted on commodities, higher (lower) interest rates, and stronger ones. It should be noted that the strong (weak) dollar may also have to curb (accelerate) future rises (falls) in raw materials.

US dollars and commodity markets

As stressed by Kowalski (2021), the US dollar is the most important reserve currency and has a significant impact on the price development of the most important raw materials. As the dollar rises, the value of commodities measured in other currencies also rises, leading to lower demand. Conversely, when the dollar is weak, the value of commodities tends to decline in other currencies, and as prices fall, demand tends to increase. The inverse relationship between the US dollar and commodity prices continues to be a problem for producers and consumers, especially during periods of high volatility.

Given the outlook for US short-term interest rates, the US dollar is expected to remain strong. The most important competitive currency for the dollar is the euro. Even after the global financial crisis was resolved, Europe's economic framework was a little weak and hit the euro. Therefore, the US dollar / euro exchange rate is essential to the commodity market and should be carefully monitored.

Interest Rates

The Federal Reserve raised rates in late 2015 (the ECB hasn't intervened yet), but it's still at historically low levels. After the global financial crisis, central banks were forced to lower interest rates and introduce quantitative easing policies. The US economy began to improve in 2015, but due to the economic downturn in Europe, the ECB launched its own quantitative easing program in early 2015. Interest rates in the US fell to zero percent low, but interest rates in Europe entered the negative territory. Expectations for further rate hikes in the US mean that the dollar will outperform other competing currencies. Higher US interest rates combined with balanced growth in the US economy will support the dollar. Interest rates are likely to remain low in the face of the COVID-19 pandemic, which could put downward pressure on commodity prices. While rising commodity prices are often pessimistic, there are many other considerations when it comes to minimizing the cost of prices for this volatile asset class.

Analysis of the Commodities Market

Fundamental analysis should be used as a tool for studying products to predict future price fluctuations. The basic tool is an analysis of supply and demand. Looking at the prices of goods, the concept of supply and demand is like a simple equation. However, things get even more complicated when trying to predict future prices. Commodities are usually traded on a regular basis, and certain commodities are undersupplied and prices may rise. In addition, supplies may be higher than necessary and prices may fall. When analyzing, it is most important to look at the products that have been trading at high or low prices for multiple years. So the question is how good it is to use fundamental analysis to predict future prices.

This said, fundamental analysis consists of collecting supply and demand data to determine if a market is in deficit, equilibrium, or oversupply. Also, fundamental analysis is an important exercise in predicting the direction of prices in commodity markets. In these markets, production is usually local, but consumption is ubiquitous. Of course, some supply and demand data are better than others, and the quality of the information often depends on the source. However, for various reasons, both supply and demand statistics are far from perfect. It is basically not easy to predict the price of a short-term trading product, as prices can fluctuate in the short term. For practical reasons, it makes sense to use data from various reports edited by the World Bank, the IMF, or government agencies such as the USDA, the Ministry of Energy, and futures exchanges. Many large commodity brokers also publish basic research for their clients.

Supply of Commodities

The delivery date of the product is the amount inherited from the production (inventory) of the previous year and the production amount of the current year. For example, the current range of soybeans includes crops and the amount left over from last year's harvest. In general, the higher the carryover from the previous season, the lower the price. Many factors affect the supply of raw materials, including weather, plant area, production strikes, plant diseases, and technology. In a basic analysis, it should be noted that the higher the raw material price, the higher the return. Everyone wants a profit, so it's more beneficial to produce a particular product when the price is high. As expected, as prices go up, demand generally falls. If demand drops enough, prices will be pushed down.

Demand for Commodities

The quantity required for a product is the quantity consumed at a particular price level. According to the law of demand, the lower the price of a product, the higher the demand. Conversely, as raw material prices rise, demand declines.

Using Fundamental Analysis to Predict Future Prices

Fundamental analysis consists of collecting supply and demand data to determine if a market is in the red, equilibrium, or oversupply. Fundamental analysis is an essential exercise in predicting the direction of prices in commodity markets. In these markets, production is often local and consumption is ubiquitous. Some supply and demand dates are better than others. However, the quality of the data often depends on the source. For a variety of reasons, both supply and demand statistics are far from perfect. Since prices fluctuate in the short term, it is not easy to basically predict the price of a product from short-term transactions. For practical reasons, it makes sense to use data from various reports edited by the World Bank, the IMF, or government agencies such as the USDA, the Ministry of Energy, and futures exchanges. Many large commodity brokers also publish basic research for their clients.

