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Long Run Relationships between Base Metals, Gold and Oil

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ABSTRACT

This paper investigates the possible presence of long-run relationships (cointegration) among base metals and between base metals, Crude oil and Gold, using the Johansen multivariate approach and VEC Engle-Granger causality tests. The commodities used are seven base metals: Aluminum, Aluminum Alloy, Copper, Nickel, Zink, and Tin (from the London Metal Exchange), Crude oil and Gold. The Johansen approach results indicate that Aluminum, Copper, Gold and Nickel share long-run relationships with each other. VEC Granger Causality test at 10% significance level shows that all nine variables are cointegrated with at least one of the remaining variables in the group which indicate the diversification possibilities are limited. As for the price discovery, price development of Aluminum and especially Copper should be given more attention, since they Granger-cause several of the other variables.

Key Words: Johansen Cointegration Test, VEC Granger Causality, Weak Exogeneity, Commodities

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1. Introduction

In July 2007 prices on three groups of commodities (crude oil, gold, and base metals) decreases, with the common factor being rallying US dollar, and an article in London South East discusses the possible relationship. Harvey (2007), the author of the article, points out that oil and gold rather often move closely together over time. Also gold and base metals seem to have a long-term relationship, even though it may be weaker than in the case of oil and gold.

On the 5th of Feb, 2010 one can read in *Financial Times* that prices on gold, base metals and oil all have gone down (Flood, C., 2010). This time the cause named is worries in the sovereign debt market.

What is the price relationship between oil and base metals? On the one hand, during the expansion phase in a business cycle, both oil prices and metal prices should rise due to increase in demand for both. On the other hand, it is known that high oil prices have a depressing effect on general business activity and there is strong evidence that too high oil prices may be causing recessions (Engemann et al., 2010).

What price links do exist between oil and gold? On the one hand, when inflation increases and energy prices go up, so does the gold price, as it is used to hedge off the effect. On the other hand, in times of high volatility demand for oil plunge and its price goes down, whereas gold price goes up as the precious metal is seen as "safe heaven" investment (Durrant, 2007). But gold has competitors in that role, not least government bonds. Thus the positive relationship between oil price and gold price could persist even in times of high market volatility, according to Peter Fertig, an analyst at Dresdner Kleinwort and cited in London South East in July 2007.

When it comes to possible long-term relationships between gold and industrial metals it may be necessary to remember in what areas gold is used. The precious metal is not merely a vehicle for wealth conservation and input for jewelry production. In fact, Goldipedia (2010) lists a range of areas where gold is used due to its numerous valuable properties: electronics, space & aeronotics, medical, cleantech /environmental, nanotechnology, dentistry, decorative, engineering, food & drink; beauty. It is suggested that recently the industrial demand for gold has been a major factor in driving the gold price up (Ibid.). Therefore, we think there could potentially be a cointegrating relationship between industrial metals prices and the gold price during bull markets. The relationship could be there during bear markets as well. According to Michael Widmer, an analyst at Clayton, price decrease for commodities is generally followed by price decrease for gold, as many investors prefer to hold cash (Harvey, J., 2007).

The three commodity groups' price movements seem to have at least short term relationships, as the variables exhibit positive correlations both in levels and in returns (see *Appendix B-G, Table 1-6*). So, is it a "normal" behavior for the three type of commodities to move together, i.e. do they have a long-term relationship, or are these just temporary co-movements? With this paper we aim to find that out using cointegration analysis.

We use 15-year daily closing prices, acquired from DataStream, for base metals traded on London Metal Exchange, for gold, traded on London Bullion Market Association, and for Brent Crude oil, traded on electronic Intercontinental Exchange.

Studies of long-run relationships between non-stationary variables have been greatly facilitated by the introduction of the notion of cointegration and a testing method by Clive Granger and Robert Engle in the 1980s. The two famous econometricians show that two time series, both containing a unit root, share a long-term relationship, i.e. are cointegrated, if a linear combination of the two is stationary. This enables researches to discriminate between spurious and meaningful regressions. It allows econometricians to utilize the information contained in levels, which previously was lost due to the, until that time, common procedure of conducting studies on first-differenced data and thus retaining only short-term information in the time series.

Although the Engle-Granger methodology from 1987 for detecting cointegration and estimating the parameters has become very popular, it has a number of deficiencies. Therefore, for this study we have chosen to mainly use the Johansen multivariate method to test the data for cointegration, and VEC Granger-causality test to determine potential lead-lag regularities.

1.1 Purpose and Motivation

This paper studies the possible presence of long-run relationship(s) among base metals, as well as between base metals, gold and oil. In the presence of the long-run relationships, the causality in the relationships for the commodities is investigated.

For an investor the results of the study concerning the possible presence of long-run relationships should be of interest as they indicate whether there are long-term diversification benefits in being active in all three markets. And identification of stable lead-lag relationships could provide the investor with some ability to "predict" future. We were not able to find studies similar to this, and therefore we wish to fill some of the gap with our little contribution.

1.2 Outline of the Study

The rest of this paper is organized as follows: Section 2 presents a brief review of relevant previous studies. In section 3 we describe the data we use for the study. In section 4 we explain our methodology. Section 5 presents the empirical results and analysis and Section 6 illustrates the limitation of the study and our suggestion for further research. The last section concludes the paper.

2. Literature Review

Few existing studies look into cointegration and lead lag relationship between crude oil, gold and base metals. The studies, we have come across, have a focus that is either narrower or wider, compared to our study. Some of the researchers choose to investigate potential long-run relationship between spot price and some financial instrument(s) with the same underlying asset. Other researchers look for cointegration between some asset(s), and macroeconomic factors.

Watkins and McAleer (2002) examine the long term relationship between copper futures and spot price based on the risk premium hypothesis and the theory of storage. They extend the previous research to take unit root and non-stationarity into account. Johansen cointegration approach with the adjusted empirical model is utilized with daily data for spot and 3-month contract settlement price of copper from the 3^{d} of Jan 1989 to the 30th of Sep 1998 obtained from the London Market Exchange. Moreover, since the contracts on LME are denominated in US Dollars, the data also includes the US dollar 3-month Treasury bill secondary market rate as interest rate to detect the macroeconomic effect. The results indicate that there exists long run correlation with the full sample set while only two out of the three sub-sample sets have this relationship if considering the structural break. This study focuses on the cointegration relationships between financial instruments on the same underlying whereas we are interested in the cointegration relationships between different commodities.

Sari et al (2010) use both Johansen methods and Pesaran's bounds testing approach to check for cointegration between the spot prices for oil, precious metals, and exchange rate. In the test, daily data of closing spot price for 4 commodities (gold, silver, platinum and palladium), oil spot price and USD/euro exchange rate with the period from the 1st of Apr 1999 to 19th Sep 2007 is used. All series are modeled in natural logarithms. Dummy variables are also considered for establishment of the oil price band by Organization of the Petroleum Exporting Countries (OPEC) in 2000, the 9/11 New York City attack and the 2003 Iraq war. Before testing the data, they use the forecast error variance decomposition (VDC) and generalized impulse response approaches to understand the impacts and reaction to shocks. The results from bounds test suggest that there is no cointegration among the precious metals spot price, oil prices and the exchange rate although they have strong correlations in the short run. JJ test confirms the results that there is no long run equilibrium relationship between the spot price returns and changes in the exchange rate. The authors conclude that the tested commodities may be not sensitive to common macroeconomic factors in the long-run but that the precious metal's spot prices and exchange rate may be closely related in the short run after shocks occur. In our study, instead of using exchange rate or other macroeconomic factors, base metals are used.

Testing and detecting cointegrating relationships between financial assets can not provide sufficient information to investors for their hedging strategies. Therefore, lead-lag relationships of the commodities need to be investigated. Many researchers have studied this issue, but often the researchers focus on cointegration between financial instruments on the same underlying asset.

Garbade and Silber (1983) point out that futures markets perform the function of price discovery which indicates that futures price lead the spot price. The following researchers apply this Garbade-Silber Model on various commodities. Silvapulle and Moosa (1999) test the crude oil market and confirm Garbade-Silber's discovery. They argue that because of the lower transaction cost and convenience of shorting, futures price responds to new information much more quickly than the spot price. Asche and Guttormsen (2002) also try to find out whether there is a lead-lag relationship between spot and futures prices for gas oil with the improvement of using the Johansen test in the multivariate framework. Monthly data from Apr 1981 to Sep 2001 with the futures contracts maturing in 1, 3 and 6 months are used. After affirming the time series are cointegrated, exogeneity test is utilized for the causality relationships. Empirical results indicate that futures price leads the spot price and it plays a price discovering role. Besides, futures contacts with longer maturity lead those with shorter maturity. In our study, we are more interested in finding out whether some commodities are performing that price discovery function towards other commodities in the system.

Nevertheless, limited researches have been conducted to explore the relationship between crude oil, base metals and gold. Cashin et al (1999) test the correlations between seven seemingly-unrelated commodities: wheat, copper, crude oil, gold, lumber and cocoa; with the time period from April 1960 to November 1985. Empirical results demonstrate that there exist significant correlations. The analysis is implemented using a longer time period, from Jan 1957 to July 1999, and the results display that crude oil and gold have significant harmony in prices. Nonetheless, their study can not find whether these commodities' prices move together. In our study we partly replicate the research with newer data, since we only test crude oil, gold, copper and several other base metals for cointegration during the period 1995-2010.

Baffes (2007) examines the price effect of crude oil on some other commodities. One of the results is that aluminum has almost zero elasticity. That happens maybe due to the fact that electricity and natural gas markets, which aluminum production is subjected to, are local, thus not responsive to global energy demand and supply conditions. The unresponsiveness of copper, nickel, and zinc prices to the price of crude oil is mainly due to the long term negotiated price between extraction companies and governments of the countries where the resource is extracted. On the contrary, iron and tin have highly significant estimate, probably due to high costs, e.g. transportation cost, and Tin Agreement, respectively. The author assumes from the beginning that it is crude oil which is affecting other commodities. We do not assume anything and allow for the possibility that other commodities may influence the crude oil price.

Most of the studies we have mentioned above focus narrowly on finding the relationship between the spot and derivatives prices with the same underlying assets or assets spot prices and some macroeconomics factors, such as interest rates and exchange rates. To the best of our knowledge, the research of base metals, crude oil and gold has not been conducted before. Therefore with this study we aim to contribute to the field of research on issues of cointegration between commodities: Crude Oil, Gold, Aluminum, Aluminum Alloy, Lead, Copper, Tin, Zinc and Nickel.

3. Data

Commodities studied in this report are Aluminum, Aluminum Alloy, Copper, Lead, Nickel, Tin, Zinc, Crude Oil and Gold. Daily data on these commodities' spot prices cover a 15-year period, from the 7th of April 1995 to the 7th of April 2010, and is obtained from *DataStream*. Each time series contains 3914 observations. Silver is excluded mainly due to the lack of data for the time period. Besides, Ciner (2001)'s study finds that gold and silver do not have long run relationship which is also consistent with the findings by Escribano and Granger in 1998.

The metal prices except gold are retrieved from London Metal Exchange (LME)[1] which is the world's premier non-ferrous metals market located in London. Gold price is obtained from London Bullion Market (LBM)[2]. Prices quoted by the LME prior to July 1993 are denominated in British Pounds while after that in US dollars. Considering the time period in this report, all the commodities are traded in US dollars[3]. Brent crude oil was originally traded on the open-outcry International Petroleum Exchange in London, but since 2005 has been traded on the electronic Intercontinental Exchange, known as ICE.

Table 3.1: Nine variables used in the study

Data name from DataStream	**Adjust name**	**Average Inventory Volume**
LME-Aluminium 99.7% Cash U$/MT	Aluminium(Almn)	1 106 364,35
LME-Aluminium Alloy Cash U$/MT	Almn Alloy	67 382,96
LME-Copper, Grade A Cash U$/MT	Copper	373 982,33
LME-Lead Cash U$/MT	Lead	110 032,58
LME-Nickel Cash U$/MT	Nickel	41 237,79
LME-Tin 99.85% Cash U$/MT	Tin	13 489,07
LME-SHG Zinc 99.995% Cash U$/MT	Zinc	425 411,61
Crude Oil-Brent M UK Close U$/BBL	Oil	N.A.
Gold Bullion LBM U$/Troy Ounce	Gold	N.A.

Where: LME: London Metal Exchange;
LBM: London Bullion Market;
Percentage of the metal represents the minimum purity of this metal;

[1] London Metal Exchange (LME) is the futures exchange with the world's largest market in options, and futures contracts on base and other metals

[2] London Bullion Market (LBM) is a wholesale over-the-counter market for the trading of gold and silver. Trading is conducted amongst members of the London Bullion Market Association (LBMA).

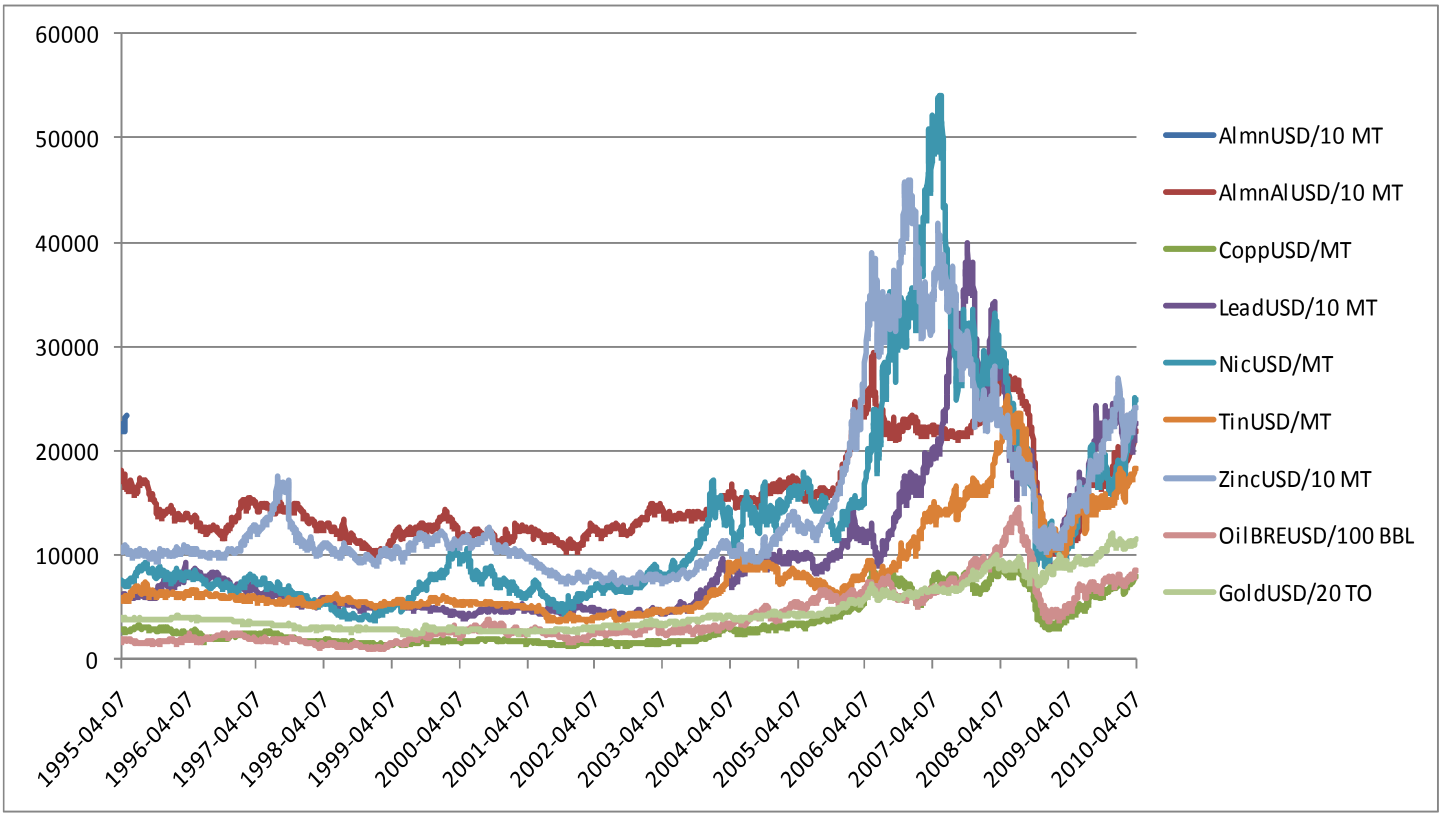
[3] However, even if the commodities are traded in different currencies, there is no need to convert them into the same one since Alexander (2001) strongly argues that cointegration analysis between markets should be completed in each indices local currency to better capture the co-movements in the different market. Subramanian (2009) also points out that using the original currency could help to avoid fluctuation in cross-country exchange rate and the restrictive assumption of holding purchasing power parity.

