

USING PLS METHODOLOGY FOR UNDERSTANDING COMMODITY MARKET BEHAVIOUR AND IMPROVING DECISION-MAKING PROCESS

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After a long and unexpected financial crisis, a period of rapid growth in China and emerging markets, unstable commodity prices behavior, the commodity trading sector confronts a very different landscape, now. In this context, our paper aims to better anticipate commodity market behavior in order to help the commodity investors to improve their decision-making process. Using the PLS methodology (partial least square) and fundamental drivers of commodity market price behavior (macroeconomic and specific indicators), our research proposes to elaborate a rational model to better understand and predict the commodity market movements. Our selecting research methodologies enables to extract the most relevant factors, key drivers, of commodity market behavior and seem to be able to capture a substantial part of systemic market risk. Furthermore, we use bootstrap techniques to identify the optimal model for market behavior. Our results are validated using widely measures used in PLS literature such as: AVE and composite reliability for the outer model validation and R-square and redundancy index for the inner model validation. The empirical results, the path coefficients and the high reliability score, come to confirm the validity of the proposed PLS model and its contribution in assisting the governments and investors in their decision-making process to improve commodity market stability and efficiency.

Key Words- commodity market behavior, key drivers, SEM, PLS model, crisis, decision making

I. INTRODUCTION

In the context of increasing integration of global financial and commodity markets and of major structural changes following the financial and economic crisis in 2008, sudden and extreme price variations have been observed in the commodities market. "The wide and sudden price variations observed on commodities markets since 2007, in particular on oil and agricultural markets, have made commodity price behaviour and volatility a vital issue for the world economy" (G20 Pittsburg Summit, 2009).

Commodity price swings have put growth and economic development at risk, and commodity price volatility has been identified as one of G20 priorities. The world leaders agreed to "improve the regulation, functioning, and transparency of financial and commodity markets" as a premise for financial stability, economic growth and development. However, few concrete measures have been taken, even if the "world commodity markets are undergoing profound changes" (UNCTAD, 2011). "Commodity prices have been particularly volatile over the last decade (IMF, 2011). This volatility has particularly hit poor countries (Stiglitz, 2011), but also developed countries as a consequences of markets internationalisation and globalisation (UNCTAD, 2012). Moreover "the commodities industry has experienced an intense period of change on the back of the rise of China. But after a decade of torrid growth, emerging markets are

slowing down. The industry is preparing new strategies for turbulent times. But change need not mean failure. On the contrary, turbulent times will create new opportunities; new trading strategies will appear, and new markets come into sight." (FT Commodities Global Summit, 2014). All occurred changes are inherent to changing conditions in global economy, and implicitly, adapted to the new exciting opportunities for this market.

II. LITERATURE REVIEW

The commodities prices (including the three major categories: energy, metals and agri-food prices) have experienced periods of boom and bust over the last 150 years (Stürmer, 2013), but after 2008 a new specific price behaviour can be observed in commodities market. This new behaviour characterised by both increasing prices and volatilities (Alquist and Kilian, 2010; Dvir and Rogo, 2010), but also increasing co-movements (Steen and Gjolberg, 2013; West and Wong, 2014) in commodity market prices have become subject of interest (apart for investors and researchers) for many governments and international bodies (World Trade Organization, 2010; IMF, 2012).

The interest to study this price behaviour and volatility in commodity market is due to the major impact that commodities prices may have on macroeconomic conditions of both developing and developed countries (World Trade Organization,

2010; IMF, 2012). “Commodity prices have been particularly volatile over the last decade (IMF, 2011). This volatility has particularly hit poor countries (Stiglitz, 2011), but also developed countries as a consequences of markets internationalisation and globalisation (UNCTAD, 2012). Prices of most commodities rose strongly in the last years, peaking sharply in 2008. For instance, during 2008, the average monthly price of rice (expressed in USD/metric ton for 5% broken milled white rice) doubled within just four months (from 394 USD in February to 1010 USD in May) and decreased strongly within the next seven months of 2008 (to 550 USD in December). These sudden and unexpected movements have renewed the interest in the long-term behaviour and determinants of commodity prices. In this context, the in the last decade the literature in this field has been enriching based on researchers and practitioners activity. The research focus mainly on the drivers (fundamentals, but also new factors) of commodities price behaviour and volatility (Erb and Harvey, 2006; Kilian, 2009; Schwartz, 2012; Prokopczuk and Symeonidis, 2013; Stürmer, 2013; Arezki et al., 2014; Daskalaki et al., 2014). Several studies concluded that commodity markets have become ‘financialized’ and more impacted by the capital markets because of the large influx from financial investors and hedge funds (Steen and Gjolberg, 2013).