Assessing the impact of commodity prices on economic activity

A VAR model

With regard of building an EWS for monitoring price developments in commodity market we use a multivariate VAR model in which we exert control specifically over inflation as well as over other variables. In this way, we implicitly account for the inflationary impact of commodity prices to commodity market turbulence. The benefit of using such an approach is that we control the major determinants of economic activity in the VAR setting. More specifically, following the VAR modeling approach of Bekaert et al. (2013), we choose to place macroeconomic variables first and the financial variables last in the VAR ordering due to the more sluggish response of the former compared to the latter. The reduced form VAR model is given in Equation (1) below:

$$Y_t = A_0 + A_1 Y_{t-1} + \cdots . + A_k Y_{t-k} + \varepsilon_t \qquad (1)$$

where A_0 is a vector of constants, A_1 to A_k are matrices of coefficients and ε_t is the vector of serially uncorrelated disturbances, Y_t is the vector of endogenous variables. The ordering of the baseline 6-factor VAR model is as follows:

[GDP DEFL UNEMP M2/GDP FRes/GDP COMM]

GDP stands for the growth of real GDP; COMM is an aggregate commodity price index[2], UNEMP is the unemployment rate; M2 is the growth of M2 money supply with respect to GDP; DEFL is the GDP deflator.[3]

Estimating regression models

Adapting the approach used by Bakas & Triantafyllou (2018), we complement our VAR analysis on the impact of commodity uncertainty shocks on economic activity by using single-equation forecasting regression models. We, thus, estimate bivariate OLS forecasting regressions in which we use commodity prices indices as the only predictor of economic activity. The bivariate time-series forecasting regression model is given in Equation (2) below:

$$\Delta GDP_t = \alpha + \beta_1 COMM_{t-k} + \varepsilon_t \qquad (2)$$

where ΔGDP is the growth of real GDP and COMM is the chosen commodity prices indices, respectively. Furthermore, and following our baseline 6-factor VAR model specification used in the VAR analysis, we estimate multivariate OLS forecasting regressions in which we include key macroeconomic and financial indicators of economic development. The multivariate time-series regression model, where we exert control over macroeconomic and financial fundamentals, is given in Equation (3) below:

[2] With regard to COMM, different estimates have been produced, including specific single commodity price index; compound indices, as well as commodity terms of trade indices.

[3] The variables (in quarterly frequency) used in the VAR analysis cover the period from 1998 Q1 to 2019 Q4.

$$\Delta GDP_t = \alpha_0 + \beta_1 \Delta COMM_{t-k} + \beta_4 \Delta DEFL_{t-k} + \beta_5 \Delta M2/GDP_{t-k} + \beta_6 \Delta FRes/GDP_{t-k} + \beta_7 \Delta UNEMP_{t-k} + \varepsilon_t \quad (3)$$

where, as before, ΔGDP is the growth of real GDP, COMM is the chosen commodity price index, and DEFL, M2/GDP, FRes/GDP and UNEMP are the macroeconomic and financial controls.

Main results

As in other pieces of research, for example Korea Development Institute (2020) and Kang et al. (2017) data presented in Appendix, Table 5 ÷ Table 6, point that uncertainty shocks in agricultural, metals and energy commodity markets do have a negative impact on economic activity and its components. More specifically, using regression analysis, presented in Table 2 and Table 3, for each individual commodity price uncertainty series on the contemporaneous change in the quarterly real GDP, we observe negative and statistically significant coefficients for all commodities. The series of energy and metals commodities have higher predictive power on real GDP growth when compared to agricultural product markets. These findings show the significantly higher predictive information power of energy and metals commodities as opposed to other commodities on Bulgaria's economic activity.

In addition, in order to find the recessionary impact of commodity price uncertainty shocks, we control endogenous interactions between commodity price fluctuations and monetary aggregates by including the money supply and the inflation rate as endogenous variables in the VAR model. As in Ryu & Yotzov (2020), we find that price uncertainty shocks, particularly with respect to changes in commodity terms of trade indices (Table 3), have significant real effects on the macroeconomy that are completely unrelated to inflation and to any systematic monetary policy interventions.

The VAR analysis shows (Figure 1) that the estimated macroeconomic impact of uncertainty shocks in these commodity markets remains robust to the inclusion of alternative economic uncertainty measures, like unemployment rate; inflation (GDP deflator); and monetary aggregates (M2 and foreign reserves). In addition, results show that unlike the metals and agricultural uncertainty shocks, oil price uncertainty shocks become insignificant when we control inflation.

Indicators to be Included in the EWS

Calculations of the CPHW[4]

According to Policy, Programme and Innovation Division (PPI) (2014), the CPHW (Commodity Price Hikes Warning) can serve several operational purposes:

Monitoring: CPHW can serve as a price monitoring tool. It enables the user to easily identify which commodities and markets are experiencing abnormal price levels, the severity and the persistence of such price abnormalities.