Cash U$: Spot price traded in US dollars;
SHG: Super high grade;
MT: Metric Ton;
BBL: the abbreviation of and oil barrel;
N.A.: not available.

Figure 3.1 plots the movement of the commodities' spot price during the 15-year period. The data used in this study is in natural logs. (See *Appendix A Figure 1*)

The descriptive statistics of all logged and raw data as well as log returns and their correlations are presented in *Appendix B-G Table 1-6*. The tables show that all of the commodities have positive correlation with each other which means diversification benefits in the short run are limited.

Figure 3.1 Commodities' spot price from 7th April 1995 to 7th April 2010



Note: AlmnUSD/10 MT and AlmnAlUSD/10 MT represent the price of Aluminum per 10 MT and the price of Aluminum Alloy per 10 MT, respectively;
CoppUSD/MT represents the price of copper per MT;
LeadUSD/10 MT represents the price of Lead per 10 MT;
NicUSD/MT and TinUSD/MT represents price for Nickel and Tin per MT, respectively;
ZincUSD/10 MT is the price of Zinc per 10 MT;
OilBREUSD/100 BBL is the price for Crude oil per 100 oil barrel;
GoldUSD/20 TO represents the price of gold per 20 troy ounce.

4. Methodology

To answer the question of this paper, we adopt the following strategy. We start by testing the variables for non-stationarity. A necessary condition for cointegration between the variables is that the variables are non-stationary, i.e. integrated of order higher than zero. We conduct confirmatory data analysis by utilizing both unit root tests (Augmented Dickey-Fuller (ADF) test, Phillips–Perron (PP) test) and a stationarity test (Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test). We proceed with the test procedures for cointegration. Our main method is the Johansen multivariate methodology based on Vector Autoregression (VAR). Akaike information criteria (AIC) is used to determine the lag length in the VAR. Next, the reduced rank regression is run on three different Vector Error Correction (VEC) models. The difference between the models is the deterministic components, i.e. a constant and trend. Applying the Pantula Principle, the optimal VEC model as well as the rank (the number of cointegrating vectors) is determined and two cointegrating vectors are obtained. Without strong economic theory to be used as a guide for identifying restrictions later on, Aluminum Alloy is excluded. The logic behind the decision is that Aluminum and Aluminum Alloy are probably strongly cointegrated. Both the Engle-Granger cointegration test and the Johansen test confirm our guess. The Granger-causality test shows a bi-directional cointegrating relationship. The reason that Aluminum Alloy is skipped but not Aluminum is their respective average inventory volume difference (see *Table 3.1*). The previous steps of the Johansen methodology are repeated on the eight variables left. The eight variables in the unrestricted Vector Error Correction Model (VECM) selected are then tested for weak exogeneity (restrictions on $\boldsymbol{\alpha}$) by imposing joint restrictions on the speed of adjustment coefficients vector $\boldsymbol{\alpha}$ and the cointegrating coefficients vector $\boldsymbol{\beta}$. The directions of the cointegrating relationships detected in the Johansen approach for both unrestricted and conditional models are examined with VEC Granger-causality test. Below, both the relevance of the methodology and the practical implementation are presented in more detail.

4.1 Stationarity

Before applying the cointegration test, it is necessary to test whether the time series are stationary. The weak form of stationarity, which is the most commonly used form for practical reasons, is present when a time series has a constant mean, a constant variance and a constant autocovariance:

$$E(y_t) = \mu \qquad (4.1)$$

$$E[(y_t - \mu)^2] = \sigma^2 < \infty \qquad (4.2)$$

$$E(y_{t1} - \mu)(y_{t2} - \mu) = \gamma_{t2-t1}, \text{ for all } t_2\text{-}t_1 \qquad (4.3)$$

A time series, consequently, is non-stationary if any of the conditions is violated, i.e. its mean, variance and covariance are time depending.

Stationary and non-stationary time series have greatly different behaviors and properties. In a stationary process a "shock" at time t has a diminishing influence on the system as time goes by, i.e. lower effect at t+1, even lower at t+2, etc., and gradually dies away. In contrast, in a non-stationary process the effect of a "shock" always persists infinitely into the future without losing its strength.

Application of standard regression techniques on economically unrelated non-stationary time series data can result in Spurious, or Nonsense, Regressions. Regressing one non-stationary time series on a different unrelated non-stationary time series can give high R^2 and significant coefficient estimates, simply because both series are trending over time, even though there is no real long-term relationship between the series.

Standard assumptions on asymptotic analysis are not valid in a regression model that is based on non-stationary time series, i.e. the t-statistic, F-statistic, etc. do not follow their respective distributions.

Among different non-stationary models, one that is frequently used and of interest for this paper is the random walk model with drift, also known as stochastic non-stationarity with stochastic trend in the data:

$$y_t = \mu + y_{t-1} + u_t \qquad (4.4)$$

where u_t is a white noise disturbance term.

The expression in (4.4) can be generalized to an autoregression model with one lag (AR(1)):

$$y_t = \mu + \varphi y_{t-1} + u_t \quad (4.5)$$

If φ =1, then the equation (4.5) is reduced to equation (4.4) which means that the time series is non-stationary. In this case y_t is equal to the sum of all the "shocks" up to time t plus an initial value of y at time 0:

$$y_t = y_0 + \sum_{t=0}^{\infty} \mu_t,\ t \rightarrow \infty. \quad (4.6)$$

This type of process is also called a unit root process, because the characteristic equation for this process has the root of one[4]. In order to make this non-stationary time series stationary one needs to difference (4.4) once:

$$y_t - y_{t-1} = \mu + y_{t-1} - y_{t-1} + u_t = \mu + u_t \quad (4.7)$$

This type of a non-stationary time-series is therefore known as difference - stationary, since the method to use to make it stationary is to difference it. (Brooks, 2008)

4.2 Stationarity and Unit Root Tests

Because of the large differences in the properties of stationary and non-stationary time series, it is important to check the data one uses for stationarity. The three most commonly used tests to decide whether a time series is stationary or non-stationary are the Augmented Dickey-Fuller test (ADF-test), Phillipls-Perron's test (PP-test), and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS-test). The three tests are hypothesis tests, but the first two tests are unit root tests and the third one, KPSS-test, is a stationarity test. ADF test and PP test have the null hypothesis that the time series is integrated of order one, usually denoted I(1), against the

[4] Theoretically, it is possible that φ >1, but this case is usually ignored as it does not describe many financial or economic time series. The case of φ >1 is also intuitively unappealing as it would mean that a "shock" at time t increases its effect into the future, instead of fading away.

alternative hypothesis, that the series is stationary, denoted I(0). The KPSS test switches the hypotheses and has as the null hypothesis that the time series is stationary.

Consider the following autoregression model, which can also include a constant term and a trend term:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p-1} \alpha \Delta y_{t-i} + \mu + \gamma_t + u_t \qquad (4.8)$$

where $\Delta y_t = y_t - y_{t-1}$, and $\psi = \varphi - 1$.

The ADF method tests the following hypothesis:

H_0: $\psi = 0$, the time series has a unit root, i.e. it is non-stationary.

H_1: $\psi < 0$, the time series does not have a unit root, i.e. it is stationary.

The lags in equation (4.8) are included in order to capture all dynamic structure in the endogenous variable and thus make certain that the residual term u_t is not autocorrelated (the residuals have to be white noise in order for this test to be valid). It is therefore important to decide on the number of lags to include. One way to decide on the number of lags to be included in the equation is by choosing the number of lags that minimizes the Akaike Information Criteria (AIC) or the Schwarz Information Criteria.

The test statistic $\left(\frac{\hat{\psi}}{\widehat{\mathrm{SE}}\,(\hat{\psi})}\right)$[5] of the ADF-test follows a non-standard distribution, Dickey-Fuller distribution, and not the normal t-distribution.

The PP test is similar to the ADF test with that difference that is allows the residuals to be autocorrelated. Therefore the ADF test and the PP test often give similar results and share pretty much the same weaknesses.

The major issue with the two tests is that they have a very low power to distinguish between a unit root process and a process that is close to unit root but nevertheless is stationary. This problem is more prominent if the sample is small. The reason the problem is present is that the null hypothesis can not be rejected in two cases. The first one is if the process is indeed non-stationary and the second one is if there is not enough information.

[5] $\widehat{\mathrm{SE}}\,(\hat{\psi})$ is the estimated standard error of ψ.

One way to mitigate the problem is by conducting a confirmatory data analysis, which means that one utilizes a stationarity test as a complement to the unit test(s) used. One such test is the KPSS test. As mentioned before, the KPSS has switched the hypotheses:

H_0: the time series does not have a unit root, i.e. it is stationary

H_1: the time series has a unit root, i.e. it is non-stationary. (Brooks, 2008)

Ideally, the three tests should give results consistent with each other, i.e. if a time series contains a unit root, then the ADF and PP- tests should accept the null, and the KPSS-test should reject the null. If the results of the unit root test are contradicting to that of the stationarity test, then either additional tests are needed or a choice has to be made. Harris and Sollis (2005) suggest that in an unclear situation, the unit root test results should be preferred, because of the consequences (see *section 4.1*) of a unit root in time series.

4.3 Cointegration

A problem one usually faces when using non-stationary variables, that have no real relationship with each other, is that one can get regressions that "look" good (high R^2, highly significant coefficients), but actually are meaningless. However, obviously, not all integrated variables lack real relationships with each other. Many financial variables move closely together in the long-term, as they are influenced by the same market forces or influence each other. Stock prices and their options prices, spot prices and futures prices or other similar time series, for example, can be expected to move together in the long-run, as they have the same underlying or otherwise are connected. Thus, such variables can be cointegrated, meaning that even though the time series in question are non-stationary, they can trend over time in a similar fashion and therefore difference between them can be expected to be constant (Harris & Sollis, 2003). Thus, non-stationary time series that exhibit a long-term equilibrium relationship are said to be cointegrated. The possibility of non-stationary time series to be cointegrated was first considered in 1970's by Engle and Granger. They define cointegrated variables in their paper from 1987 in the following way.

Consider two non-stationary time series, y_t and x_t where each of the time series become stationary after differencing once, i.e. they are both integrated of order one, I(1). These non-stationary time series are then said to be cointegrated of order one-one, CI(1,1) if there exists a cointegrating vector α that in a linear combination of the two variables yields a stationary disturbance term $\mu_t \sim I(0)$, in the regression $\mu_t = y_t - \alpha x_t$. Cointegration means that these non-stationary variables share a long run relationship, and thus the new time series from combining the related non-stationary time series is stationary, i.e. the deviations have finite variance and a constant mean. Note that non-stationary variables can also have a non-linear cointegrating relationship(s), but that is outside the scope of this paper.

In general, two series are cointegrated if they are both integrated of order d, I(d) and a linear combination of them has a lower order of integration, (d-b), where b>0. Time series have to be non-stationary for them to be able to be cointegrated. Thus, one stationary variable and one non-stationary variable cannot have a long-term co-movement, as the first one has a constant mean and finite variance, whereas the second one does not, so the gap between the two will not be stationary. But, if there are more than two time series in a system, it is possible for them to have different order of integration. Consider three time series, $y_t \sim I(2)$, $x_t \sim I(2)$, $q_t \sim I(1)$. If y_t and x_t are cointegrated, so that their linear combination results in a disturbance term $\mu_t = y_t - \alpha x_t$ which is integrated of order 1, I(1), then it is potentially possible that u_t and q_t are cointegrated with resulting stationary disturbance term $s_t = q_t - \beta u_t$., where α,β are cointegrating vectors. In general, with n integrated variables there can potentially exist up to n-1 cointegrating vectors.

4.3.1 Error Correction Model

Engle and Granger (1987) show that if two variables are cointegrated then there must exist an Error Correction Model (ECM) and vice versa. An error correction model, also called an equilibrium correction model, is a model belonging to a class of dynamic models that can be used to estimate a long-run relationship between cointegrated variables. The model includes a combination of lagged values, as well as first differences of the variables being tested:

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \gamma x_{t-1}) + u_t \qquad (4.9)$$

where $\Delta x_t = x_t - x_{t-1}$

An error correction model includes both short-run and long-run effects that determine how the dependent variable evolves over time. The term ($y_{t-1} - \gamma x_{t-1}$) in the error correction model above is called *error correction term* and is stationary, if x_t and y_t are cointegrated with the cointegrating coefficient γ. This term is equal to zero when the system of the two variables is in its long-term equilibrium, otherwise it is different from zero and measures the distance from equilibrium at time t (Harris and Sollis, 2003). The parameter β_2 then measures how fast the endogenous variable y_t adjusts back to equilibrium. Thus, in an ECM y_t reacts to changes in the explanatory variable, Δx_t, between time t-1 and t, and to the disequilibrium between itself and x_t in time t-1. If the theory behind the possible cointegrating relationship of the variables suggests it, one can insert a constant term in the error correction model, error correction term, or both, thus the model can be modified as:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \alpha - \gamma x_{t-1}) + u_t \qquad (4.10)$$

An error correction model can also be extended to include more variables than just two. With three variables, x_t, y_t, and q_t an error correction model can look like this, if no constants are included:

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 \Delta q_t + \beta_3 (y_{t-1} - \gamma_1 x_{t-1} - \gamma_2 q_{t-1}) + u_t \qquad (4.11)$$

Another useful feature of an ECM is that all the components included in it are stationary, allowing a valid application of standard statistical methods and procedures, eg. OLS.

4.3.2 Engle-Granger (EG) Univariate Cointegration Test and Parameter Estimation Method

In 1987, Engle and Granger proposed a two-step modeling strategy when dealing with non-stationary and possibly cointegrated panel data. The method is a residual-based univariate, or single equation, process for estimating cointegration parameters. The logic of the approach is intuitive, straightforward and easy to apply. Before applying the method, it is necessary to make sure that the time series contain one unit root, because time series need to be integrated to be able to be cointegrated.

In the first step a cointegrating regression is run using OLS in order to obtain the parameter values, although no inference can be conducted on the coefficients. A simple static model can be used:

$$\Delta y_t = C + \beta x_t + u_t \tag{4.12}$$

The residuals are then saved and tested for stationarity. ADF test can be applied on the autoregression model:

$$\hat{u}_t = \psi \hat{u}_{t-1} + \upsilon t \tag{4.13}$$

where the error term $\upsilon_t \sim$ IID.

Because the test is applied on the residuals and not on the raw data, one cannot use the critical values from the ADF test. Instead one uses the critical values tabulated by Engle and Granger in 1987[6]. If the $\hat{u}_t$ is stationary, then according to the definition, the time series are cointegrated. One can thus proceed to the second part of the method. But if the error term is not stationary then the model needs to be estimated on the first differences instead of the levels.

The second stage estimates the cointegration parameters as the residuals term is put as an explanatory variable into the error correction model, for example of the following simple short-run form:

$$\Delta y_t = \beta_1 x_t + \beta_2 \hat{u}_{t-1} + \upsilon t \tag{4.14}$$

Where $\hat{u}_{t-1} = y_{t-1} - \hat{\tau}\, x_{t-1}$. By combining the non-stationary variables in this manner this linear stationary relationship, also known as the cointegrating vector, can be obtained. In this particular case our cointegrating vector is [*1*-$\hat{\tau}$]. (Brooks, 2008).

The EG method is popular due to several reasons. The approach is simple in execution, as it is easy to run OLS on the cointegrating equation and then run unit root tests on the residuals term. Moreover, the ECM model in the second step can be extended into a general dynamic form by including a larger number of lags of either one or both cointegrated variables, y_t and x_t. Furthermore, since all variables in (4.14) are stationary, application of

[6] later, Engle and MacKinnon (1991) presented a way of calculating critical values for the ADF unit root test on the residuals, which we are using in this study

standard statistical tests, such as t-test or F-test, is possible in order to be able to make valid inference about β_1 and β_2.