The newest researches related to commodity market are focus on five main directions: (1) key drivers of commodity prices (Arezki et al., 2014; Daskalaki et al., 2014; Frankel, J.A., 2014; Mirantes, A.G., Población, J., Serna, G., 2013); (2) commodity price and volatility forecasting and modelling (Fakhri, A., Ghatee, M., 2014.; Gargano, A., Timmermann, A., 2014; West, K.D., Wong, K. F., 2014); (3) new trends and regulations in commodity markets (Mckinsey, 2012; KPMG, 2013; Stichele, 2013). (4) macro- and microeconomics effects of commodity price behaviour (Dauvin, 2014; Zhang, C., Chen, X., 2014.); (5) speculation, heading and arbitrage in commodity markets (Acharya et al., 2013; Frankel, J.A., 2014).

Our paper framed into the first category, key drivers of commodity prices. Understanding key drivers of commodity prices and volatility, but also major trends in the commodities markets is very important (G20, IMF, 2010). Misperceptions regarding the determinants and consequences of price changes and volatility can lead to inappropriate policy decisions with negative impact on micro and macro-economic environment.

III. RESEARCH METHODOLOGY

As we previously mentioned, the commodity market has three large categories of commodities – energy, Table 1 summarizes the Matrices, Constructs and Indicators, and Model Equation Notation generally endorsed in the specialized literature.

metals and agri-food commodities -, and each category includes many elements. The market for each commodity represents several particularities in price evolution compared with other commodities groups, but generally they present many common characteristics.

The research questions is: (1) what are the main key drivers of commodity market prices; (2) what are the cause-effect relationship between these and commodity prices?

In order to answer to these research questions we use the quantitative research methods based on structural equation modeling approach and partial least square methodology.

There are five main stages concerning the empirical part of our research: (1) collect historical indicators; (2) select only the representative indicators and prepare the work database, (3) determine and identify the numbers of commodity price drivers’ clusters and (4) identify the cause-and-effect link between all commodity price drivers’ clusters (5) identify the candidate models and select the optimal one.

Our analysis took into consideration monthly data for the period January 2008 – March 2014. We selected this period because, there are no available data for earlier periods (even if we can isolate find several indicators, there are no data available for all 82 indicators taken into consideration in our analysis). The data used in our paper are extracted from Eikon Thomson Reuters platform.

IV. STRUCTURAL EQUATION MODELING – OVERVIEW

Structural equation modeling (SEM) is a statistical multivariate technique for testing and estimating causal relationships using a combination of statistical data and qualitative causal assumptions. This technique combines aspects of statistical multivariate techniques such as:

multiple regression and factor analysis, but is distinguished by two characteristics: (1) estimation of multiple and interrelated dependence relationships, and (2) the ability to represent unobserved concepts in these relationships and account for measurement error in the estimation process.

SEM is based on causal relationships, in which the change in one variable is assumed to result in a change in another variable. For a mathematical simple representation of the causal relationships between variables, the matrices are used to build the fundamental equations both for structural and measurement models. For a better understanding of SEM mathematical modeling, the

Table 1. SEM Mathematical Modeling Summary

Model Element	Notation		
	Description	Matrix	Element
Structural Model Beta Gamma Phi Psi	Relationships of endogenous to endogenous constructs Relationships of exogenous to endogenous constructs Correlation among exogenous constructs Correlation of structural equations or endogenous constructs	B Γ Φ Ψ	β_{nn} γ_{nm} ϕ_{mm} ψ_{nn}
Measurement Model Lambda –X Lambda –Y Theta – delta Theta – epsilon	Correspondence (loadings) of exogenous indicators Correspondence (loadings) of endogenous indicators Correlation matrix of prediction error for exogenous construct indicators Correlation matrix of prediction error for endogenous construct indicators	Λ_x Λ_y θ_δ θ_ϵ	λ_{pm}^x λ_{qn}^y θ_{pp}^δ θ_{qq}^ϵ
Construct Ksi - Exogenous Eta - Endogenous Indicator X- Exogenous Y- Endogenous	Exogenous construct Endogenous construct Exogenous indicator Endogenous indicator	ξ η X Y	ξ_n η_m x_p y_q
Structural Model StructuralEquation	Relationships between exogenous and endogenous constructs	$\eta = \Gamma \xi + B \eta + \zeta$	
Measurement Model Exogenous equations Endogenous equations	Specification of indicators for exogenous constructs Specifications of indicators for endogenous constructs	$X = \Lambda_x \xi + \delta$ $Y = \Lambda_y \eta + \epsilon$	
Size Subscripts for Matrixes	Number of exogenous constructs Number of endogenous constructs Number of exogenous construct indicators Number of endogenous constructs indicators	m n p q	