Early warning: The CPHW provides a sense of the intensity of price fluctuations through an ordered and standardized compilation of the prices that remain in constant fluctuation over time. Therefore, the CPHW can generate timely warning information on price dynamics that enables the users to prepare and act appropriately. As such the information from CPHW can serve to trigger further assessment and analysis to evaluate how abnormal price hikes affect market functioning.

Early response: The early detection of price alerts and price crises and the understanding of the underlying reasons can trigger preparedness measures and contingency planning as well as programme adjustments.

The CPHW could be based on three different methodologies[5], all of which use a trend analysis of monthly price data. These are: a standard HP filter; a 12-month moving average; and a specific methodology as described below. The idea behind this approach is to compare the long-term trend of a commodity's price series at each market with the last observed price on the same market. The assumption is that the estimated trend reflects the dynamics of the price series beyond the spikes and abnormal levels, something which – in other words – can be defined as the "normal" pattern of the price series. Results from the three different approaches are shown in the appendix.

The four steps of the calculation of the specific indicator

The calculation of the indicator follows four steps:

Step 1: Estimation of the seasonal price trend

Step 2: Calculation of the difference between market price and estimated price

Step 3: Calculation of the CPHW indicator considering price volatility

Step 4: Calculation of the different thresholds of the indicator

Step 1: Estimation of the seasonal price trend

Seasonal price trend values are obtained by regressing market price series on a deterministic trend with monthly dummies with an ordinary least square estimator (equation (4)). The price trend is estimated for each market over the

[4] The methodology used draws on the one used in World Food Programme "Calculation and Use of Alert for Price Spikes (ALPS) Indicator", WFP.org

[5] The results from the different approaches are shown in the Appendix.

entire period. The seasonal monthly dummies ($\sum \mathbf{D}_{12m=1}$) catch the monthly price fluctuations related to the production or demand cycle, and the trend T captures long term movement (e.g., related to population growth).

$$Price_t = \alpha * T_t + \sum_{m=1}^{12} \beta_m * D_{mt} + \varepsilon_t \qquad (4)$$

where α is the coefficient of the trend, βm are the m coefficients of the monthly dummies, T is the trend D_{mt} = monthly dummies (m = {1,… , 12} = {January, ..., December}), e.g.: D1 = January dummy ⇔1 if month = January, 0 if not.

The estimated price trend is given by:

$$\widehat{Price}_t = \hat{\alpha} * T_t + \sum_{m=1}^{12} \widehat{\beta_m} * D_{mt} \qquad (5)$$

Where $\widehat{Price}_t$ is the estimated price at time t, $\hat{\alpha}$ and $\widehat{\beta_m}$ are the estimated parameters of the seasonal trend equation. In this note, we define the price trend at a specific time *t* as the "estimated price" or the "normal price" at that time. In contrast, the market price at a specific time t is called "observed price".

Step 2. Calculation of the difference between market price and estimated price

The second step is to calculate for each month the difference between the market price and the estimated price. This represents the estimated error of the model at each period ($\hat{\varepsilon}_t$)

$$\varepsilon_t = Price_t - \widehat{Price}_t \qquad (6)$$

Step 3. Calculation of an indicator considering price volatility

The CPHW indicator (equation (7)) is calculated for each period (month) by dividing the price difference between the observed and estimated price by the standard deviation (σ_t) of the error term:

$$CPHW = \frac{Price_{it} - \widehat{Price}_{it}}{\sigma i_t} \qquad (7)$$

$Price_{it}$ Observed market price for the "ith" commodity at time "t"

$\widehat{Price}_{it}$: Estimated price

$\varepsilon_t = Price_{it} - \widehat{Price}_{it}$= residuals, difference between market price and estimated price

σ_{it}: Standard deviation of the residuals

Step 4. Calculation of the different thresholds of the indicator

The CPHW provides a sense of the intensity of the price difference between the trend and the market price. The higher the difference, the more severe the alert.

Table 1: CPHW categories and thresholds

Assessment	CPHW thresholds
Normal	CPHW < 0.25
Stress	0.25 ≤ CPHW < 1
Alert	1 ≤ CPHW < 2
Crisis	CPHW ≥ 2

Source: Adapted from Policy, Programme and Innovation Division (PPI) (2014).