4.3.2.1 Limitations of the Engle-Granger Approach

However, there are some limitations to the EG two-step method. **1**. The approach is a single-equation method and thus allows only <u>one</u> cointegrating relationship, although hypothetically n-1 cointegrating vectors can exist among n non-stationary variables. **2**. When it comes to finite samples, this approach suffers from lack of power, both at the first stage (testing for unit root) and the second stage (testing for cointegration). **3**. Also, due to this problem changing the roles of the variables would lead to different conclusions. **4**. Moreover, it can suffer from simultaneous equations bias. Two non-stationary variables are treated asymmetrically, because one has to be defined as exogenous and the other one as endogenous, even though the causal relationship can be going both directions simultaneously. **5**. Furthermore, because of the sequential construction of this approach misspecifications in the first phase migrate into the second one. **6**. Finally, the approach is not applicable when one wants to test hypotheses concerning the actual cointegrating relationship defined in the long-run regression equation in the first phase.

The most serious problem among them is the last one, as the first five problems are expected to disappear asymptotically. To avoid the problems of the EG test, the Johansen multivariate procedure, which is based on estimation of VAR systems, is applied.

4.3.3 Johansen Multivariate Cointegration Test

Johansen method extends the EG univariate method to a multivariate version. The non-stationary, I(1), variables being tested for cointegration together form an autoregressive vector (VAR), e.g. if we have three variables in a vector $\mathbf{z}_t = [y_{1t}, y_{2t}, x_t]'$ and all three variables are assumed to be endogenous:

$$\Delta \boldsymbol{z}_t = \boldsymbol{A}_1 \boldsymbol{z}_{t-1} + \cdots + \boldsymbol{A}_k \boldsymbol{z}_{t-k} + \boldsymbol{u}_t \,, \; \boldsymbol{u}_t \sim \mathrm{IN}(0, \boldsymbol{\Sigma}). \qquad (4.15)$$

where **A** an (n x n) matrix of parameters.

An important issue constructing the VAR is the number of lags to be included in the model, so that we get Gaussian residuals in the error correction model later on. An often used way to solve the problem is to use the Akaike information criteria when deciding on the number of lags.

The univariate error correction model in (4.9) can be readjusted to the multivariate framework as well and becomes a vector error correction model (VECM):

$$\Delta \boldsymbol{z}_t = \boldsymbol{\Gamma}_1 \boldsymbol{z}_{t-1} + \cdots + \boldsymbol{\Gamma}_{k-1} \boldsymbol{z}_{t-k+1} + \boldsymbol{\Pi} \boldsymbol{z}_{t-k} + \boldsymbol{u}_t \tag{4.16}$$

where $\mathbf{\Pi} = -(\mathbf{I}-\mathbf{A}_1- ...- \mathbf{A}_k)$ and $\mathbf{\Gamma}_i = -(\mathbf{I}-\mathbf{A}_1 - ... - \mathbf{A}_i)$ ($\mathbf{I}$ = 1,...k-1). $\mathbf{\Pi}$ is a (3x3) matrix with long-run information content, as $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$. $\boldsymbol{\alpha}$ gives us the speed of adjustment to disequilibrium, whereas matrix $\boldsymbol{\beta}$ contains long-run coefficients.

With two lags the full model looks as follows:

$$\begin{vmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \end{vmatrix} = \begin{vmatrix} \Delta y_{1t-1} \\ \Delta y_{2t-1} \\ \Delta y_{3t-1} \end{vmatrix} + \begin{vmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \\ \alpha_{31} & \alpha_{32} \end{vmatrix} \times \begin{vmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \end{vmatrix} \times \begin{vmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{vmatrix} \tag{4.17}$$

In this multivariate model the error correction term, or cointegrating relationship, contains up to n-1 vectors and is represented by $\boldsymbol{\beta}'*\mathbf{z}_{t-1}$, which in turn is embedded in $\mathbf{\Pi z}_{t-k}$ in equation (4.16). $\mathbf{\Pi z}_{t-k}$ has to be stationary in order for the residuals term u_t to be "white noise". This is possible in three cases:

1. All variables in $\mathbf{z}_t$ are actually stationary, and not I(1) as assumed, i.e. $\mathbf{\Pi}$ has full rank;

2. The variables are non-stationary, but lack a long-run relationship with each other, i.e. $\mathbf{\Pi}$ has zero rank;

3. There are up to (n-1) cointegrating relationships, i.e. $\mathbf{\Pi}$ has reduced rank.

Because we are dealing with non-stationary variables and are looking for cointegration, only the third case is interesting for us. In the third case r $\leq$ (n-1) stationary cointegration vectors and (n-r) non-stationary vectors exist in $\boldsymbol{\beta}$. But only the cointegration vectors will be present in (4.16), in order for $\mathbf{\Pi z}_{t-k}$ to be stationary, which in turn implies that (n-r) columns in $\boldsymbol{\alpha}$ are effectively equal to zero. Therefore in Johansen test one is interested in finding the rank of $\mathbf{\Pi}$. In 1988 Johansen proposed a maximum likelihood method for estimating $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ which is called reduced rank regression. Expression (4.16) can be rewritten as follows:

$$\Delta\boldsymbol{z}_t + \boldsymbol{\alpha\beta}'\boldsymbol{z}_{t-k} = \boldsymbol{\Gamma}_1\Delta\boldsymbol{z}_{t-1} + \cdots + \boldsymbol{\Gamma}_{k-1}\Delta\boldsymbol{z}_{t-k+1} + \boldsymbol{u}_t \quad (4.18)$$

Next, the effects of short-run dynamics are removed from (4.18) by separately regressing the right-hand side of (4.18) and two vectors of residual terms are obtained, $\mathbf{R}_{0t}$ and $\mathbf{R}_{kt}$:

$$\Delta\mathbf{z}_t = \mathbf{P}_1\Delta\mathbf{z}_{t-1} + \mathbf{P}_2\Delta\mathbf{z}_{t-2} + \cdots + \mathbf{P}_{k-1}\Delta\mathbf{z}_{t-(k+1)} + \mathbf{R}_{0t} \quad (4.19)$$

$$\mathbf{z}_{t-k} = \mathbf{T}_1\Delta\mathbf{z}_{t-1} + \mathbf{T}_2\Delta\mathbf{z}_{t-2} + \cdots + \mathbf{T}_{k-1}\Delta\mathbf{z}_{t-(k+1)} + \mathbf{R}_{kt} \quad (4.20)$$

The two vectors of the residuals are then used to form residual matrices:

$$\mathbf{S}_{ij} = \mathbf{T}^{-1}\sum_{\mathbf{i=1}}^{\mathbf{T}}\mathbf{R}_{0t}\mathbf{R}'_{kt} \qquad i,j = 0, k \quad (4.21)$$

Finally, we solve the equation:

$$|\lambda\mathbf{S}_{kk} - \frac{\mathbf{S}_{k0}\mathbf{S}_{0k}}{\mathbf{S}_{00}}| = 0 \quad (4.22)$$

and obtain eigenvalues, $\hat{\lambda}_1 > \hat{\lambda}_2 > \hat{\lambda}_3 > \ldots > \hat{\lambda}_n$, with corresponding eigenvectors

$\widehat{\boldsymbol{V}} = [\,\widehat{\boldsymbol{v}}_1,\ldots,\widehat{\boldsymbol{v}}_n\,]$. The largest eigenvectors up to r give us the maximum likelihood estimate of $\boldsymbol{\beta}$, $\boldsymbol{\beta} = [\,\widehat{\boldsymbol{v}}_1,\ldots,\widehat{\boldsymbol{v}}_r\,]$. The estimated $\boldsymbol{\beta}$ and levels of $\mathbf{z}_t$ deliver combinations with high correlation with the stationary parts in (4.16), i.e. $\Delta\mathbf{z}_t$ terms. This is only possible if $\widehat{\boldsymbol{\beta}}_j'\mathbf{z}_t$ is itself stationary, therefore $\widehat{\boldsymbol{\beta}}$ is the cointegrating vector, and eigenvalues left outside $\widehat{\boldsymbol{\beta}}$, i.e. $\hat{\lambda}_{r+1}\ldots\hat{\lambda}_n$ should be equal to zero, whereas $\hat{\lambda}_1\ldots\hat{\lambda}_r > 0$. (Johansen, 1992)

4.3.3.1 Determining the number of cointegrating vectors in the Johansen approach

In order to determine the number of cointegrating vectors one can conduct two different hypotheses tests (Harris and Sollis, 2005). In the first case one tests the null hypothesis that there exist at most r cointegrating vectors in the system, stating that eigenvalues beyond the restriction values of r are equal to zero:

H_0: $\lambda_i = 0$, where $i = r + 1, \ldots, n$

The log of maximized likelihood function for the restricted model is then compared to that of the unrestricted model using a standard likelihood ratio test, the so-called *trace* statistic:

$$\lambda_{trace} = -2 \log (Q) = -T \sum_{i=r+1}^{n} \log (1 - \hat{\lambda}_i), \text{ where } r = 0, 1, 2, \ldots, n\text{-}2, n\text{-}1 \quad (4.23)$$

Here, $Q = \frac{\text{Restricted maximized likelihood}}{\text{Unrestricted maximized likelihood}}$. The test follows a non-standard distribution.

In the second case one tests the null hypothesis that there are r cointegration vectors. The alternative is that there are r + 1 cointegration vectors. The null is tested using the maximal eigenvalue statistic:

$$\lambda_{max} = -T \log (1 - \hat{\lambda}_{r+1}), \text{ where } r = 0, 1, 2, \ldots, n\text{-}2, n\text{-}1 \quad (4.24)$$

Harris and Sollis (2005) suggest using only trace statistic, because it results in a consistent test procedure, whereas using maximal eigenvalue statistic does not.

4.3.3.2 Specifying the Vector Error Correction Model

If the variables tested are found to be cointegrated, we can proceed to the next step and build a vector error correction model (VECM). A VECM is a restricted VAR with cointegration condition already built in. A VECM allows for short-term adjustments, but limits the long-term behavior of the endogenous variables (Eviews 7.0 Users Guide II). To model the behavior accurately one needs to decide on the composition of the VECM. An important issue to consider is whether some deterministic components should enter the model. One group of the additional components to consider are dummy variables in order to take into account different characteristics of the data behavior, such as seasonality or structural breaks due to effects of e.g. regulatory changes or important events. Other deterministic components to think about in the context are a constant and trend. Also, an important issue is how many lags of the variables should be included in the model.

It can be difficult to see from graphs or economic intuition whether deterministic components should be included. It is also not unproblematic to include dummies except for an intercept, trend and seasonality, because, as Harris and Sollis (2005) point out, it affects the underlying distribution of test statistics so much that the critical values used become only indicative. Seasonality adjustments can have some negative consequences as well as Lee & Siklos (1997) show that data adjusted for seasonality can result in that important cointegrating relationships remain undetected. Therefore, we consider only including a constant and trend in the VECM. A constant and trend can be included in the short- and/or long-run model. The general equation of a VECM, assuming two lags (k = 2), looks as:

$$\Delta\mathbf{z}_t = \mathbf{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\alpha} \begin{bmatrix} \boldsymbol{\beta} \\ \mu_1 \\ \delta_1 \end{bmatrix} \tilde{\mathbf{z}}_{t-k} + \boldsymbol{\alpha}_\perp \mu_2 + \boldsymbol{\alpha}_\perp \delta_2 + \mathbf{u}_t, \text{ where } \tilde{\mathbf{z}}'_{t-k} = (\mathbf{z}'_{t-k}, 1, t) \quad (4.25)$$

Five models are then possible:

1) $$\Delta\mathbf{z}_t = \mathbf{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\alpha}\, \boldsymbol{\beta}\tilde{\mathbf{z}}_{t-k} + \mathbf{u}_t, \text{ i.e. } \mu_1 = \delta_1 = \mu_2 = \delta_2 = 0. \quad (4.26)$$

which means there are no deterministic components in the model.

2) $$\Delta\mathbf{z}_t = \mathbf{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\alpha} \begin{bmatrix} \boldsymbol{\beta} \\ \mu_1 \end{bmatrix} \tilde{\mathbf{z}}_{t-k} + \mathbf{u}_t, \text{ i.e. } \delta_1 = \mu_2 = \delta_2 = 0. \quad (4.27)$$

The data has no trend in the levels, the first differenced series has zero mean, thus the intercept is present only in the long-run part of the model.

3) $$\Delta\mathbf{z}_t = \mathbf{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\alpha} \begin{bmatrix} \boldsymbol{\beta} \\ \mu_1 \end{bmatrix} \tilde{\mathbf{z}}_{t-k} + \boldsymbol{\alpha}_\perp \mu_2 + \mathbf{u}_t, \text{ i.e. } \delta_1 = \delta_2 = 0. \quad (4.28)$$

This model accounts for linear trends in the levels of the data used, thus the short run movements are allowed to drift. Therefore we have an intercept both in the long-run and the short-run model, although in reality what we get is a constant in the short-run, as the long-run intercept gets cancelled out by the short-run one.

4) $$\Delta\mathbf{z}_t = \mathbf{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\alpha} \begin{bmatrix} \boldsymbol{\beta} \\ \mu_1 \\ \delta_1 \end{bmatrix} \tilde{\mathbf{z}}_{t-k} + \boldsymbol{\alpha}_\perp \mu_2 + \mathbf{u}_t, \text{ i.e. } \delta_2 = 0. \quad (4.29)$$

Now the model is able to deal with long-run linear trend in the data by including a trend-stationary variable time.

5) $\Delta\mathbf{z}_t = \mathbf{\Gamma}_1\Delta\mathbf{z}_{t-1} + \boldsymbol{\alpha} \begin{bmatrix} \boldsymbol{\beta} \\ \mu_1 \\ \delta_1 \end{bmatrix} \tilde{\mathbf{z}}_{t-k} + \boldsymbol{\alpha}_{\perp}\mu_2 + \boldsymbol{\alpha}_{\perp}\delta_2 + \mathbf{u}_t,$ i.e. there no restrictions. (4.30)

The model implies that the data has linear trends both in the long- and short-run.

In reality, though, only models 2-4 are considered practically possible. The Model 1 is not plausible, because an intercept is needed at least for the purpose of accounting for the measurement units, and Model 5 is not suggested either, because it implies quadratic trends in the system, $\mathbf{z}_t$, which is difficult to justify economically. Therefore the choice to be made is among the models 2, 3 and 4.

Model specification for the VECM has to be decided upon simultaneously with the determination of the rank order. To solve this simultaneous equation, one can use the joint test to determine the appropriateness of a constant and trend in the model, and the number of cointegrating vectors in the system, the so-called Pantula principle, also recommended by Johansen(1992). We estimate all three models (models 2-4). The trace statistics for the models are calculated and compared to their critical values, from the most restrictive model to the least restrictive one within the same rank. The starting null hypothesis is that there are no cointegrating vectors in the data and VECM has only a long-term intercept. With each step, the null is more relaxed, the process is stopped when the null hypothesis no longer can be rejected.

4.3.4 Weak Exogeneity and Conditional VECM

One of the advantages of the Johansen approach is that one does not need to treat the variables asymmetrically by making implicit assumptions about the endogeneity or exogeneity of the variables. Instead all the variables are treated as endogenous. Nevertheless, since correct model specification is an important issue also in the Johansen approach, we may be interested in determining which variables can be considered exogenous. Usually, when talking about exogeneity, we mean weak exogeneity.

Consider two stochastic variables, y_t and x_t, and a simple data generating processes for y_t and x_t:

$$y_t = \alpha_1 x_t + \alpha_2 y_{t-1} + u_t \tag{4.31}$$

$$x_t = \beta x_{t-1} + \varepsilon_t \text{ , where } |\beta| < 1 \text{ and } \varepsilon_t \sim (0, \sigma_\varepsilon^2) \tag{4.32}$$

The second variable, x_t, is said to be *strongly* exogenous to the first one, y_t, if it is possible to treat x_t as fixed in (4.31), i.e. $E(x_t u_t) = 0$. This is possible if the two error terms are not correlated, $E(u_t \varepsilon_t) = 0$. The exogenous variable x_t is considered *weakly* exogenous if it still can be treated as fixed, i.e. $E(x_t u_t) = 0$, but equation (4.32) also contains past values of y_t,:

$$x_t = \beta_1 x_{t-1} + \beta_2 y_{t-1} + \varepsilon_t \tag{4.33}$$

In this case x_t and y_t both are influenced by own past values *and* past values of each other, but the weakly exogenous x_t is not correlated with the error term in the equation for y_t. (Harris & Sollis, 2005).