4.1. The equation for structural model

Structural model describes certain relationships among the exogenous and endogenous latent variables. This model can give us the responses at the following three questions: (1) Are endogenous variables related to the predictor (exogenous) variables?; (2) Exactly how strong is the influence of each exogenous variable on endogenous variable?; (3) How well does the model fit the data?.

Mathematically, the structural model is represented in the following equation:

$$\eta = \beta\eta + \Gamma\xi + \zeta$$

where η stands for the vector of dependent latent variables (dimension $m \times 1$), ξ is a vector of the independent latent variables (dimension $n \times 1$), ζ is the inner vector of residual variance or the vector of residual variables (dimension $m \times 1$, that is assumed to have an expected value of zero and which is uncorrelated with ξ), β is the $m \times m$ coefficient matrix showing the influence of the latent dependent variables on each other and Γ is the $m \times n$ coefficient matrix for the effects of ξ on η .

More detailed the structural model can be represented as in the following relation:

Table 2. The matrix equations of SEM structural model

Element	Mathematical notations		
Structural model $\eta = \beta\eta + \Gamma\xi + \zeta$	$\begin{pmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_i \\ \vdots \\ \eta_m \end{pmatrix} = \begin{pmatrix} \beta_{11} & \beta_{12} & \dots & \beta_{1j} & \dots & \beta_{1m} \\ \beta_{21} & \beta_{22} & \dots & \beta_{2j} & \dots & \beta_{2m} \\ \vdots & \vdots & & \vdots & & \vdots \\ \beta_{i1} & \beta_{i2} & \dots & \beta_{ij} & \dots & \beta_{im} \\ \vdots & \vdots & & \vdots & & \vdots \\ \beta_{m1} & \beta_{m2} & \dots & \beta_{mj} & \dots & \beta_{mm} \end{pmatrix} \times \begin{pmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_i \\ \vdots \\ \eta_m \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{12} & \dots & \gamma_{1h} & \dots & \gamma_{1n} \\ \gamma_{21} & \gamma_{22} & \dots & \gamma_{2h} & \dots & \gamma_{2n} \\ \vdots & \vdots & & \vdots & & \vdots \\ \gamma_{i1} & \gamma_{i2} & \dots & \gamma_{ih} & \dots & \gamma_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ \gamma_{m1} & \gamma_{m2} & \dots & \gamma_{mh} & \dots & \gamma_{mn} \end{pmatrix} \times \begin{pmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_h \\ \vdots \\ \xi_n \end{pmatrix} + \begin{pmatrix} \zeta_1 \\ \zeta_2 \\ \vdots \\ \zeta_i \\ \vdots \\ \zeta_m \end{pmatrix}$		
Covariance matrix of exogenous constructs	$\Phi = \begin{pmatrix} \phi_{11} & \dots & \phi_{1n} \\ \vdots & \ddots & \vdots \\ \phi_{n1} & \dots & \phi_{nn} \end{pmatrix}$	Covariance matrix of errors among endogenous constructs	$\Psi = \begin{pmatrix} \psi_{11} & \dots & \psi_{m1} \\ \vdots & \ddots & \vdots \\ \psi_{m1} & \dots & \psi_{mm} \end{pmatrix}$

4.2. The equations for measurement model

Measurement model specifies the relationship between the latent variables and the observed variables. This model can give us the responses at the following three questions: (1) To what extent are the observed variables actually measuring the hypothesized latent variables; (2) Which observed variable is the best measure of a particular latent variable; (3) To what extent are the observed variables actually measuring something other than the hypothesized latent variable? Mathematically, we can write this model as in the below equations:

$$x = \Lambda_x \xi + \delta \quad \text{where } x \text{ is the vector of}$$

$$y = \Lambda_y \eta + \varepsilon$$

exogenous manifest variables ($p \times 1$), y is the vector (Table 3):