Market pressure index

Using the methodology described in Policy, Programme and Innovation Division (PPI) (2014) and in order to develop a trigger value for a potential price EWS we calculate a market pressure index. This index can be used to define threshold values to establish a system of market pressure alerts on a continuous basis with respect to the diferent forecasting horizons. These threshold values are yet to be defined. Ideally, an expert panel of specific user groups should define such threshold values for their individual use cases.Market pressure index, MPI_m, for each commodity m under consideration (oil, gas, etc.) was calculated as follows

$$MPI_{m,t} = 100\log(\frac{\hat{P}_{m,t+h|t}}{P_{m,t}}) \tag{8}$$

where $MPI_{m,t}$ is the price of commodity *m* at time t and $\hat{P}_{m,t+h|t}$ is the price forecast of commodity *m* at time t for time t + h. The price forecasts might be generated by a specific model, or taken by the IMF, WB, or other institutions. For a given commodity, this variable provides the percent diference between the predicted price and actual price where the predicted prices are based on market fundamentals and macroeconomic and financial developments. The index indicates whether the prevalent economic conditions are expected to lead to an increase or a decrease of the price of a particular commodity at a given horizon (from one to twelve months ahead) and by how much the price is expected to change.

Concluding Remarks and Discussion

The purpose of this study was to elaborate on the development of EWS for Bulgarian raw materials. Commodity early warning systems can help authorities minimize their negative impact on the economy in order to prepare for the risks that may arise from irregular commodity price movements. The main achievements of this study can be summarized as follows.

- The Comprehensive Price Index was created based on the weighting of imports from the energy and non-energy sectors, including the crude oil sector. The definition of crisis and crisis index was derived from this comprehensive price index. Meanwhile, the explanatory variables that explain the crisis index were analyzed and predicted by an ordered Probit model. This makes it possible to determine how the explanatory variables contribute to the early warning index.
- The EWS system has improved the accuracy of understanding the current situation. The EWS system developed in this study takes into account the most important measurable variables that affect the raw material market, and based on this understanding, we focus on which variables can represent risk.

All pieces of research have some limitations in terms of scope. *First*, this model focuses on economic variables. Indeed, the early warning system constructed in this study was built on measurable economic variables, and it was not enough to consider non-economic factors. For example, commodity prices, especially oil prices, are often determined primarily by non-economic factors that are difficult to quantify, such as war, terrorism, and OPEC subtraction. However, the EWS model does not take these factors into account. *Second*, the current model is designed to predict disruptions or even crises six months into the future. This predictive model finds regularity from past crisis experiences and predicts the occurrence of a crisis if similar regularities are repeated. Therefore, if the cause of the crisis is different from the cause of the past crisis, the prediction may be incorrect. For example, in past crises, supply-side variables have evolved, demand-side variables and financial variables have responded to the crisis, but the market has been caused by demand-side factors or financial speculative behavior. Then the demand will be reversed. Factors related to finance and financial variables precede the crisis, followed by supply variables. In this case, the model's predictive power for the crisis is very low. *Third*, the shorter the prediction period of the model, the more accurate the model. Even the 6-month forecast may not be accurate due to the great uncertainty, and the 1, 2, or 3 month forecast will be fairly accurate.

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United Nations Conference on Trade and Development (UNCTAD), available at: https://unctad. org

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Appendix

Table 2: OLS Estimates of equation (3)

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Included observations: 83 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(GDP(-1))	-0.395310	0.108932	-3.628973	0.0005
DLOG(CTOT1(-1))	-1.039109	0.558411	-1.860833	0.0669
DLOG(CTOT1(-2))	-0.998312	0.552543	-1.806759	0.0750
DLOG(CTOT1(-4))	-1.451004	0.523997	-2.769111	0.0072
DLOG(DEFL(-3))	0.093268	0.040187	2.320857	0.0232
DLOG(Fres/GDP(-1))	0.026524	0.021771	1.218284	0.2271
DLOG(UNEMP)	-0.049355	0.014479	-3.408650	0.0011
LOG(GDP(-1))	-0.295513	0.047866	-6.173783	0.0000
LOG(CTOT1(-1))	0.996011	0.419657	2.373395	0.0203
LOG(UNEMP(-1))	-0.026805	0.007286	-3.679198	0.0005
LOG(M2/GDP(-1))	0.155023	0.024077	6.438624	0.0000
C	-2.243884	1.942613	-1.155086	0.2519
R-squared	0.558011	Mean dependent var		0.008137
Adjusted R-squared	0.489534	S.D. dependent var		0.014786
S.E. of regression	0.010564	Akaike info criterion		-6.129757
Sum squared resid	0.007923	Schwarz criterion		-5.780045
Log likelihood	266.3849	Hannan-Quinn criter.		-5.989262
F-statistic	8.148861	Durbin-Watson stat		2.148651
Prob(F-statistic)	0.000000			

CTOT1 – Commodity terms of trade, Net Export, fixed weights
Source: Own calculations