In Johansen (1995) framework testing for weak exogeneity amounts to testing whether some variable's speed of adjustment vector, $\boldsymbol{\alpha}_{ij} (i = row, variable; j = 1, \ldots, r)$ in the cointegration system is equal to zero, and it is therefore said that the variable is weakly exogenous to the system. The system loses no information if the short-run determinants of $\boldsymbol{\Delta z}_{it}$ are not modeled when estimating the parameters [$\boldsymbol{\Gamma}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\Pi}$] of the model, although $\boldsymbol{\alpha}_{\mathrm{ij}}$ remains in the long-run model.

When having concluded that a particular variable is weakly exogenous, we can proceed with a conditional, or partial, model:

$$\boldsymbol{\Gamma}_0^* \Delta \boldsymbol{z}_t = \boldsymbol{\alpha}^* \boldsymbol{\beta}' \boldsymbol{z}_{t-1} + \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_i^* \Delta \boldsymbol{z}_{t-i} + \boldsymbol{\varepsilon}_t^* \tag{4.34}$$

where $\boldsymbol{\varepsilon}_t^* = \Gamma_0^* \boldsymbol{\varepsilon}_t$ is Gaussian $N_p(0, \Omega^*)$, the variance matrix $\Omega^* = \Gamma_0^* \Omega \Gamma_0^{*\prime}$.

Harris and Sollis (2005) give two reasons why one should test the variables in an unrestricted model for weak exogeneity when using the Johansen approach and construct the conditional model. One potential advantage of a conditional model against the unrestricted one is that the restricted model might have better stochastic properties if the "problematic" features happen to be concentrated to the variable(s) that is(are) found to be weakly exogenous to the system. By better stochastic properties is meant that the residuals of the short-run equations in the conditional model are free from unwanted features.

The second advantage of the conditional model is that it reduces the number of short-run variables in the VECM, which makes it computationally easier to deal with the short-run model.

Despite the named advantages Harris and Sollis (2005) do not recommend to assume weak exogeneity and start with a conditional model, but to start with a general model and later test for exogeneity. The reasons are that conditioning affects the asymptotic distributions of the rank test statistics, and that one usually wants to test for exogeneity, not just assume it.

In reality, testing for weak exogeneity is usually done alongside with testing hypotheses on the cointegration coefficients vector $\boldsymbol{\beta}$. That is due to the fact that a given cointegration vector can indeed be a vector describing a structural relationship between the variables, or it can be just a linear combination of stationary vectors. The latter is possible because the Johansen approach shows how many cointegrating vectors $\boldsymbol{\beta}$ *span* the cointegration space. But a linear combination of cointegrating vectors (which are stationary) results in a new stationary vector, and therefore the cointegrating vectors we obtain may not be unique.

4.3.4.1 Limitations of the Johansen Approach

Despite the numerous advantages the Johansen approach has over the Engle- Granger approach, the Johansen method suffers from some deficiencies itself. Two of the limitations have to do with the fact that Johansen approach is based on VAR systems. Because the variables in a VAR system are treated symmetrically as endogenous, it is not as straightforward to read the output in the Johansen method and to interpret the results in terms of exogenous and endogenous variables, as it is in the Engle-Granger approach. The second disadvantage of the method is due to that all the variables are modeled simultaneously, which can cause problems if any of the variables are flawed, e.g. the VAR system can be biased. To mitigate this, one could condition on the problematic variable, instead of having the unrestricted model (see also section 4.3.4, the part on weak exogeneity). And, finally, a multidimensional VAR system consumes many degrees of freedom. (Sörensen,1997).

Another weakness of the Johansen method is that it does not always fulfill the transitivity property. The Johansen test can fail to detect a cointegrating relationship between two variables, A and B, that are cointegrated with each other through the fact that both A and B are cointegrated with a third variable, C. Ferré (2004) explains the paradox by the behavior of the residuals and their variances in the relationship between the variables.

The Johansen method is very sensitive to model specification of the VECM, particularly when it comes to deterministic components in the model. Including or excluding a linear trend component can make all the difference between the robust positive results and the unfavorable ones (Ahking 2002).

4.3.5 Vector Error Correction Granger-Causality Test

When investigating the causal relationships between different time series, two strategies are identified by Kirchgässner and Wolters (2007). The first one is the bottom up strategy with the assumption that the time series are generated independently of each other. Granger (1969) popularized this strategy with causality test and tried to answer whether there are some specific time series that are related to each other. The other one is the top down strategy under the assumption that the generating process is not independent; hence it aims to find out whether some specific time series are generated independently.

4.3.5.1 Bottom Up Approach

Granger (1969) defines the causality between the weakly stationary time series x and y as follows: x is (simply) Granger causal to y if and only if the application of an optimal linear prediction function leads to:

$$\sigma^2 (y_{t+1} \mid I_t) < \sigma^2 (y_{t+1} \mid I_t\text{-}\overline{X_t}), \qquad (4.35)$$

where I_t is the information set, includes the two time series X and Y, available at time t.

$\overline{X_t}$ is the set of all current and past value of X. $\overline{X_t}=\{x_t, x_{t-1}, \dots x_{t-k}, \dots\}$

$\sigma^2(\cdot)$ is the variance of the corresponding forecast error which indicates with a smaller forecast error variance, the future value of y could be predicted better within the current and past values of x available.

a) The direct bivariate Granger procedure

Sargent (1976) derives a simple procedure for testing the causality directly from Granger definition of causality. Regressing two stationary variables, x and y, using the following equation:

$$Y_t = \sum_{i=1}^{p} \alpha_i Y_{t-1} + \sum_{i=1}^{p} \beta_i X_{t-1} + \mu_t \tag{4.36}$$

$$X_t = \sum_{i=1}^{p} \delta_i Y_{t-1} + \sum_{i=1}^{p} \gamma_i X_{t-1} + v_t \tag{4.37}$$

Wald test is used to test whether all of the lagged values of X in the Y equation are simultaneously equal to zero in order to find out whether X Granger-causes Y.

If $\sum \beta \neq 0$, X Granger causes Y;

If both $\sum \delta \neq 0$ and $\sum \beta \neq 0$, then there exists a bidirectional causality between Y and X.

b) Granger Causality in a trivariate Model

The simple Granger procedure could be extended since it is possible that a third variable would affect the variables under consideration. If the information set I_t contains the past information on a third variable Z besides $\overline{X}_t$ and $\overline{Y}_t$, the null hypothesis of X does not cause Y conditional on Z could be tested with a Wald test in a model where Y depends on lagged values of Y and Z.

4.3.5.2 Top down Approach

When it comes to VAR models, causality is tested on the basis of the pre-testing for unit roots and cointegration. If the time series are stationary, then a VAR model in levels is constructed. If the variables are difference stationary, or integrated of order one, I(1), the VAR is specified in first differences. If the series are cointegrated then vector error correction (VECM) models are used. Sims et al (1990) show that if the variables are cointegrated of order 1, Wald tests of Granger non-causality in levels VAR could be used based on the error correction model. Toda and Phillips (1993) further improve this and point out that the Wald tests are valid asymptotically if there is sufficient cointegration among the variables. As Granger representation theorem[7] suggests, if the variables are cointegrated then there must be a causal relationship among them running at least in one direction, and therefore a pairwise Granger causality and VEC Granger-causality test for zero restrictions on the coefficients on the VAR or VEC model can be employed.

When we know that some, or all, variables in our VAR are cointegrated (from the reduced rank regression results), we would like to know what the causal relationships between them are. To obtain the answer we utilize the VEC Granger-Causality Test. One has to understand from the beginning the actual meaning of the VEC Granger-causality test. The test does not say that changes in one variable cause changes in another. What Granger-causality test gives is the correlation between the current value of one variable and past values of the other variables. That is, if we say that x_{1t} , $x_{2t}, \ldots, x_{nt}$ Granger-cause y_t , we mean that past value(s) of x_{it} (i= 1,2,…,n) are correlated with the current value of y_t. Granger-causality can go in one direction between two variables, both ways, or there is no Granger-causality at all. (Brooks, 2008)

[7] Granger representation theorem: Let $x_t \sim I(1)$ and $y_t \sim I(1)$ then x_t and y_t are cointegrated if and only if there exist theerror correction model (ECM) such that

$\Delta x_t = -\gamma_1 z_{t-1} + \text{lagged}(\Delta x_t, \Delta y_t) + \delta(L)\varepsilon_{1t}$

$\Delta y_t = -\gamma_2 z_{t-1} + \text{lagged}(\Delta x_t, \Delta y_t) + \delta(L)\varepsilon_{2t}$,

Where $z_t = y_t - Ax_t \sim I(0)$

$\delta(L) = 1+\delta_1 L+\cdots+\delta_p L^p$.is the same in both equations, and $|\gamma_1| + |\gamma_2| \neq 0$ (Engle and Granger 1987).

5. Empirical Results and Analysis

We carry out the tests on the nine commodities mentioned in Data part using the statistical software EViews 7.0 in three stages. Firstly, the unit root tests are applied to examine whether all the time series are stationary. If it is established that non-stationarity exist, Johansen test is utilized to check for cointegration relationship(s). On the basis of these tests, lead-lag relations are assessed at the end.

Our tests follow the steps below:

1. Testing the order of integration of each time series that is in the multivariate model;
2. Setting the appropriate lag length of the VAR model;
3. Formulating the optimal Vector Error Correction model with regards to deterministic components (trend and intercept) in the long- and short-run part of the VECM among the five possible models;
4. Testing for the weak exogeneity;
5. Testing for the unique cointegration vectors and joint tests involving restrictions on $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$;
6. Identifying the lead-lag relationships between the commodities by using VEC Granger-Causality test.

5.1 Integration: Unit root tests and stationarity test results

Augmented Dickey-Fuller (ADF) (1979) test is conducted on the logged price levels using the lag structure indicated by Schwarz Information Criterion (SIC), see the table below. We start our unit root test with the most general model, containing an intercept and a trend:

$$\Delta y_t = \gamma_0 + \gamma t + \varphi y_{t-1} + \sum Bi\Delta y_{t-1} + \varepsilon_t \qquad (5.1)$$

We test the following null hypothesis

H$_0$**:** $\varphi = 0$; Time series is non stationary

H$_1$**:** $\varphi < 0$; Time series is stationary.

Next we test for the presence of a trend by setting $\gamma t = 0$:

$$\Delta y_t = \gamma_0 + \varphi y_{t-1} + \sum Bi\Delta y_{t-1} + \varepsilon_t \qquad (5.2)$$

And, finally, we test for the presence of a drift, by adding one more restriction, namely $\gamma_0 = 0$:

$$\Delta y_t = \varphi y_{t-1} + \sum Bi\Delta y_{t-1} + \varepsilon \qquad (5.3)$$

Phillips–Perron (PP) tests and KPSS test (Kwaitkowski et al.1992) are conducted to double check the results obtained from the ADF test. The PP test has the same null hypothesis as the ADF test while the KPSS test has the opposite null hypothesis, i.e. that the time series is stationary. All the three tests give the consistent results presented in *Appendix H Table7*.

The results indicate that we are unable to reject the null hypothesis for any the nine commodities at any of the three significance levels commonly used: 1% level, 5% level and 10% level, which means there exists a unit root in each time series. To test whether there are two unit roots, the same procedure is applied to the first differences (see *Appendix I Table 8*) under the same hypotheses. The results are equally conclusive and indicate that the time series are stationary at first difference. Thus, all the variables are integrated of order one and stationary upon differencing once, this also supports Brooks (2008)'s statement that the majority of financial and economic time series contain a single unit root.

5.2 Cointegration: Johansen test results

We have tested the variables for stationarity and the number of unit roots, and have come to that the ordinary Johansen method, which is designed for variables with at most one unit root, can be applied. We proceed by formulating the appropriate vector autoregression model (VAR) (see *Appendix J Table 9*). The Akaike information criteria indicate that two lags should be included. Next, applying the Pantula principle we arrive to the conclusion that Model 2 and rank 2 describe the data best (see equation(4.27)) where $\mathbf{z}_t$ = **[ALUM_ALLOY$_t$, ALUMINIUM$_t$ COPPER$_t$, GOLD$_t$, LEAD$_t$, NICKEL$_t$, OIL$_t$, TIN$_t$, ZINC$_t$]**

The test for exogeneity reveals that Copper, Nickel and Tin are weakly exogenous variables in the system, and thus the model can be conditioned upon them.

Gonzalo (1994) finds that the Johansen cointegration test is quite sensitive to the lag length. Emerson (2007) supports Gonzalo's opinion and concludes from his empirical study that the rank of cointegration among the variables depends on the number of lags included in the underlying VAR. Hence it is necessary to determine the lag length before conducting the Johansen test. Within the four usual criteria: final prediction error (FPE), Akaike (AIC), Schwarz (SC), Hannan-Quinn (HQ), Ozcicek et al(1999) suggest that without knowing the true lag length and whether the lags are symmetric or asymmetric, AIC is preferred. Liew (2004) points out that AIC and FPE are recommended to estimate autoregression lag length. Gutiérrez et al (2007) support Liew's opinion and further suggest using AIC criteria to choose the lag rank if the VAR model contain the weak form and cointegration restriction. According to the previous study we follow the result demonstrated by AIC criteria which indicates lag length of two, FPE criteria supports it. The output of the lag length choice is shown as below:

Table 5.1: VAR Lag Order Selection Criteria

Lag	FPE	AIC	SC	HQ
0	1.64e-14	-6.202264	-6.187810	-6.197134
1	2.83e-34	-51.70771	-51.56317*	-51.65641*
2	2.71e-34*	-51.75074*	-51.47612	-51.65328
3	2.72e-34	-51.74562	-51.34091	-51.60198

Note: * indicates lag order selected by the criterion
FPE: Final prediction error,
AIC: Akaike information criterion,
SC: Schwarz information criterion,
HQ: Hannan-Quinn information criterion

Within the choice of 2 lags and one unit root in each time series, the Johansen cointegration test can be conducted. Applying the Pantula principle, which indicates the optimal model when the null hypothesis is firstly not rejected, model 2 is selected.

Table 5.2: Choice of the optimal model

Trace Value Test: With the critical value of MHM								
r<= n-1, the number of relations of the variables,n: number of variables								
Level: 5%								
H_0:	r	n-r	Model 2	critical value	Model 3	critical value	Model 4	critical value
	0	9	230.0943	208.4374	225.6325	197.3709	246.3626	228.2979
	1	8	174.0268	169.5991	170.5407	159.5297	189.2299	187.4701
	2	7	129.1710*	134.6780	125.8645	125.6154	144.4701	150.5585
	3	6	91.05584	103.8473	88.35935	95.75366	100.8243	117.7082

Note: * means the null hypothesis is firstly not rejected.

There are two kinds of cointegration tests, maximal eigenvalue test and trace test. Toda (1994) reports that within small-sample properties, trace test performs better than the other one when the power is low. Lutkepohl et al (2001) confirm this and conclude a preference of trace tests from their study as well. Hence we follow the trace test; the result is shown in Table 5.3 (For the whole table see *Appendix K Table 10*).

Table 5.3: Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.014234	230.0943	208.4374	0.0029
At most 1 *	0.011404	174.0268	169.5991	0.0286
At most 2	0.009698	129.1710	134.6780	0.1007
At most 3	0.008065	91.05584	103.8473	0.2579

Note: * denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The trace test indicates that there exist two cointegrating vectors at the 5% level which means there are two linear combinations among the variables.

5.3 Tests for the Separate Models

The tests indicate that there are two cointegrating vectors among the nine variables. However, it is a well-known problem to identify the unique cointegrating vectors, i.e. to identify the restrictions on $\boldsymbol{\beta}$, when there are more than one cointegration equations and there is no strong theory to backup the restrictions, as in our case (Larsson et al, 2010). To reduce the number of the cointegrating vectors to one, we test Aluminum and Aluminum Alloy separately for cointegration and Granger-causality. If they are cointegrated, we exclude Aluminum Alloy from the original nine-variable group. The reason we exclude Aluminum Alloy instead of Aluminum is their respective average inventory volume, 67,382.96 against 1,106, 364.35 metric tons *(See Table 3.1)*. Thus, we continue with the remaining eight variables.