Table 3. The matrix equations of SEM measurement model

Element	Mathematical notations					
Exogenous variables	$x = \Lambda_x \xi + \delta$	$\begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_p \end{pmatrix} = \begin{pmatrix} \lambda_{11}^x & \lambda_{12}^x & \cdots & \lambda_{1j}^x & \cdots & \lambda_{1n}^x \\ \lambda_{21}^x & \lambda_{22}^x & \cdots & \lambda_{2j}^x & \cdots & \lambda_{2n}^x \\ \vdots & \vdots & & \vdots & & \vdots \\ \lambda_{i1}^x & \lambda_{i2}^x & \cdots & \lambda_{ij}^x & \cdots & \lambda_{in}^x \\ \vdots & \vdots & & \vdots & & \vdots \\ \lambda_{p1}^x & \lambda_{p2}^x & \cdots & \lambda_{pj}^x & \cdots & \lambda_{pn}^x \end{pmatrix} \times \begin{pmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_i \\ \vdots \\ \xi_p \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_i \\ \vdots \\ \delta_p \end{pmatrix}$				
Endogenous variables	$y = \Lambda_y \eta + \varepsilon$	$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_i \\ \vdots \\ Y_q \end{pmatrix} = \begin{pmatrix} \lambda_{11}^y & \lambda_{12}^y & \cdots & \lambda_{1j}^y & \cdots & \lambda_{1m}^y \\ \lambda_{21}^y & \lambda_{22}^y & \cdots & \lambda_{2j}^y & \cdots & \lambda_{2m}^y \\ \vdots & \vdots & & \vdots & & \vdots \\ \lambda_{i1}^y & \lambda_{i2}^y & \cdots & \lambda_{ij}^y & \cdots & \lambda_{im}^y \\ \vdots & \vdots & & \vdots & & \vdots \\ \lambda_{q1}^y & \lambda_{q2}^y & \cdots & \lambda_{qj}^y & \cdots & \lambda_{qm}^y \end{pmatrix} \times \begin{pmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_i \\ \vdots \\ \eta_q \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_i \\ \vdots \\ \varepsilon_q \end{pmatrix}$				
Covariance matrix of measurement errors for exogenous varx	Diagonal matrix	$\Theta_\delta = \text{diag}(\theta_{11}^\delta, \theta_{22}^\delta, \dots, \theta_{pp}^\delta)$	Covariance matrix of measurement errors for exogenous variables	Diagonal matrix	$\Theta_\varepsilon = \text{diag}(\theta_{11}^\varepsilon, \theta_{22}^\varepsilon, \dots, \theta_{qq}^\varepsilon)$	

V. PARTIAL LEAST SQUARE METHODOLOGY – OVERVIEW

Partial least squares regression (PLS) is “a statistical method that bears some relation to principal components regression; instead of finding hyper planes of maximum variance between the response and independent variables, it finds a linear model by projecting the predicted variables and the observable variables to a new space. It is used to find the fundamental relations between two matrices (X and Y), i.e. a latent variable approach to modeling the covariance structures in these two spaces. A PLS model will try to find the multidimensional direction in the X space that explains the maximum multidimensional variance direction in the Y space. PLS-regression is particularly suited when the matrix of predictors has more variables than observations, and when there is multicollinearity among X values”. PLS is a form of variance-based or component-based structural equation modeling. (Wold et al., 2001)

of endogenous manifest variables ($q \times 1$), ξ is a vector of the independent latent variables ($n \times 1$), η is the vector of dependent latent variables ($m \times 1$). Λ_x (dimension $p \times n$) and Λ_y (dimension $q \times m$) are the loadings matrices indicating simple regression coefficients linking the latent variables and their indicators. Consecutively, the remaining variance for the manifest variables δ and ε can be translated as measurement errors or noise. More detailed the measurement model can be represented (

In order to understand the Partial Least Square (PLS) technique for SEM, Chin (1998) studies a simple hypothetical two-block model, referring to the state where two blocks of indicators are summarizing some fundamental issue or construct. In PLS language this is similar to two latent variables each being represented by a block of indicators/variables. The following figure (Figure 2) illustrates a path diagram of a two-block model with two variables per block.