Table 3: CTOT2 and GDP

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(GDP(-1))	-0.144186	0.105135	-1.371436	0.1743
DLOG(CTOT2(-1))	0.400709	0.191071	2.097175	0.0393
DLOG(CTOT2 (-2))	0.446831	0.199492	2.239838	0.0281
DLOG(CTOT2 (-4))	0.658390	0.193269	3.406605	0.0011
LOG(CTOT2 (-1))	-0.097490	0.056776	-1.717107	0.0901
C	0.455849	0.260461	1.750164	0.0842
R-squared	0.213442	Mean dependent var		0.008773
Adjusted R-squared	0.161005	S.D. dependent var		0.014318
S.E. of regression	0.013115	Akaike info criterion		-5.758947
Sum squared resid	0.012900	Schwarz criterion		-5.581581
Log likelihood	239.2374	Hannan-Quinn criter.		-5.687786
F-statistic	4.070440	Durbin-Watson stat		1.912510
Prob(F-statistic)	0.002531			

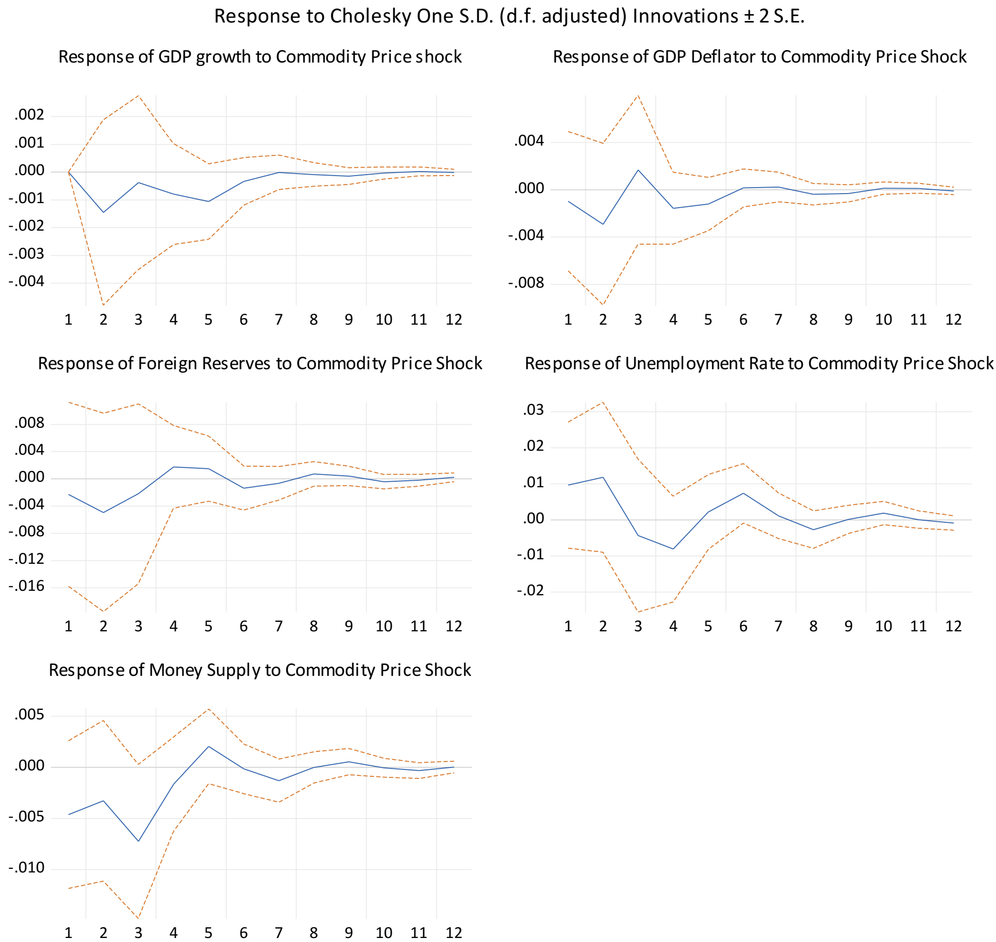
CTOT2 – Commodity terms of trade, Exports, fixed weights
Source: Own calculations

Table 4: CTOT3 and GDP

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Sample: 1999Q4 2019Q4				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(GDP(-1))	-0.089157	0.103772	-0.859161	0.3930
DLOG(CTOT3(-1))	0.392962	0.162055	2.424867	0.0177
DLOG(CTOT3 (-4))	0.500452	0.159980	3.128214	0.0025
LOG(CTOT3 (-1))	-0.082608	0.052003	-1.588510	0.1163
C	0.387216	0.238352	1.624551	0.1084
R-squared	0.177873	Mean dependent var		0.008773
Adjusted R-squared	0.134603	S.D. dependent var		0.014318
S.E. of regression	0.013320	Akaike info criterion		-5.739409
Sum squared resid	0.013483	Schwarz criterion		-5.591604
Log likelihood	237.4461	Hannan-Quinn criter.		-5.680108
F-statistic	4.110772	Durbin-Watson stat		1.961351
Prob(F-statistic)	0.004545			