5.3.1 Tests Results for Aluminum and Aluminum Alloy

Aluminum and Aluminum Alloy are tested for cointegration by using both the Engle-Granger univariate method and the Johansen multivariate method.

Firstly, the long run relationship by regressing Aluminum on Aluminum Alloy and a constant is formulated. Next, we test the residuals for unit root(s) with the ADF test. The standard ADF critical values in this test can not be used since the unit root test is applied to residuals but not raw data. Instead, we calculate the critical values as explained by McKinnon (1996) and check the test-statistic against them. With the implication of the results that the residuals are stationary, we conclude that the two variables are indeed cointegrated. The results are double checked by repeating the Engle-Granger test, but with the roles for the two variables reversed: aluminum alloy is the endogenous variable this time. The output for the regressions is given in the *Appendix M Table 12*. The residuals are tested for unit root in the same way as before and the previous result is confirmed. Finally, the Granger-causality test is conducted to determine the direction of the relationship and the result indicates that the two variables share a bi-directional relationship (See *Appendix N Table 13*). The Johansen method gives results identical to those obtained with the Engle-Granger method (*Appendix Q-R Table 16-17*). According to *table 3.1*, the average inventory volume of Aluminum Alloy is far less than that of Aluminum, which is 67,382.96 compared to 1,106,364.35. Therefore, Aluminum Alloy is removed from the group and Johansen method is applied just on the eight-variable group, i.e. $\mathbf{z}_t = [\,\mathbf{ALUMINIUM}_t, \mathbf{COPPER}_t, \mathbf{GOLD}_t, \mathbf{LEAD}_t, \mathbf{NICKEL}_t, \mathbf{OIL}_t, \mathbf{TIN}_t, \mathbf{ZINC}_t\,]$.

5.3.2 Tests Results for the Eight-Variable Group

The tests conducted are the same as before starting with formulating the VAR. The Akaike Information Criteria suggests two lags (*Appendix S, Table 18*). Then, the rank and the model are determined simultaneously using the Pantula principle. Model 2 (see *equation 4.27*) is selected and one cointegrating vector is found (See *Appendix T, Table 19*).

Table 5.4: Unrestricted Cointegrating Coefficients

ALMN	Copper	Gold	Lead	Nickel	Oil	Tin	Zinc	C
-12.35154	4.679840	-3.472042	0.608426	2.937729	-0.222967	-0.913560	0.226387	51.92919

Table 5.5: Unrestricted Adjustment Coefficients (alpha)

D(ALMN)	D(Copper)	D(Gold)	D(Lead)	D(Nickel)	D(Oil)	D(Tin)	D(Zinc)
0.001093	0.001084	0.000441	0.001506	0.000408	0.001398	0.000776	0.001071

Table 5.4 and 5.5 above display the estimated coefficients of **α** and **β** for each variables individually. However, the individual coefficients do not provide us with useful information, since they do not say anything about the relationships between the variables. Thus, we need ratios between individual coefficients which are acquired by normalizing on the coefficient of a certain variable in the system (Johansen, 1995). After formulating the unrestricted Vector Error Correction Model, normalized on Aluminum, the results of t-statistics for the cointegrating vector **β** are acquired. The results show that cointegrating coefficients for Aluminum, Copper, Gold and Nickel are significant at 5% level. (See *Table 5.6* and *Appendix U Table 20* for the full output).

Table 5.6 Unrestricted Cointegrating Coefficients (Normalized β coefficient on Aluminum to 1)

Almn(-1)	Copper(-1)	Gold(-1)	Lead(-1)	Nickel(-1)	Oil(-1)	Tin(-1)	Zinc(-1)	C
1.000000	-0.378887	0.281102	-0.049259	-0.237843	0.018052	0.073963	-0.018329	-4.204268
	(0.09485)	(0.08780)	(0.07894)	(0.05579)	(0.04682)	(0.08125)	(0.06578)	(0.45480)
	[-3.99458]	[3.20159]	[-0.62404]	[-4.26292]	[0.38552]	[0.91031]	[-0.27864]	[-9.24422]

Note: (-1) means difference once, standard errors in ( ) & t-statistics in [ ], Log likelihood: 88088.43

The coefficients of **β** are interpreted as follows.

$\mathbf{ALUMINIUM}_t = 0.378887\mathbf{COPPER}_t - 0.281102\mathbf{GOLD}_t + 0.049259\ \mathbf{LEAD}_t + 0.237843\ \mathbf{NICKEL}_t - 0.018052\mathbf{OIL}_t - 0.073963\mathbf{TIN}_t + 0.018329\mathbf{ZINC}_t + 4.204268$

Copper and Nickel have a positive relationship with Aluminum. 1% increase of Copper will lead to 0.37% increase of Aluminum in the long term; 1% increase in Nickel will lead to 0.23% increase in Aluminum in the long term; while the coefficient of Gold shows a negative relationship with Aluminum which indicates 1% increase in Gold will lead to 0.28% decrease in Aluminum in the long term.

Table 5.7 below displays the speed of adjustment back to the equilibrium represented by the error correction term. Aluminum has the fastest speed of adjustment while Nickel has the slowest one. These imply that in the short run, all commodities respond to their last period's equilibrium error. Besides, the error correction term of Nickel is not significantly different from zero which indicates weak exogeneity of the variable.

Table 5.7 Speed of adjustment for unrestricted model (Alpha Vector)

D(Almn(-1))	D(Copper(-1))	D(Gold(-1))	D(Lead(-1))	D(Nickel(-1))	D(Oil(-1))	D(Tin(-1))	D(Zinc(-1))
-0.013500 (0.00258) [-5.24193]	-0.013384 (0.00345) [-3.87739]	-0.005451 (0.00202) [-2.70396]	-0.018606 (0.00403) [-4.61153]	-0.005043 (0.00461) [-1.09515]	-0.017266 (0.00447) [-3.86042]	-0.009580 (0.00317) [-3.02158]	-0.013229 (0.00361) [-3.66109]

Note: (-1) means difference once, standard errors in ( ) & t-statistics in [ ]

To investigate whether a conditional model would be a better choice, weak exogeneity of the variables is tested. The results indicate that Nickel and Tin are weakly exogenous (See *Appendix V Table 21*). Due to lack of a strong economic theory on which to base **β**-restrictions, we only condition the VECM on the speed-of-adjustment coefficients **α** and the only restriction on **β** is the normalization on one **β** coefficient, which is a restriction but not a constraint and therefore it does not affect our results.

Table 5.8 below shows a consistent result with the unrestricted model with only a slight difference. A 1% increase in Copper and Nickel will lead to 0.5% and 0.12% increase, respectively, in Aluminum. 1% increase in Gold will lead to a 0.41% decrease in Aluminum. The restricted model displays a much stronger relationship among Aluminum, Copper and Gold.

Table 5.8 Restricted Cointegrating Coefficients (Normalized β coefficient of Aluminum to 1)

Almn(-1)	Copper(-1)	Gold(-1)	Lead(-1)	Nickel(-1)	Oil(-1)	Tin(-1)	Zinc(-1)	C
1.000000	-0.504197 (0.08165) [-6.17504]	0.410922 (0.07558) [5.43676]	0.023726 (0.06795) [0.34915]	-0.121061 (0.04803) [-2.52058]	-0.038550 (0.04031) [-0.95636]	-0.056756 (0.06994) [-0.81145]	0.008392 (0.05663) [0.14820]	-4.389347 (0.39151) [-11.2114]

Note: (-1) means difference once, standard errors in ( ) & t-statistics in [ ], Log likelihood: 88086.99

Table 5.9 exhibits the speed of adjustment when taking the weakly exogenous variables into account and it shows that after omitting Nickel and Tin, all other variables are significant at 5% level.

Table 5.9 Speed of adjustment for unrestricted model (Alpha Vector)

D(Almn(-1))	D(Copper(-1))	D(Gold(-1))	D(Lead(-1))	D(Nickel(-1))	D(Oil(-1))	D(Tin(-1))	D(Zinc(-1))
-0.015005 (0.00260) [-5.76092]	-0.009304 (0.00329) [-2.82664]	-0.005781 (0.00236) [-2.45298]	-0.016617 (0.00416) [-3.99135]	0.000000 (0.00000) [NA]	-0.013998 (0.00524) [-2.67189]	0.000000 (0.00000) [NA]	-0.013613 (0.00358) [-3.80358]

Note: (-1) means difference once, standard errors in ( ) & t-statistics in [ ]

The graph and the output for the restricted VECM are given in the *Appendix W Table 22*. It can be seen that the model is improved with conditioning on these variables, since now the fluctuations are concentrated closer around the long-run equilibrium.

Finally, we look at the directions of the cointegrating relationships through the VEC Granger-causality test in both the unrestricted (*Appendix X Table 23*) and restricted models (*Appendix Y Table 24*). The results are virtually identical for the two models which indicate that Aluminum is Granger-caused by Copper, but Aluminum itself Granger-causes Gold. Copper shows bi-directional causality with Gold, whereas Nickel seems to lack causality with the other three commodities. Additionally, the VEC Granger-causality test indicates that there exist other causality relations. At 5% significance level all variables, except Lead, are cointegrated, since there is a causality relationship in at least one direction. Oil is Granger-caused by Aluminum. Copper Granger-causes Zinc and Tin Granger causes Aluminum. Tin itself is Granger-caused by Nickel. At 10% significance level all eight variables seem to be cointegrated. Copper starts to Granger-cause Lead. Both Copper and Oil Granger-cause Tin. Gold Granger-causes Zinc while Zinc Granger-causes Aluminum. On the block level, Aluminum, Copper, Gold, Tin and Zinc are Granger-caused by the other seven variables on both 5% and 10% significance level.

It is an interesting question why the Johansen method and the VEC Granger-causality test give different results when it comes to the number of cointegrating relationships. We know that the results in the VEC Granger-causality test are dependent on the way the variables are ordered in. But the changes are not large enough to explain the discrepancy. Since the main focus in this paper is the Johansen method, we only use the Granger-causality test to see the direction in the cointegration relationships suggested by the Johansen method results. Investigation of the causes for the different results in the two tests should be an interesting topic for further research. Our guess is that some of our variables are cointegrated through other (macroeconomic) variables, that are not included in our group, and the Johansen approach is failing to fulfill the transitivity condition in the cointegrating relationships (see section Limitations of the Johansen Approach).

6. Limitations of the Study and Suggestions for Further Research

Some limitations of this study are identified in the area of Data and Methodology. For the data part, only daily data with just one time interval, 15 years from 1995 to 2010, is used due to time and space constraints of this study. The study could have been improved with additional tests on different time frequencies beside daily data such as weekly, monthly and /or quarterly. Furthermore, the 15-year time period could also be both extended and complemented with different sub-samples, e.g. five-year, ten-year, etc. Moreover, the number of commodities in this paper is limited to nine due partly to the lack of data for some commodities traded on the LME and the software used. E-Views 7.0 allows at most 10 variables to be tested with the Johansen approach. More variables would probably reveal more long-term relationships.

The methodology used, with the emphasis on the Johansen approach, potentially limits the quality of the study. The Johansen method has both own weaknesses (see *Section 4.3.4.1*) and shares the common weakness of other linear cointegration methods. Firstly, it is potentially unable to detect cointegration between variables that are cointegrated through cointegrating relationship with a common variable. Secondly, it is difficult to test hypothesis by imposing restrictions on the cointegrating coefficients, i.e. vector $\boldsymbol{\beta}$, as well as interpret the results without a strong economic theory. Also, as a method for linear cointegrating relationships, the Johansen method can not detect possible non-linear cointegration between variables. Therefore, we would suggest replicating the study with different linear and non-linear methods

Consideration should have been taken for the important macroeconomic shocks, e.g. the latest global financial crisis, when designing the study. During financial crises it is common that both volatility of assets and their correlations with other assets increase, probably affecting their cointegration patterns as well.

7. Conclusion

The purpose of this study is to investigate the potential long-term relationships among base metals as well as between base metals, Crude oil and Gold. The results obtained from the tests indicate that there exist several cointegrating relationships among the base metals. Some of the base metals seem to have long run relationship with both Crude oil and some with Gold. However, the results for Gold and Crude oil do not show any cointegration with each other.

More specifically, Aluminum, Copper, Gold and Nickel are cointegrated according to the Johansen Approach. The VEC Engle-Granger Causality test indicates more cointegrating relationships exist within the eight-variable group. At the 10 % significance level all eight variables are cointegrated with at least one of the remaining seven variables. Therefore, diversification possibilities for the long-term perspective are generally poor among the base metals, between the base metals and Gold as well as between base metals and Crude Oil. But since no cointegration is detected between Gold and Crude Oil, diversification benefits exist between the two commodities.

According to the results, price developments of Aluminum and especially Copper should be given more attention. The two metals Granger-cause several other commodities in the group. Therefore, Aluminum and Copper have lead-lag relationships with the variables they Granger-cause.

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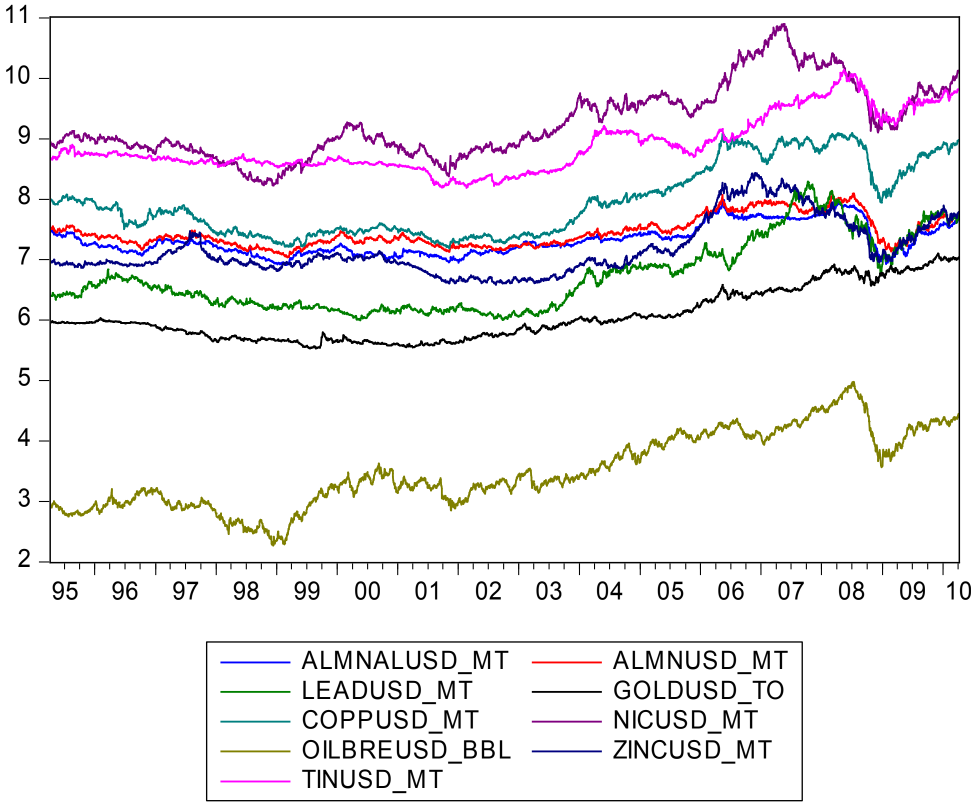
9. Appendix

A. Figure 1:Log price for each commodity



B. Table 1: Daily Closing Price in Levels

Sample: 4/07/1995 4/07/2010

	ALUM_ALLOY	ALUMINIUM	COPPER	GOLD	LEAD	NICKEL	OIL	TIN	ZINC
Mean	1554.926	1770.764	3411.279	473.1523	995.1098	12883.54	40.18061	8139.268	1460.873
Std. Dev.	423.0768	481.0437	2220.145	235.0627	720.3848	9394.112	26.41368	4471.752	829.2400
Skewness	1.108736	1.176338	1.080043	1.291635	1.723024	1.876299	1.274576	1.525296	1.769216
Kurtosis	3.229653	3.247165	2.693060	3.486411	5.387826	6.550609	4.255872	4.582675	5.273884
Jarque-Bera	810.5114	912.6435	776.3059	1126.886	2866.509	4352.501	1316.962	1926.174	2885.115
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	3914	3914	3914	3914	3914	3914	3914	3914	3914