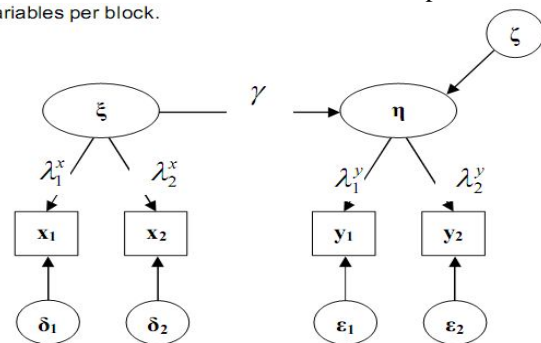


Figure 2. Two-structure model with reflective indicators

In above figure, the variables (x_1 , x_2 , y_1 , y_2), representing observed indicators, are illustrated as influenced by two distinct (i.e., orthogonal) factors labeled as the underlying constructs ξ and η , including an error term ζ . The degree to which these indicators are capable of describing their respective construct is revealed to a large extent by the power of the loadings (λ_1^x , λ_2^x , λ_1^y , and λ_2^y). When building up path diagrams, it is essential to take into account the path relations among blocks as well as between blocks and their respective indicators. In above example, the assumption is a one-way causal relationship between two constructs (ξ and η). Inasmuch as ξ can only account for a fraction of the variance in η , the residual variance at this structural level is supposed to be inherent in ζ . Given a sample series of observed variables, the objective is to work out a procedure for approximating parameters for the measurement model (factor loadings λ_1^x , λ_2^x , λ_1^y , and λ_2^y) and structural model (path coefficient γ and residual variance ζ). The PLS method commences with the aim of determining values of the latent variables for predictive intentions. From this viewpoint, the model from Figure 2 is regarded and used in a different way. Rather than using the model for explaining the covariation of all the variables, it is being altered to minimizing the variance of all latent variables. Therefore, parameter results are computed derived from the facility to minimize the residual variances of latent and observed variables. Overall, all latent variable path models in PLS consist of three suites of relations: (1) the inner model, which describes the links between latent variables, (2) the outer model, which identifies the associations between latent variables and their associated manifest or observed variables, and (3) the weight relations whereupon case values for the latent variable can be estimated. To start with, it can be supposed that latent variables and manifest variables are normalized thus scaled to zero means and unit variances so that the constant parameter terms can be removed in the following equations.

VI. EMPIRICAL CASE STUDY

This empirical part of our paper presents a rationalization approach based on structural equations modelling (SEM) and (graphical) path modeling for commodity market. In order to be more precisely and rigorous in our analysis we focused on crude oil market, because of the availability of more accurate and relevant data related to this market. This is in strong relationship with the increased interest of governments and investors in this market.

4.3. Data Description and Methodology Steps

As mentioned in the introductory, literature review and research methodology parts of our paper, we