CTOT3 – Commodity terms of trade, Imports, fixed weights
Source: Own calculations

Figure 1: Commodity price effect on Economic Activity (Impulse Response Function)



Source: Own calculations

Table 5: Impact of Energy Prices on GDP Growth

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Sample: 1999Q4 2019Q4				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(ENERGY(-2))	0.016016	0.009741	1.644195	0.1042
DLOG(ENERGY(-4))	0.028469	0.009562	2.977456	0.0039
LOG(ENERGY(-1))	-0.005982	0.003294	-1.816272	0.0732
C	0.033661	0.014160	2.377223	0.0199
R-squared	0.142722	Mean dependent var		0.008773
Adjusted R-squared	0.109322	S.D. dependent var		0.014318
S.E. of regression	0.013513	Akaike info criterion		-5.722234
Sum squared resid	0.014060	Schwarz criterion		-5.603990
Log likelihood	235.7505	Hannan-Quinn criter.		-5.674793
F-statistic	4.273074	Durbin-Watson stat		2.074407
Prob(F-statistic)	0.007616			

Source: Own calculations

Table 6: Impact of Base Metals Prices on GDP Growth

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Sample: 1999Q4 2019Q4				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(METALS(-1))	0.026670	0.014132	1.887156	0.0630
DLOG(METALS(-4))	0.030483	0.013743	2.218079	0.0295
LOG(GDP(-1))	-0.014070	0.012864	-1.093704	0.2775
LOG(METALS(-1))	0.000987	0.006747	0.146362	0.8840
C	0.142667	0.105213	1.355992	0.1791
R-squared	0.138891	Mean dependent var		0.008773
Adjusted R-squared	0.093570	S.D. dependent var		0.014318
S.E. of regression	0.013632	Akaike info criterion		-5.693084
Sum squared resid	0.014123	Schwarz criterion		-5.545279
Log likelihood	235.5699	Hannan-Quinn criter.		-5.633783
F-statistic	3.064580	Durbin-Watson stat		2.222325
Prob(F-statistic)	0.021380			

Source: Own calculations

Table 7: Impact of Prices of Agricultural Products on GDP Growth

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Sample: 1999Q4 2019Q4				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(GDP(-1))	-0.215323	0.109782	-1.961360	0.0535
DLOG(AGR(-1))	0.052050	0.025503	2.040981	0.0447
DLOG(AGR(-2))	0.058044	0.026867	2.160446	0.0339
LOG(GDP)	0.010999	0.003044	3.613232	0.0005
LOG(AGR(-1))	-0.022600	0.006817	-3.315348	0.0014
R-squared	0.198606	Mean dependent var		0.008773
Adjusted R-squared	0.156427	S.D. dependent var		0.014318
S.E. of regression	0.013151	Akaike info criterion		-5.764952
Sum squared resid	0.013143	Schwarz criterion		-5.617146
Log likelihood	238.4805	Hannan-Quinn criter.		-5.705650
Durbin-Watson stat	1.875564			

Source: Own calculations

Table 8: Impact of Oil Prices on GDP Growth

Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Sample: 1999Q4 2019Q4				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOGGDP(-1)	-0.108465	0.105197	-1.031057	0.3058
DLOG(OIL(-2))	0.017256	0.008474	2.036308	0.0452
DLOG(OIL(-4))	0.028158	0.008174	3.444728	0.0009
LOG(OIL(-1))	-0.005589	0.002985	-1.872323	0.0650
C	0.031302	0.012193	2.567314	0.0122
R-squared	0.180613	Mean dependent var		0.008773
Adjusted R-squared	0.137487	S.D. dependent var		0.014318
S.E. of regression	0.013297	Akaike info criterion		-5.742748
Sum squared resid	0.013438	Schwarz criterion		-5.594942
Log likelihood	237.5813	Hannan-Quinn criter.		-5.683446
F-statistic	4.188053	Durbin-Watson stat		1.849813
Prob(F-statistic)	0.004057			