C. Table 2: Correlation for daily closing price in levels

	ALUM_ALLOY	ALUMINIUM	COPPER	GOLD	LEAD	NICKEL	OIL	TIN	ZINC
ALUM_ALLOY	1.000000								
ALUMINIUM	0.967030	1.000000							
COPPER	0.913955	0.921467	1.000000						
GOLD	0.654331	0.647983	0.845293	1.000000					
LEAD	0.768715	0.779582	0.893909	0.836397	1.000000				
NICKEL	0.813704	0.867530	0.853857	0.624414	0.788745	1.000000			
OIL	0.848394	0.846142	0.909142	0.829395	0.835453	0.740933	1.000000		
TIN	0.752799	0.764931	0.875105	0.898253	0.891815	0.703019	0.898333	1.000000	
ZINC	0.814823	0.865026	0.861629	0.592985	0.731463	0.885737	0.667578	0.606128	1.000000

D. Table 3: Daily Closing Price in Natural Log

Sample: 4/07/1995 4/07/2010

	ALUM_ALLOY	ALUMINIUM	COPPER	GOLD	LEAD	NICKEL	OIL	TIN	ZINC
Mean	7.316428	7.446967	7.951996	6.058551	6.707635	9.263872	3.499841	8.886142	7.169508
Std. Dev.	0.248827	0.245701	0.582752	0.428024	0.585732	0.600383	0.614284	0.460654	0.449870
Skewness	0.743565	0.855032	0.603959	0.816418	0.841343	0.648340	0.286852	0.835877	1.096800
Kurtosis	2.545911	2.631861	1.953429	2.405678	2.585889	2.651839	2.092670	2.671587	3.207872
Jarque-Bera	394.2956	499.0095	416.5762	492.4087	489.7258	293.9729	187.9347	473.3682	791.7848
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	3914	3914	3914	3914	3914	3914	3914	3914	3914

E. Table 4: Correlation for daily closing price in natural log

	ALUM_ALLOY	ALUMINIUM	COPPER	GOLD	LEAD	NICKEL	OIL	TIN	ZINC
ALUM_ALLOY	1.000000								
ALUMINIUM	0.960145	1.000000							
COPPER	0.899511	0.916678	1.000000						
GOLD	0.718079	0.714366	0.904258	1.000000					
LEAD	0.804495	0.823033	0.941446	0.918264	1.000000				
NICKEL	0.864699	0.889229	0.901524	0.782077	0.855653	1.000000			
OIL	0.791973	0.809869	0.864597	0.830584	0.829080	0.879391	1.000000		
TIN	0.753359	0.781864	0.903608	0.916327	0.939776	0.803158	0.811807	1.000000	
ZINC	0.833540	0.884541	0.885411	0.710364	0.820989	0.840393	0.716071	0.744350	1.000000

F. Table 5: Daily Closing price in log return

Date: 04/28/10
Time: 22:30
Sample: 4/10/1995 4/07/2010

	ALUM_ALLOY	ALUMINUM	COPPER	GOLD	LEAD	NICKEL	OIL	TIN	ZINC
Mean	4.86E-05	5.94E-05	0.000252	0.000273	0.000338	0.000301	0.000390	0.000292	0.000211
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000266	0.000000	0.000000
Maximum	0.117145	0.060679	0.117259	0.073820	0.130072	0.133096	0.188557	0.153854	0.096101
Minimum	-0.126752	-0.082551	-0.104755	-0.071434	-0.131992	-0.183586	-0.158605	-0.114532	-0.126185
Std. Dev.	0.011668	0.013115	0.017560	0.010258	0.020517	0.023331	0.022692	0.016104	0.018357
Skewness	-0.103320	-0.247658	-0.171499	-0.039291	-0.155839	-0.081408	-0.087630	-0.144441	-0.306891
Kurtosis	14.69917	5.743632	7.838661	9.756245	6.933179	7.098094	6.982970	11.85065	7.325075
Jarque-Bera	22322.55	1267.299	3836.417	7443.345	2538.076	2742.505	2591.509	12785.32	3111.325
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.190313	0.232398	0.986909	1.067205	1.323794	1.176228	1.527833	1.142301	0.824006
Sum Sq. Dev.	0.532591	0.672906	1.206226	0.411680	1.646824	2.129416	2.014330	1.014553	1.318244
Observations	3913	3913	3913	3913	3913	3913	3913	3913	3913

G. Table 6: Correlation for daily closing price in log return

	ALUM_ALLOY	ALUMINUM	COPPER	GOLD	LEAD	NICKEL	OIL	TIN	ZINC
ALUM_ALLOY	1.000000								
ALUMINUM	0.694661	1.000000							
COPPER	0.528346	0.658183	1.000000						
GOLD	0.194963	0.232568	0.257800	1.000000					
LEAD	0.383624	0.484833	0.542257	0.199266	1.000000				
NICKEL	0.363609	0.484731	0.548896	0.169393	0.446381	1.000000			
OIL	0.168841	0.171165	0.216860	0.180650	0.184907	0.176690	1.000000		
TIN	0.332164	0.398089	0.449068	0.185491	0.393566	0.400016	0.171412	1.000000	
ZINC	0.452923	0.593261	0.650764	0.235618	0.588677	0.513227	0.193039	0.410327	1.000000

H. Table 7: ADF, PP, KPSS test for I(1)

	ADF TEST			PP TEST			KPSS TEST	
	H0: time series is non stationary			H0: time series is non stationary			H0: time series is stationary	
	T&C	T	None	T&C	T	None	T&C	T
AlmnUSD/MT	-2,385	-1,448	0,235	-2,346	-1,403	0,245	0,705	3,616
AlmnAlUSD/MT	-2,273	-1,071	0,258	-2,538	-1,399	0,185	0,692	3,559
CoppUSD/MT	-1,892	-0,114	0,888	-1,887	-0,109	0,892	1,316	4,998
LeadUSD/MT	-1,714	-0,464	0,987	-1,664	-0,402	1,033	1,390	5,057
NicUSD/MT	-2,034	-0,857	0,749	-2,019	-0,841	0,753	0,642	5,229
TinUSD/MT	-1,594	-0,208	1,122	-1,576	-0,185	1,137	1,433	4,874
ZincUSD/MT	-1,605	-0,944	0,657	-1,531	-0,864	0,705	0,810	3,350
OilBREUSD/BBL	-2,694	-0,829	0,917	-2,686	-0,827	0,918	0,494	6,593
GoldUSD/TO	-1,544	1,001	1,729	-1,551	0,992	1,723	1,816	5,756
1% level	-3,960	-3,432	-2,566	-3,960	-3,432	-2,566	0,216	0,739
5% level	-3,411	-2,862	-1,941	-3,411	-2,862	-1,941	0,146	0,463
10% level	-3,127	-2,567	-1,617	-3,127	-2,567	-1,617	0,119	0,347

I. Table 8: ADF, PP, KPSS test for I(2)

	ADF TEST			PP TEST			KPSS TEST	
	H0: time series is non stationary			H0: time series is non stationary			H0: time series is stationary	
	T&C	T	None	T&C	T	None	T&C	T
AlmnUSD/MT	-64,254	-64,251	-64,258	-64,263	-64,258	-64,265	0,065	0,130
AlmnAlUSD/MT	-66,045	-66,024	-66,031	-66,384	-66,391	-66,398	0,072	0,186
CoppUSD/MT	-65,412	-65,370	-65,364	-65,347	-65,306	-65,301	0,094	0,394
LeadUSD/MT	-59,762	-59,756	-59,748	-59,744	-59,733	-59,720	0,063	0,190
NicUSD/MT	-61,892	-61,894	-61,892	-61,889	-61,891	-61,889	0,074	0,113
TinUSD/MT	-61,173	-61,157	-61,145	-61,187	-61,156	-61,143	0,050	0,233
ZincUSD/MT	-64,372	-64,374	-64,373	-64,433	-64,434	-64,433	0,100	0,152
OilBREUSD/BBL	-62,290	-62,295	-62,284	-62,289	-62,294	-62,284	0,041	0,062
GoldUSD/TO	-62,160	-62,077	-62,041	-62,168	-62,077	-62,045	0,024	0,653
1% level	-3,960	-3,432	-2,566	-3,960	-3,432	-2,566	0,216	0,739
5% level	-3,411	-2,862	-1,941	-3,411	-2,862	-1,941	0,146	0,463
10% level	-3,127	-2,567	-1,617	-3,127	-2,567	-1,617	0,119	0,347

J. Table 9: Vector Autoregression Estimates

Sample (adjusted):
4/11/19954/07/2010
Included observations: 3912 after adjustments

	ALMNAL	ALMN	LEAD	GOLD	COPPER	NICKEL	OILBRE	ZINC	TIN
AlmnAlloy(-1)	0,8239	-0,0737	-0,0519	-0,0196	-0,0620	-0,0411	0,0149	-0,0519	-0,0914
Standard errors	-0,0223	-0,0252	-0,0395	-0,0198	-0,0338	-0,0450	-0,0438	-0,0354	-0,0310
t-statistics	[37,0147]	[-2,92412]	[-1,31400]	[-0,99171]	[-1,83523]	[-0,91210]	[0,33985]	[-1,46740]	[-2,94956]
AlmnAlloy(-2)	0,1754	0,0831	0,0464	0,0189	0,0715	0,0511	-0,0109	0,0548	0,0956
Standard errors	-0,0223	-0,0252	-0,0395	-0,0198	-0,0338	-0,0451	-0,0439	-0,0354	-0,0310
t-statistics	[7,87877]	[3,29445]	[1,17492]	[0,95871]	[2,11407]	[1,13478]	[-0,24929]	[1,54705]	[3,08205]
Almn(-1)	0,1951	1,0448	-0,0030	0,0140	-0,0008	-0,0238	0,0288	0,0450	0,0122
Standard errors	-0,0232	-0,0263	-0,0412	-0,0206	-0,0352	-0,0469	-0,0457	-0,0369	-0,0323
t-statistics	[8,41517]	[39,7786]	[-0,07173]	[0,67855]	[-0,02407]	[-0,50803]	[0,63167]	[1,22039]	[0,37863]
Almn(-2)	-0,2044	-0,0703	-0,0079	-0,0193	-0,0172	0,0104	-0,0432	-0,0617	-0,0172
Standard errors	-0,0232	-0,0263	-0,0411	-0,0206	-0,0352	-0,0469	-0,0456	-0,0368	-0,0323
t-statistics	[-8,82389]	[-2,67786]	[-0,19319]	[-0,94044]	[-0,48765]	[0,22162]	[-0,94689]	[-1,67598]	[-0,53284]
LEAD(-1)	-0,0024	-0,0075	1,0801	0,0165	0,0083	-0,0319	0,0352	0,0142	-0,0047
Standard errors	-0,0118	-0,0134	-0,0209	-0,0105	-0,0179	-0,0239	-0,0232	-0,0187	-0,0164
t-statistics	[-0,20634]	[-0,56446]	[51,6342]	[1,57789]	[0,46299]	[-1,33732]	[1,51822]	[0,75811]	[-0,28421]
LEAD(-2)	0,0060	0,0081	-0,0857	-0,0145	-0,0077	0,0291	-0,0326	-0,0157	0,0086
Standard errors	-0,0118	-0,0134	-0,0209	-0,0105	-0,0179	-0,0239	-0,0232	-0,0188	-0,0164
t-statistics	[0,50932]	[0,60854]	[-4,09711]	[-1,38404]	[-0,42913]	[1,22059]	[-1,40554]	[-0,83566]	[0,52449]
GOLD(-1)	-0,0065	-0,0097	-0,0343	0,9759	-0,0944	0,0039	-0,0233	-0,0765	-0,0239
Standard errors	-0,0189	-0,0214	-0,0335	-0,0168	-0,0287	-0,0382	-0,0372	-0,0300	-0,0263
t-statistics	[-0,34571]	[-0,45181]	[-1,02198]	[58,2141]	[-3,29280]	[0,10138]	[-0,62691]	[-2,54740]	[-0,91027]
GOLD(-2)	0,0060	0,0056	0,0365	0,0212	0,0977	0,0047	0,0215	0,0766	0,0283
Standard errors	-0,0189	-0,0214	-0,0336	-0,0168	-0,0287	-0,0383	-0,0372	-0,0301	-0,0263
t-statistics	[0,31525]	[0,25965]	[1,08763]	[1,26106]	[3,40348]	[0,12160]	[0,57849]	[2,54998]	[1,07443]
COPPER(-1)	-0,0136	-0,0021	-0,0316	0,0447	0,9993	-0,0469	0,0208	-0,0265	-0,0310
Standard errors	-0,0164	-0,0186	-0,0292	-0,0146	-0,0250	-0,0333	-0,0324	-0,0261	-0,0229
t-statistics	[-0,82536]	[-0,11140]	[-1,08452]	[3,06601]	[40,0370]	[-1,40888]	[0,64397]	[-1,01234]	[-1,35492]
COPPER(-2)	0,0143	0,0067	0,0396	-0,0426	-0,0025	0,0447	-0,0200	0,0360	0,0284
Standard errors	-0,0164	-0,0186	-0,0292	-0,0146	-0,0250	-0,0333	-0,0324	-0,0261	-0,0229
t-statistics	[0,86796]	[0,36201]	[1,35584]	[-2,92038]	[-0,09916]	[1,34337]	[-0,61748]	[1,37585]	[1,24195]
NICKEL(-1)	0,0030	0,0105	-0,0006	0,0000	0,0012	1,0406	0,0224	-0,0106	0,0524
Standard errors	-0,0100	-0,0114	-0,0178	-0,0089	-0,0152	-0,0203	-0,0198	-0,0160	-0,0140
t-statistics	[0,30291]	[0,92744]	[-0,03544]	[-0,00145]	[0,07795]	[51,2696]	[1,13511]	[-0,66719]	[3,75329]
NICKEL(-2)	-0,0022	-0,0093	0,0069	0,0003	0,0023	-0,0406	-0,0163	0,0125	-0,0498
Standard errors	-0,0100	-0,0114	-0,0178	-0,0089	-0,0153	-0,0203	-0,0198	-0,0160	-0,0140
t-statistics	[-0,21417]	[-0,81874]	[0,38629]	[0,03243]	[0,15099]	[-1,99780]	[-0,82677]	[0,78147]	[-3,56450]
OILBRE(-1)	-0,0009	0,0041	-0,0042	0,0054	-0,0012	0,0267	0,9923	0,0063	0,0007
Standard errors	-0,0085	-0,0096	-0,0150	-0,0075	-0,0128	-0,0171	-0,0167	-0,0134	-0,0118