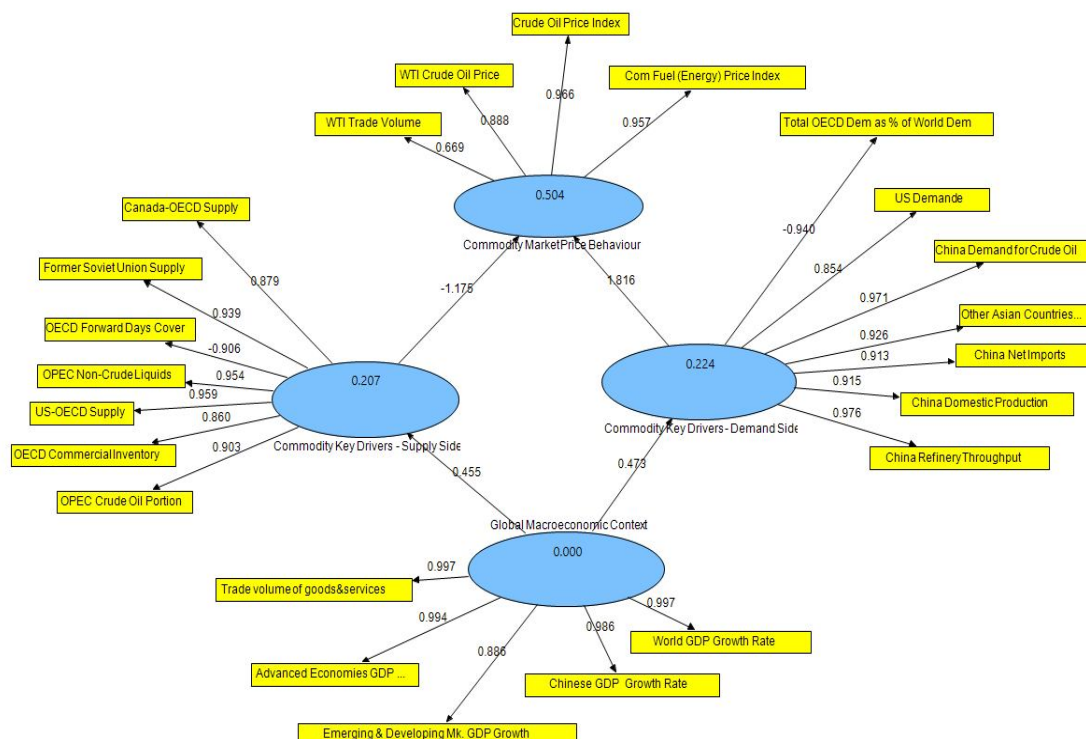
identified numerous different factors with impact on commodity prices (82 quantifiable factors taken into consideration in this paper). These quantifiable factors represent monthly data for the period January 2008 – March 2014, extracted from Eikon Thomson Reuters platform. We selected this period because there are no available data for earlier periods (even if we can isolate find several indicators, there are no data available for all 82 indicators taken into consideration in our analysis) or because of some inconsistencies regarding the computing of these indicators for previous periods. The main idea of this structural modelling is to select from all them, only the key factors with major impact (key drivers) on crude oil price behaviour. Furthermore our approach allows us to classify the selected key drivers in many categories (clusters) and identify the cause-effect relationship (path modeling) between the drivers clusters. As we said, the build of a suitable model is based on SEM approach and the estimation of the model parameters was made using the PLS methodology. More concretely, our empirical statistical analysis, focus specially on three aspects: (1) to identify and cluster the key drivers of commodity prices; (2) to statistically determine and check the cause-effect relationship between the drivers clusters; (3) to validate obtained results.

As we know it is very difficult to correctly select for a specified period, without a statistical tool, the most representative factors with impact on the market and judge the evolution of the influence of the main indicators of market price behaviour. Fortunately, the PLS methodology give us the possibility to solve this type of problem. Furthermore, in order to select the most suitable model for our commodity market, we proposed more alternative models and estimated the parameters for each of proposed alternative models using SmartPLS software. Moreover we proceeded at the evaluation of each alternative model using the SmartPLS validation. For the assessment of overall model (global fit measures), SmartPLS does not offers indicators, but it gives us local fit measure for the assessment both of measurement model (average extracted variance, composite reliability, communality) and for structural model (R-squared of latent endogenous variables, redundancy).

4.4. The Optimal Model selected as Most Appropriate for Commodity Market

Finally, after we applied for each proposed alternative model the above mentioned algorithm, we retained a model with four axes - "Global Macroeconomic Context", "Commodity Key Drivers - Supply Side", "Commodity Key Drivers - Demand Side" and "Commodity Market Price Behaviour" - and for each axis we selected three to six observed variables that we considered as being representative for the respective axis. A graphical representation of our selected model is presented in the following chart:

Figure 1: Commodity Market Key Drivers Cause-and-Effect Chain Using PLS Approach



This graphic illustration represents the optimal model of connection between the four clusters of commodity (crude oil) key drivers. This final indicators and axes were selected using the bootstrap methodology, as representing the most stable PLS graph.

In the above chart we can see both structural model (inner model) and measurement model (outer model). Follow-up we will present the chosen four axes of the optimal structural model for crude oil commodity market:

❖ “Global Macroeconomic Context” Axis: As we can see in the above figure, the composition of this axis is given by macroeconomic indicators. Even if we initially taken into consideration many other macroeconomic indicators related to unemployed, general government revenues, US exchange rate or US interest rate (US being the currency for crude oil quotation and trade), the software selected as being the most relevant only the indicators related to gross domestic product growth rate (with one exception-trade volume of good and services). The five selected indicators for this axis are: “World GDP Growth Rate” and “Trade volume of Goods& Services”, “Advanced Economies GDP Growth”, “Chinese GDP Growth” and “Emerging & Developing Mk. GDP Growth”. One can notice that the relationship of all these five indicators with the axis is positive, that is to say each indicator has a positive impact on the “Global Macroeconomic Context” axis. In fact, it is easy understandable that the increasing in GDP leads to an increasing in demand for crude oil, and implicitly an increasing in supply of crude oil (the supply has to adapt to demand).