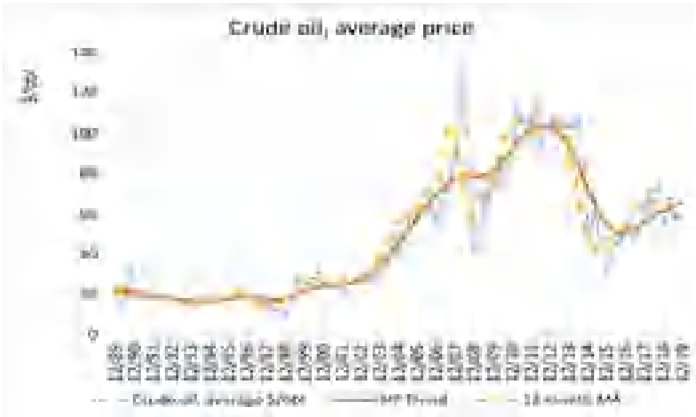
Source: Own calculations

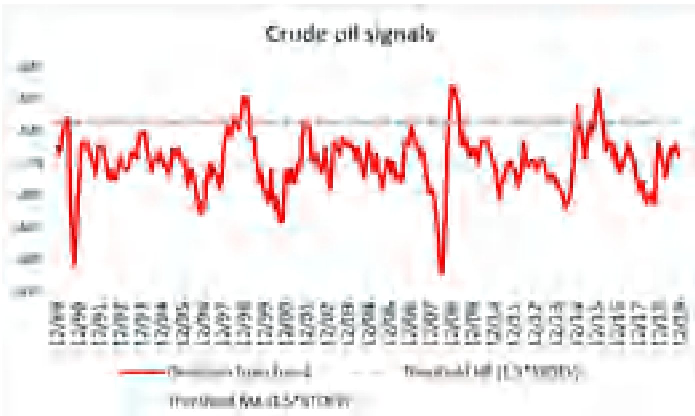
Table 9: Impact of Natural Gas Prices on GDP Growth

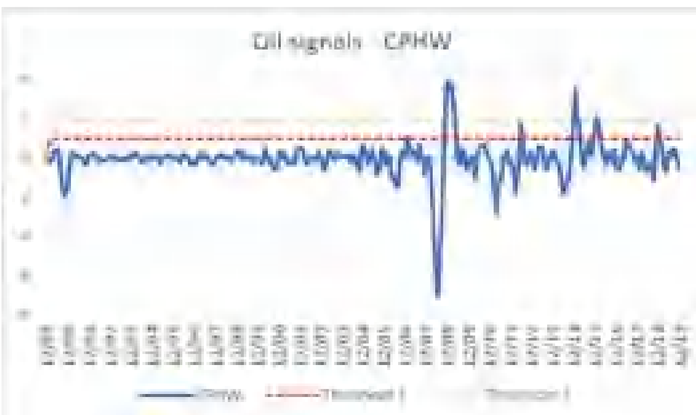
Dependent Variable: DLOG(GDP)				
Method: Least Squares				
Sample: 1999Q4 2019Q4				
Included observations: 81				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(GDP(-2))	0.150151	0.104344	1.439002	0.1543
DLOG(GAS)	0.012532	0.011528	1.087008	0.2805
LOG(GDP(-1))	-0.007435	0.009712	-0.765543	0.4463
LOG(GAS(-1))	-0.004066	0.004205	-0.966773	0.3367
C	0.088344	0.091438	0.966171	0.3370
R-squared	0.106478	Mean dependent var		0.008773
Adjusted R-squared	0.059451	S.D. dependent var		0.014318
S.E. of regression	0.013886	Akaike info criterion		-5.656134
Sum squared resid	0.014654	Schwarz criterion		-5.508329
Log likelihood	234.0734	Hannan-Quinn criter.		-5.596833
F-statistic	2.264177	Durbin-Watson stat		2.156038
Prob(F-statistic)	0.069977			