t-statistics	[-0,10700]	[0,43063]	[-0,28041]	[0,71755]	[-0,09725]	[1,56305]	[59,6047]	[0,46577]	[0,05700]
OILBRE(-2)	0,0023	-0,0023	0,0021	-0,0042	0,0023	-0,0264	0,0038	-0,0062	-0,0018
Standard errors	-0,0085	-0,0096	-0,0150	-0,0075	-0,0128	-0,0171	-0,0166	-0,0134	-0,0118
t-statistics	[0,27094]	[-0,23975]	[0,14016]	[-0,55397]	[0,17914]	[-1,54614]	[0,22856]	[-0,45933]	[-0,15118]
ZINC(-1)	-0,0240	-0,0378	-0,0345	0,0058	-0,0303	0,0167	-0,0477	0,9911	0,0050
Standard errors	-0,0149	-0,0169	-0,0264	-0,0132	-0,0226	-0,0301	-0,0293	-0,0237	-0,0207
t-statistics	[-1,61192]	[-2,24489]	[-1,30696]	[0,43610]	[-1,34240]	[0,55465]	[-1,62690]	[41,8891]	[0,23963]
ZINC(-2)	0,0257	0,0406	0,0350	-0,0057	0,0330	-0,0118	0,0480	0,0077	-0,0037
Standard errors	-0,0149	-0,0169	-0,0264	-0,0132	-0,0226	-0,0301	-0,0293	-0,0236	-0,0207
t-statistics	[1,73085]	[2,40795]	[1,32553]	[-0,43338]	[1,46196]	[-0,39098]	[1,63777]	[0,32448]	[-0,17916]
TIN(-1)	-0,0234	-0,0138	0,0198	-0,0107	-0,0006	-0,0076	-0,0191	-0,0248	1,0197
Standard errors	-0,0134	-0,0152	-0,0238	-0,0119	-0,0204	-0,0271	-0,0264	-0,0213	-0,0187
t-statistics	[-1,74294]	[-0,90983]	[0,83202]	[-0,89734]	[-0,02865]	[-0,28182]	[-0,72155]	[-1,16245]	[54,5947]
TIN(-2)	0,0191	0,0126	-0,0223	0,0095	-0,0026	0,0025	0,0186	0,0195	-0,0273
Standard errors	-0,0134	-0,0152	-0,0238	-0,0119	-0,0204	-0,0271	-0,0264	-0,0213	-0,0187
t-statistics	[1,42085]	[0,82890]	[-0,93738]	[0,79823]	[-0,12888]	[0,09346]	[0,70349]	[0,91243]	[-1,46218]
C	0,0612	0,0787	0,0514	0,0358	0,0396	0,0197	0,0246	0,0767	0,0131
Standard errors	-0,0143	-0,0162	-0,0254	-0,0127	-0,0217	-0,0289	-0,0281	-0,0227	-0,0199
t-statistics	[4,28607]	[4,86420]	[2,02758]	[2,82032]	[1,82543]	[0,68131]	[0,87249]	[3,37391]	[0,65856]
R-squared	0,9979	0,9972	0,9988	0,9994	0,9991	0,9985	0,9986	0,9984	0,9988
Adj, R-squared	0,9979	0,9972	0,9988	0,9994	0,9991	0,9985	0,9986	0,9983	0,9988
Sum sq, resids	0,5151	0,6612	1,6226	0,4059	1,1879	2,1089	1,9978	1,3021	0,9991
S,E, equation	0,0115	0,0130	0,0204	0,0102	0,0175	0,0233	0,0227	0,0183	0,0160
F-statistic	101477,80	77052,32	178702,20	381763,40	241733,70	144412,50	159559,50	131311,60	179519,70
Log likelihood	11926,26	11438,06	9682,04	12392,43	10292,04	9169,25	9275,14	10112,48	10630,62
Akaike AIC	-6,0876	-5,8380	-4,9402	-6,3259	-5,2521	-4,6780	-4,7322	-5,1603	-5,4252
Schwarz SC	-6,0571	-5,8075	-4,9097	-6,2954	-5,2216	-4,6476	-4,7017	-5,1298	-5,3947
Mean dependent	7,3163	7,4469	6,7078	6,0586	7,9520	9,2640	3,5001	7,1696	8,8863
S,D, dependent	0,2489	0,2458	0,5858	0,4281	0,5829	0,6005	0,6143	0,4500	0,4607
Determinant resid covariance (dof adj,)		2,57E-34							
Determinant resid covariance		2,46E-34							
Log likelihood		101416,1							
Akaike information criterion		-51,76128							
Schwarz criterion		-51,48712							

K. Table 10: Choice of the optimal model

Trace Value Test: With the critical value of MHM								
r<= n-1, the number of relations of the variables,n: number of variables								
Level: 5%								
H_0:	r	n-r	Model 2	critical value	Model 3	critical value	Model 4	critical value
	0	9	230.0943	208.4374	225.6325	197.3709	246.3626	228.2979
	1	8	174.0268	169.5991	170.5407	159.5297	189.2299	187.4701
	2	7	129.1710*	134.6780	125.8645	125.6154	144.4701	150.5585
	3	6	91.05584	103.8473	88.35935	95.75366	100.8243	117.7082
	4	5	59.38492	76.97277	56.69000	69.81889	69.11097	88.80380
	5	4	31.82397	54.07904	29.14251	47.85613	41.09981	63.87610
	6	3	16.81814	35.19275	14.14743	29.79707	22.88500	42.91525
	7	2	7.694576	20.26184	5.393028	15.49471	13.09607	25.87211
	8	1	2.214778	9.164546	0.055022	3.841466	5.066655	12.51798

Note: * means the null hypothesis is firstly not rejected.

L. Table 11: MacKinnon Critical Value

n = 2(Total number of time series)						Dep.variable:	
Critical value = $\varphi_\infty + \varphi_1/T + \varphi_2/T^2$	(T: Number of observations)					Aluminum	Alum Alloy
Model	Significance (%)	ϕ_∞	ϕ_1	ϕ_2	Crit.Values	ADF t-stat	ADF t-stat
constant	1	-3,900	-10,534	-30,030	-3,903	**-3,973**	
	5	-3,338	-5,967	-8,980	-3,339		**-3.866399**
	10	-3,046	-4,069	-5,730	-3,047		
constant and trend	1	-4,327	-15,531	-34,030	-4,331		
	5	-3,781	-9,421	-15,060	-3,783	**-3,952**	**-3.896110**
	10	-3,496	-7,203	-4,010	-3,498		

(source: MacKinnon 2010 & Hjertstrand P.2010)

M. Table 12: VAR Lag Order Selection Criteria for Aluminum and Aluminum Alloy

VAR Lag Order Selection Criteria
Endogenous variables: ALMNALUSD_MT ALMNUSD_MT
Exogenous variables: C
Sample: 4/07/1995 4/07/2010
Included observations: 3864

Lag	LogL	LR	FPE	AIC	SC	HQ
0	4735.755	NA	0.000296	-2.450184	-2.446944	-2.449033
1	24257.14	39012.45	1.21e-08	-12.55235	-12.54263	-12.54890
2	24316.76	119.0944	1.18e-08	-12.58114	-12.56494*	-12.57539*
3	24323.07	12.58472	1.18e-08	-12.58233	-12.55965	-12.57428
4	24327.73	9.309725	1.18e-08	-12.58268	-12.55352	-12.57232
5	24328.87	2.278875	1.18e-08	-12.58120	-12.54556	-12.56854
6	24337.37	16.94172	1.18e-08	-12.58353	-12.54141	-12.56857
7	24339.53	4.303302	1.18e-08	-12.58257	-12.53398	-12.56532
8	24342.31	5.527217	1.18e-08	-12.58194	-12.52686	-12.56238
9	24346.72	8.767334	1.18e-08	-12.58215	-12.52059	-12.56029
10	24351.51	9.536597	1.18e-08	-12.58256	-12.51452	-12.55840
11	24356.63	10.17911	1.18e-08	-12.58314	-12.50862	-12.55668
12	24359.62	5.947562	1.18e-08	-12.58262	-12.50162	-12.55386
13	24365.10	10.87278	1.18e-08	-12.58338	-12.49591	-12.55232
14	24367.28	4.330787	1.18e-08	-12.58244	-12.48849	-12.54908
15	24374.06	13.45794	1.17e-08*	-12.58388*	-12.48345	-12.54822
16	24375.61	3.061151	1.18e-08	-12.58261	-12.47570	-12.54465

N. Table 13: Pairwise Granger Causality Test for Aluminum and Aluminum Alloy

Pairwise Granger Causality Tests
Sample: 4/07/1995 4/07/2010
Lags: 2 Obs: 3912

Null Hypothesis:	F-Statistic	Prob.
Aluminum Alloy does not Granger Cause Aluminum	10.4600	3.E-05
Aluminum does not Granger Cause Aluminum Alloy	33.4454	4.E-15

O. Table 14: Identify the optimal model for Aluminum and Aluminum Alloy

Trace Test: With the critical value of MHM
r<= n-1, the number of relations of the variables,n: number of variables

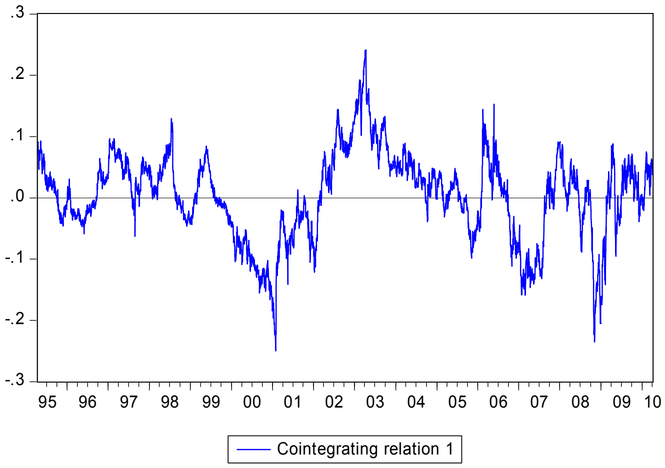
Level: 5%								
H_0:	r	n-r	Model 2	critical value	Model 3	critical value	Model 4	critical value
	0	9	23.09927	20.26184	22.98777	15.49471	28.91358	25.87211
	1	8	2.729943*	9.164546	2.644508	3.841466	8.548827	12.51798

P. Table 15: Restrictions on Alpha

Restrictions on Alpha	
	prob.
a(1,1)=0	0.502986
a(2,1)=0	0.000680

Q. Table 16: Cointegration test without restriction

Vector Error Correction Estimates



Sample (adjusted): 5/01/1995 4/07/2010

Included observations: 3898 after adjustments

Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
ALMNALUSD_MT(-1)	1.000000	
ALMNUSD_MT(-1)	-0.996424	
	(0.06127)	
	[-16.2620]	
C	0.106721	
	(0.45650)	
	[0.23378]	
Error Correction:	D(ALMNALUSD_MT)	D(ALMNUSD_MT)
CointEq1	-0.000469	0.009608
	(0.00273)	(0.00310)
	[-0.17184]	[3.09813]

R. Table 17: Cointegration test with restriction a(1,1)=0

Vector Error Correction Estimates
Date: 05/18/10 Time: 18:25

Sample (adjusted): 5/01/1995 4/07/2010

Included observations: 3898 after adjustments

Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:

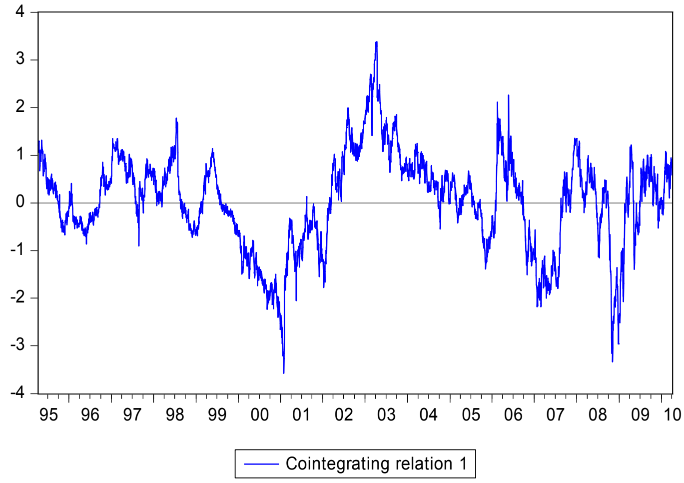
A(1,1)=0

Convergence achieved after 3 iterations.

Not all cointegrating vectors are identified

LR test for binding restrictions (rank = 1):

Chi-square(1)	0.025785	
Probability	0.872426	
Cointegrating Eq:	CointEq1	
ALMNALUSD_MT(-1)	14.82286	
ALMNUSD_MT(-1)	-14.82633	
C	2.005051	
Error Correction:	D(ALMNALUSD_MT)	D(ALMNUSD_MT)
CointEq1	0.000000	0.000672
	(0.00000)	(0.00015)
	[NA]	[4.49829]



S. Table 18: VAR Lag Order Selection Criteria for commodities exclude Aluminum Alloy

VAR Lag Order Selection Criteria
Endogenous variables: ALMN,COPP, GOLD, LEAD, NIC, OILBRE, TIN, ZINC
Exogenous variables: C
Sample: 4/07/1995 4/07/2010
Included observations: 3904

Lag	LogL	LR	FPE	AIC	SC	HQ
0	6965.490	NA	3.91e-12	-3.564288	-3.551440	-3.559728
1	87830.24	161356.7	4.12e-30	-44.95811	-44.84248*	-44.91707*
2	87928.67	196.0146	4.05e-30*	-44.97575*	-44.75734	-44.89824
3	87979.47	100.9380	4.08e-30	-44.96899	-44.64779	-44.85499
4	88030.77	101.7489	4.10e-30	-44.96249	-44.53851	-44.81201
5	88069.11	75.86290	4.16e-30	-44.94934	-44.42258	-44.76238
6	88135.66	131.4276	4.15e-30	-44.95064	-44.32110	-44.72721
7	88190.03	107.1595	4.17e-30	-44.94571	-44.21338	-44.68580
8	88248.24	114.4794*	4.19e-30	-44.94275	-44.10764	-44.64636

9	88289.35	80.68656	4.24e-30	-44.93102	-43.99313	-44.59815
10	88328.72	77.10289	4.29e-30	-44.91840	-43.87773	-44.54905

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

T. Table 19: Identify the optimal model for all the variables exclude Aluminum Alloy

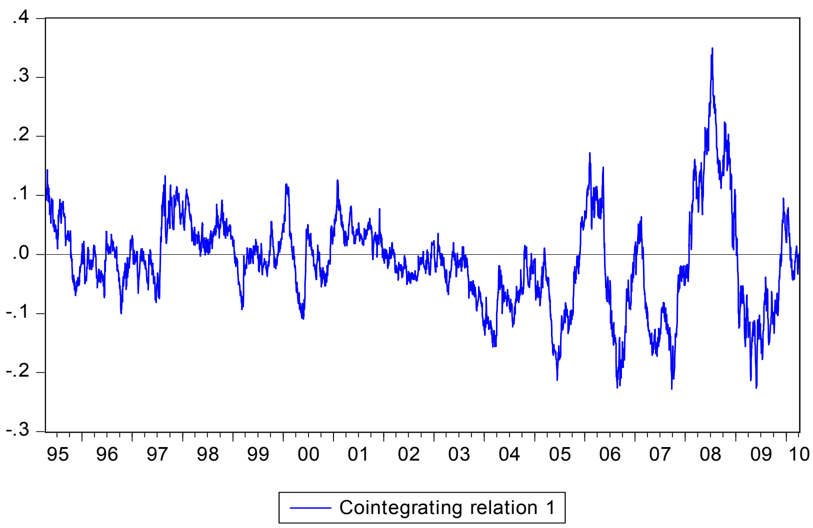
Trace Test: With the critical value of MHM
r<= n-1, the number of relations of the variables,n: number of variables
Level: 5%

H0: r	n-r	Model 2	critical value	Model 3	critical value	Model 4	critical value
0	8	179.2387	169.5991	174.7601	159.5297	195.5191	187.4701
1	7	130.0744*	134.6780	126.4496	125.6154	146.9876	150.5585
2	6	90.54740	103.8473	87.82500	95.75366	105.4059	117.7082
3	5	55.34397	76.97277	52.79404	69.81889	66.79317	88.80380
4	4	32.57192	54.07904	30.20791	47.85613	42.77544	63.87610
5	3	15.58938	35.19275	13.25965	29.79707	21.97389	42.91525
6	2	6.747086	20.26184	4.581430	15.49471	12.70920	25.87211
7	1	2.166670	9.164546	0.058508	3.841466	4.351572	12.51798

U. Table 20: Cointegration test without restriction (all the variables exclude Aluminum Alloy)

Vector Error Correction Estimates
Sample (adjusted): 4/12/1995 4/07/2010
Included observations: 3911 after adjustments
Standard errors in ( ) & t-statistics in [ ]

CointEq:	CointEq1
ALMN(-1)	1.000000
COPP(-1)	-0.378887
	(0.09485)
	[-3.99458]
GOLD(-1)	0.281102
	(0.08780)
	[3.20159]
LEAD(-1)	-0.049259
	(0.07894)
	[-0.62404]
NIC(-1)	-0.237843