❖ “Commodity Key Drivers - Supply Side” Axis: As we can be seen in the above figure, the “Commodity Key Drivers - Supply Side” axis includes seven indicators. The seven selected indicators for this axis are: “US-OECD Supply”, “Canada-OECD Supply”, “Former Soviet Union Supply”, “OECD Commercial Inventory”, “OPEC Crude Oil Production”, “OPEC Non-Crude Oil Liquids”, “OECD Forward Days Cover”. The influence of six of these indicators is positive and of one indicator “OECD Forward Days Cover” is negative. All these variables have a high impact on the axis. The factor loadings are very close or above 0.90 which denotes a very high influence of these variables as well as a confirmation for the validation of axis measurement model. That means that a significant change in one of the variables will generate a strong influence on the axis and the global model. We want to underline the negative correlation between “OECD Forward Days Cover” indicator and the “Commodity Key Drivers - Supply Side” axis. Thus, the lower this indicator, the more uncertainty in the market and, the price has the tendency to increase.

❖ “Commodity Key Drivers - Demand Side” Axis: For the construction of this axis there was selected seven indicators: “Total OECD Demand as % of World Demand”, “US Demand”, “China Demand for Crude Oil”, “Other Asian Countries Demand”, “China Net Imports”, “China Domestic Production”, “China Refinery Throughput”. As we can observe from the above figure, the impact of these indicators on the “Commodity Key Drivers - Demand Side” axis is relatively high (given by the factor loadings). That means that a significant

change in observed indicators will strongly affect the demand axis as well as the global model. Factor loadings greater than 0.9 (except one) confirm a suitable selection of the indicators for “Commodity Key Drivers - Demand Side” construct in the measurement model. It is important to emphasize that the correlations between indicators and axis are absolutely normal in real crude oil commodity market. Furthermore, we want to underline the selection of four indicators related to Chinese implied demand for crude oil. This is a distinguished characteristic observed more in commodity market after the financial and commodity crisis, coinciding with the starting period of boom for China economy.

❖ “Commodity Market Price Behaviour” Axis: The composition of the “Commodity Market Price Behaviour” axis is given by indicators related to crude oil market price. The four selected indicators for this axis are: “Crude Oil Price Index”, WTI Crude Oil Price”, “WTI Trade Volume”, “Commodity Fuel (Energy) Price Index”. As there was normally, the market price indicators are influenced by supply and demand. The obtained results - indicators with opposite sign for the impact of supply and demand axe on “Commodity market Price Behaviour” axis – indicate the correctness of statistical results, and reconfirmation in this particularly study case of the “Supply and Demand Law”.

As we can see in the above Figure 1, the selected optimal model highlights the following aspects:

- The “Global Macroeconomic Context” axis represents the basis for commodity market pricing as it is also the case in other financial and capital markets. Furthermore it is important to emphasize one particularity for crude oil market: the stronger impact of indicators related to GDP evolution.
- The “Global Macroeconomic Context” axis has a direct relatively high impact on the following

two axes: “Commodity Key Drivers - Demand Side” and “Commodity Key Drivers - Supply Side” and an indirect impact on the “Commodity Market Price Behaviour” axis. This means that the GDP growth indicators and trade volume of goods and services have a direct influence on commodity demand and supply.

- The “Commodity Key Drivers - Demand Side” axis has a direct positive impact on the “Commodity Market Price Behaviour” axis. That means the higher the level of commodity demand, the higher the level of prices.
- The “Commodity Key Drivers - Supply Side” have a direct negative impact on the “Commodity Market Price Behaviour” axis. That means the higher the levels of commodity supply, the lower the level of prices.

4.5. Data analysis and validation

As we previously mentioned, we proposed more alternative models and estimated the parameters for each of proposed alternative models using SmartPLS software. Moreover we proceeded at the evaluation of each alternative model using the SmartPLS validation. For the assessment of overall model (global fit measures), SmartPLS does not offers indicators, but it gives us local fit measure for the assessment both of measurement model (average extracted variance, composite reliability, communality) and for structural model (R-squared of latent endogenous variables, redundancy). Also, the factors loadings figures are considered as indicators for assessments of the measurement model.