Source: Own calculations

Figure 2: Crude Oil – Indices and signals





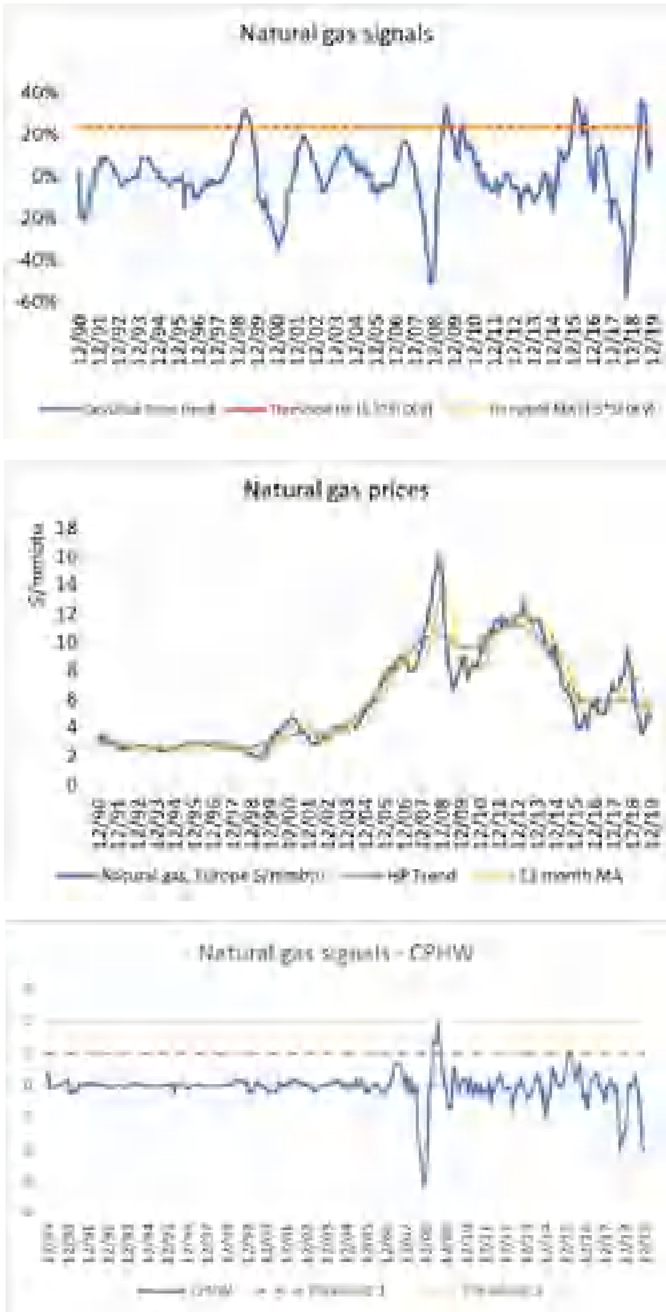


Source: UNCTAD & own calculations

Figure 3: Base metals Indices and signals

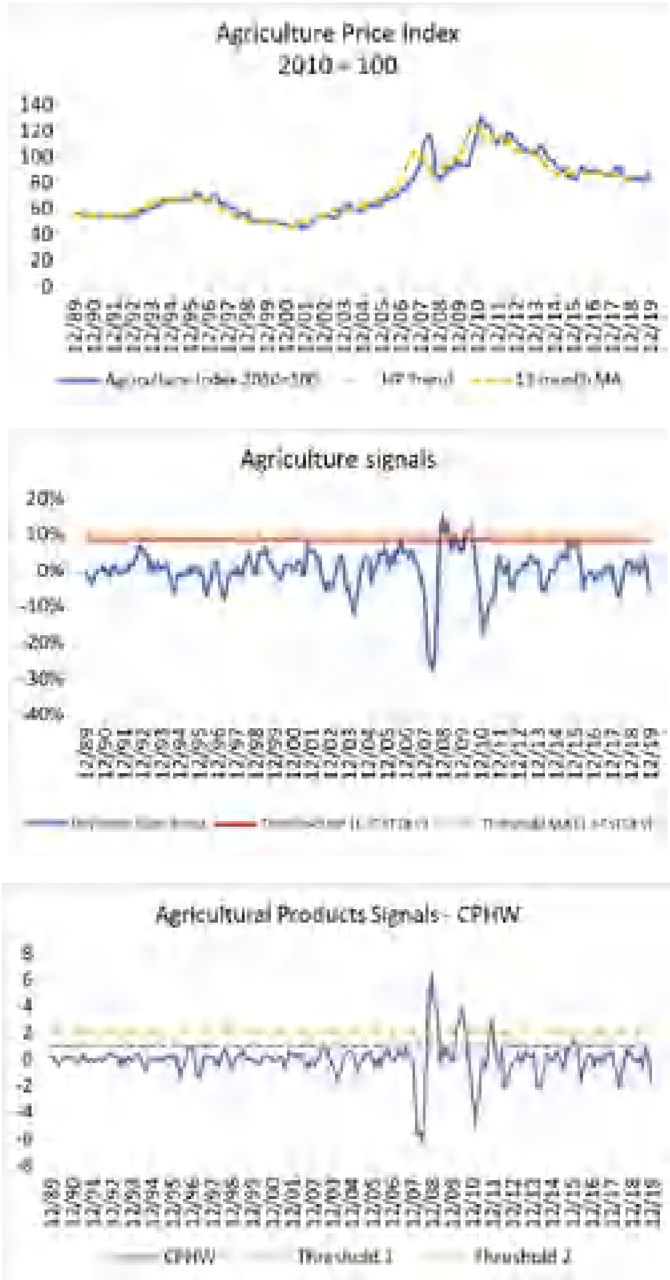
Source: UNCTAD & own calculations

Figure 4: Natural gas Signals



Source: UNCTAD & own calculations

Figure 5: Agricultural Products Signals



Source: UNCTAD & own calculations