In our actual paper we will present the model evaluation only for the model chosen by us as being the most suitable crude oil commodity market. The validation criteria calculated for our final model are presented in the following table:

Table 4. PLS model evaluation criteria

	AVE	Composite Reliability	Communality	R-Square	Redundancy
Commodity Key Drivers - Demand Side	0.8622	0.9566	0.8622	0.2241	0.1888
Commodity Key Drivers - Supply Side	0.8370	0.9486	0.8370	0.2072	0.1612
Commodity Market Price Behaviour	0.7707	0.9295	0.7707	0.5038	0.1894
Global Macroeconomic Context	0.9469	0.9888	0.9469	0.000	0.0000

Generally the validation measures (indicators) indicate us the construction of a good and relevant model for commodity market. All the loading factors have values higher than 0.8 which means that more than 64% ($0.8^2 \sim 0.64$) from the variance of each manifest variable is explained by the associated latent variable.

Also for each of all four latent variables, the AVE indicator is higher than 0.5, indicating that the chosen latent variable for each observed indicator, explain

better the variance of its own indicators than the other latent variables.

Furthermore the composite reliability and communality (shows the contribution of a latent variable in explaining the variance of all associated manifest variables) indicators, as measure of internal consistency, have values greater than 0.6, indicating a good measurement model. The values closed to 1 indicate us that the model explains the most part of the variance of observed variables.

When it comes to structural model assessment, the most suitable indicators calculated by SmartPLS are: R-Square and Redundancy measures.

Regarding to redundancy criterion that expresses how much of the variance in one set of variables can be explained by the others (the redundancy coefficient is a measure of the amount of variance in one set of variables that is “redundant” or shared with the variance in the other set of variables), we can affirm that our structural model is also a valid model for commodity market.

Concerning R-Squared, as we know, values of 0.67, 0.33 and 0.17 are considered to be strong, moderate and respectively weak for the inner model valuation. The R-square measures indicate a strong to moderate value for “Commodity Market Price Behaviour”, but a weak value for “Commodity Key Drivers - Demand Side” and “Commodity Key Drivers - Supply Side” axes. This indicator calculated only for the dependent latent variables in the inner path model (structural model) show us the influence of one or more exogenous latent variables of one endogenous latent variable. The R-Square value for “Commodity Market Price Behaviour” axes indicates that more than 50% from variance in “Commodity Market Price Behaviour” construct is explained by our model. But, the less values of R-Square for “Commodity Key Drivers - Demand Side” and “Commodity Key Drivers - Supply Side” constructs indicate that only 22%, and respectively 20%, of the total variance is explained by the model (the difference until 100% being explained by other factors that are not considered by our model). There is a limit of our model indicating that real database is uncompleted, having no other indicators with direct impact on “Supply” or “Offer”. Also these segments are influenced by other external factors (financialization of commodity market, production of bio-fuel, weather, etc) not find for the moment in international monthly statistics for the period 2008-2014, but which could be considered in order to develop a better model.

Overall we can conclude that the identified optimal model for commodity market is a good model (but can be improved) and the best from other alternative models that can be constructed with the current database using PLS methodology.

V. SUMMARY AND CONCLUSIONS

The need for developing simple, comprehensive and relevant instruments for commodity market behaviour modeling was behind of our idea to find and develop a rationalization structural model for crude oil market. The most important, but also the most difficult part in the applying of the PLS methodology is the choice of the axis (latent variables or balanced scored perspectives) and of the corresponding variables (observable indicators or manifest variables). Once identified, the PLS approach give us

the possibility to represent and measure the cause-and-effect connections between variable and axes, on one hand, and between the axes themselves (a hierarchy of them), on the other hand. The use of this approach allows not only understanding the chain of causality, but also understanding better the commodity market price behaviour for the period taken into consideration. In our illustration, we concluded, using SmartPLS software a theoretical framework for a pragmatic approach. Our proposed model highlights the following aspects: the starting point for commodity market prices is represented by global macroeconomic environment. Furthermore the macroeconomic environment has a direct relatively high impact on “commodity demand” and “commodity supply” and an indirect impact on the “commodity market prices”. Also the “commodity demand” has a direct positive impact on the “commodity prices”, and “commodity supply” has a direct negative impact on “commodity prices”, being perfectly in accordance with the law of demand and supply. Overall, the empirical results obtained in our example, the path coefficients and the high reliability score, come to confirm the validity of the proposed structural model and its values in assisting the governments and investors in their decision-making process for improving commodity market stability and efficiency.

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