	(0.05579)							
	[-4.26292]							
OILBRE(-1)	0.018052							
	(0.04682)							
	[0.38552]							
TIN(-1)	0.073963							
	(0.08125)							
	[0.91031]							
ZINC(-1)	-0.018329							
	(0.06578)							
	[-0.27864]							
C	-4.204268							
	(0.45480)							
	[-9.24422]							
Error Correction:	D(ALMN)	D(COPP)	D(GOLD)	D(LEAD)	D(NIC)	D(OILBRE)	D(TIN	D(ZINC)
CointEq1	-0.013500	-0.013384	-0.005451	-0.018606	-0.005043	-0.017266	-0.009580	-0.013229
	(0.00258)	(0.00345)	(0.00202)	(0.00403)	(0.00461)	(0.00447)	(0.00317)	(0.00361)
	[-5.24193]	[-3.87739]	[-2.70396]	[-4.61153]	[-1.09515]	[-3.86042]	[-3.02158]	[-3.66109]
D(ALMN(-1))	0.023528	-0.022226	0.010866	-0.019834	-0.040295	0.045981	-0.031292	0.029427
	(0.02255)	(0.03022)	(0.01765)	(0.03533)	(0.04032)	(0.03916)	(0.02776)	(0.03164)
	[1.04336]	[-0.73537]	[0.61554]	[-0.56142]	[-0.99933]	[1.17412]	[-1.12718]	[0.93008]
D(ALMN(-2))	-0.009412	0.052195	-0.043481	-0.018559	0.011421	0.103786	0.002899	0.011482
	(0.02253)	(0.03020)	(0.01764)	(0.03530)	(0.04029)	(0.03913)	(0.02774)	(0.03162)
	[-0.41766]	[1.72819]	[-2.46503]	[-0.52573]	[0.28345]	[2.65211]	[0.10449]	[0.36316]
D(COPP(-1))	-0.010816	-0.001947	0.041635	-0.047053	-0.051280	0.019502	-0.039663	-0.038261
	(0.01859)	(0.02492)	(0.01455)	(0.02913)	(0.03324)	(0.03229)	(0.02289)	(0.02608)
	[-0.58177]	[-0.07815]	[2.86095]	[-1.61553]	[-1.54261]	[0.60404]	[-1.73298]	[-1.46679]
D(COPP(-2))	-0.053460	-0.085709	-0.001905	-0.047591	-0.031557	-0.035578	-0.036393	-0.065720
	(0.01857)	(0.02489)	(0.01454)	(0.02909)	(0.03320)	(0.03225)	(0.02286)	(0.02605)
	[-2.87898]	[-3.44381]	[-0.13104]	[-1.63597]	[-0.95042]	[-1.10327]	[-1.59201]	[-2.52252]
D(GOLD(-1))	-0.001403	-0.087646	-0.019095	-0.022630	0.003799	-0.019255	-0.018525	-0.067656
	(0.02151)	(0.02882)	(0.01683)	(0.03369)	(0.03845)	(0.03735)	(0.02647)	(0.03017)
	[-0.06525]	[-3.04076]	[-1.13429]	[-0.67169]	[0.09880]	[-0.51558]	[-0.69974]	[-2.24224]
D(GOLD(-2))	0.026610	0.029291	0.022363	0.000992	-0.002126	0.008332	-0.008884	0.022735
	(0.02143)	(0.02872)	(0.01678)	(0.03357)	(0.03832)	(0.03722)	(0.02638)	(0.03007)
	[1.24164]	[1.01976]	[1.33305]	[0.02954]	[-0.05549]	[0.22386]	[-0.33675]	[0.75611]
D(LEAD(-1))	-0.013211	0.002842	0.013253	0.085357	-0.035016	0.036240	-0.008544	0.008919
	(0.01338)	(0.01793)	(0.01047)	(0.02095)	(0.02392)	(0.02323)	(0.01647)	(0.01877)
	[-0.98764]	[0.15850]	[1.26578]	[4.07335]	[-1.46404]	[1.56011]	[-0.51889]	[0.47524]
D(LEAD(-2))	0.000694	0.006379	0.016041	-0.025423	0.012689	-0.016496	0.021533	0.033662
	(0.01339)	(0.01795)	(0.01048)	(0.02098)	(0.02394)	(0.02326)	(0.01649)	(0.01879)
	[0.05181]	[0.35541]	[1.53032]	[-1.21186]	[0.52993]	[-0.70934]	[1.30623]	[1.79164]
D(NIC(-1))	0.008103	0.000128	-0.001940	-0.003081	0.045474	0.018939	0.052526	-0.010300
	(0.01137)	(0.01524)	(0.00890)	(0.01782)	(0.02033)	(0.01975)	(0.01400)	(0.01596)
	[0.71251]	[0.00838]	[-0.21797]	[-0.17292]	[2.23634]	[0.95897]	[3.75193]	[-0.64552]

D(NIC(-2))	-0.004527	-0.006527	-0.000243	0.003414	-0.036213	0.008190	-0.014613	-0.016393
	(0.01138)	(0.01526)	(0.00891)	(0.01783)	(0.02035)	(0.01977)	(0.01401)	(0.01597)
	[-0.39769]	[-0.42779]	[-0.02728]	[0.19145]	[-1.77914]	[0.41431]	[-1.04276]	[-1.02638]
D(OILBRE(-1))	0.003069	-0.002347	0.005067	-0.003718	0.025568	-0.005278	0.000231	0.004464
	(0.00957)	(0.01282)	(0.00749)	(0.01499)	(0.01711)	(0.01661)	(0.01178)	(0.01342)
	[0.32079]	[-0.18302]	[0.67670]	[-0.24805]	[1.49476]	[-0.31770]	[0.01962]	[0.33262]
D(OILBRE(-2))	0.018092	0.011630	0.000932	-0.016405	0.022283	-0.011634	0.026724	0.007167
	(0.00956)	(0.01282)	(0.00748)	(0.01498)	(0.01710)	(0.01661)	(0.01177)	(0.01342)
	[1.89209]	[0.90746]	[0.12447]	[-1.09512]	[1.30332]	[-0.70063]	[2.27030]	[0.53419]
D(TIN(-1))	-0.016438	0.000104	-0.010530	0.018098	-0.002989	-0.015019	0.026860	-0.024335
	(0.01519)	(0.02036)	(0.01189)	(0.02380)	(0.02716)	(0.02638)	(0.01870)	(0.02131)
	[-1.08203]	[0.00512]	[-0.88546]	[0.76045]	[-0.11005]	[-0.56927]	[1.43622]	[-1.14169]
D(TIN(-2))	0.036085	0.041036	-0.004811	0.027979	0.013627	0.009045	-0.019876	0.033844
	(0.01517)	(0.02033)	(0.01187)	(0.02376)	(0.02712)	(0.02634)	(0.01867)	(0.02128)
	[2.37928]	[2.01878]	[-0.40525]	[1.17758]	[0.50248]	[0.34341]	[-1.06457]	[1.59047]
D(ZINC(-1))	-0.037307	-0.033332	0.006465	-0.033685	0.014808	-0.051339	0.001069	-0.003805
	(0.01685)	(0.02259)	(0.01319)	(0.02641)	(0.03014)	(0.02927)	(0.02075)	(0.02365)
	[-2.21341]	[-1.47550]	[0.49002]	[-1.27570]	[0.49135]	[-1.75392]	[0.05152]	[-0.16089]
D(ZINC(-2))	0.007365	0.001322	0.005593	0.016528	0.005021	-0.022479	-0.003205	-0.019447
	(0.01685)	(0.02259)	(0.01319)	(0.02640)	(0.03014)	(0.02927)	(0.02075)	(0.02365)
	[0.43697]	[0.05851]	[0.42398]	[0.62599]	[0.16661]	[-0.76804]	[-0.15446]	[-0.82243]
R-squared	0.015999	0.013911	0.014165	0.013152	0.005337	0.007921	0.010908	0.011145
Adj. R-squared	0.011956	0.009859	0.010114	0.009097	0.001250	0.003845	0.006844	0.007082
Sum sq. resids	0.662139	1.189434	0.405716	1.625056	2.116984	1.996925	1.003469	1.303446
S.E. equation	0.013040	0.017477	0.010207	0.020428	0.023316	0.022646	0.016053	0.018296
F-statistic	3.957064	3.433317	3.496933	3.243408	1.305909	1.943179	2.684006	2.742946
Log likelihood	11431.76	10286.31	12389.60	9676.066	9158.934	9273.104	10618.77	10107.31
Akaike AIC	-5.837257	-5.251501	-6.327080	-4.939436	-4.674986	-4.733369	-5.421515	-5.159967
Schwarz SC	-5.809996	-5.224240	-6.299819	-4.912175	-4.647725	-4.706109	-5.394254	-5.132706
Mean dependent	5.93E-05	0.000254	0.000275	0.000340	0.000312	0.000387	0.000293	0.000213
S.D. dependent	0.013119	0.017564	0.010259	0.020522	0.023331	0.022689	0.016108	0.018361
Determinant resid covariance (dof adj.)			3.91E-30					
Determinant resid covariance			3.77E-30					
Log likelihood			88088.43					
Akaike information criterion			-44.97235					
Schwarz criterion			-44.73983					

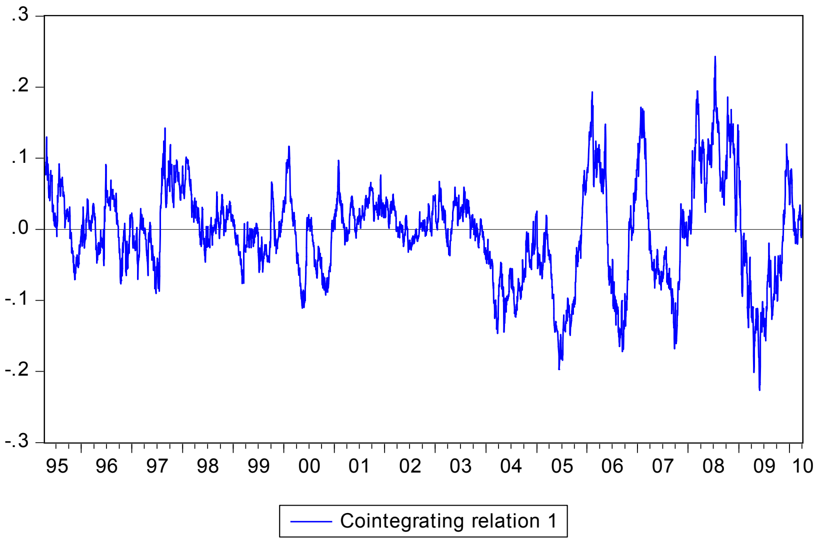
V. Table 21: Weakly Exogeneity Test (all the variables exclude Aluminum Alloy)

	prob.
a(1,1)=0	0.003679
a(2,1)=0	0.011661
a(3,1)=0	0.028243
a(4,1)=0	0.007364
a(5,1)=0	0.459552
a(6,1)=0	0.010844
a(7,1)=0	0.091410
a(8,1)=0	0.034469

W. Table 22: Cointegration test with restriction (all the variables exclude Aluminum Alloy)

Vector Error Correction Estimates
Sample (adjusted): 4/12/1995 4/07/2010
Included observations: 3911 after adjustments
Standard errors in ( ) & t-statistics in [ ]
Cointegration Restrictions:
A(5,1)=0, A(7,1)=0,
B(1,1)=1
Convergence achieved after 19 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(2)	2.871761
Probability	0.237906
Cointegrating Eq:	CointEq1
ALMN(-1)	1.000000
COPP(-1)	-0.504197
	(0.08165)
	[-6.17504]
GOLD(-1)	0.410922
	(0.07558)
	[5.43676]
LEAD(-1)	0.023726
	(0.06795)
	[0.34915]
NICKEl(-1)	-0.121061
	(0.04803)
	[-2.52058]
OILBRE(-1)	-0.038550
	(0.04031)
	[-0.95636]
TIN(-1)	-0.056756



	(0.06994)							
	[-0.81145]							
ZINC(-1)	0.008392							
	(0.05663)							
	[0.14820]							
C	-4.389347							
	(0.39151)							
	[-11.2114]							
Error Correction:	D(ALMN)	D(COPP)	D(GOLD)	D(LEAD)	D(NIC)	D(OILBRE)	D(TIN)	D(ZINC)
CointEq1	-0.015005	-0.009304	-0.005781	-0.016617	0.000000	-0.013998	0.000000	-0.013613
	(0.00260)	(0.00329)	(0.00236)	(0.00416)	(0.00000)	(0.00524)	(0.00000)	(0.00358)
	[-5.76092]	[-2.82664]	[-2.45298]	[-3.99135]	[NA]	[-2.67189]	[NA]	[-3.80358]
D(ALMN(-1))	0.024100	-0.024208	0.010947	-0.020992	-0.042393	0.043875	-0.034942	0.029655
	(0.02256)	(0.03027)	(0.01766)	(0.03537)	(0.04034)	(0.03921)	(0.02780)	(0.03166)
	[1.06817]	[-0.79979]	[0.61986]	[-0.59342]	[-1.05080]	[1.11887]	[-1.25682]	[0.93673]
D(ALMN(-2))	-0.008640	0.050125	-0.043335	-0.019659	0.009138	0.101618	-0.001065	0.011868
	(0.02255)	(0.03025)	(0.01765)	(0.03535)	(0.04032)	(0.03919)	(0.02779)	(0.03164)
	[-0.38315]	[1.65697]	[-2.45513]	[-0.55607]	[0.22664]	[2.59283]	[-0.03834]	[0.37511]
D(COPP(-1))	-0.011887	-0.001106	0.041314	-0.047076	-0.049954	0.020251	-0.037394	-0.039062
	(0.01861)	(0.02496)	(0.01456)	(0.02917)	(0.03327)	(0.03234)	(0.02293)	(0.02611)
	[-0.63888]	[-0.04429]	[2.83669]	[-1.61374]	[-1.50150]	[0.62623]	[-1.63098]	[-1.49623]
D(COPP(-2))	-0.054748	-0.085080	-0.002313	-0.047911	-0.030310	-0.035104	-0.034274	-0.066733
	(0.01859)	(0.02493)	(0.01455)	(0.02914)	(0.03323)	(0.03230)	(0.02290)	(0.02608)
	[-2.94574]	[-3.41223]	[-0.15900]	[-1.64416]	[-0.91202]	[-1.08670]	[-1.49654]	[-2.55894]
D(GOLD(-1))	0.000910	-0.086605	-0.018234	-0.020398	0.003527	-0.017691	-0.018878	-0.065553
	(0.02152)	(0.02887)	(0.01684)	(0.03374)	(0.03848)	(0.03740)	(0.02652)	(0.03019)
	[0.04230]	[-2.99990]	[-1.08247]	[-0.60456]	[0.09166]	[-0.47300]	[-0.71191]	[-2.17099]
D(GOLD(-2))	0.029222	0.030880	0.023359	0.003827	-0.002058	0.010558	-0.008623	0.025164
	(0.02144)	(0.02877)	(0.01678)	(0.03362)	(0.03834)	(0.03727)	(0.02642)	(0.03009)
	[1.36284]	[1.07350]	[1.39173]	[0.11385]	[-0.05367]	[0.28331]	[-0.32637]	[0.83639]
D(LEAD(-1))	-0.011883	0.004698	0.013821	0.087599	-0.034029	0.038539	-0.006742	0.010290
	(0.01337)	(0.01794)	(0.01046)	(0.02096)	(0.02391)	(0.02324)	(0.01647)	(0.01876)
	[-0.88888]	[0.26196]	[1.32067]	[4.17909]	[-1.42348]	[1.65858]	[-0.40924]	[0.54854]
D(LEAD(-2))	0.002147	0.008327	0.016658	-0.023032	0.013692	-0.014072	0.023372	0.035152
	(0.01338)	(0.01795)	(0.01048)	(0.02098)	(0.02393)	(0.02326)	(0.01649)	(0.01878)
	[0.16046]	[0.46378]	[1.59005]	[-1.09762]	[0.57212]	[-0.60497]	[1.41718]	[1.87190]
D(NIC(-1))	0.009397	0.001250	-0.001427	-0.001420	0.045812	0.020415	0.053189	-0.009052
	(0.01137)	(0.01526)	(0.00890)	(0.01783)	(0.02034)	(0.01977)	(0.01401)	(0.01596)
	[0.82628]	[0.08194]	[-0.16031]	[-0.07961]	[2.25274]	[1.03281]	[3.79536]	[-0.56727]
D(NIC(-2))	-0.003335	-0.005472	0.000231	0.004960	-0.035883	0.009574	-0.013969	-0.015241
	(0.01138)	(0.01527)	(0.00891)	(0.01785)	(0.02036)	(0.01979)	(0.01403)	(0.01597)
	[-0.29296]	[-0.35828]	[0.02591]	[0.27791]	[-1.76277]	[0.48386]	[-0.99578]	[-0.95416]
D(OILBRE(-1))	0.002893	-0.001897	0.005033	-0.003483	0.026069	-0.004808	0.001099	0.004374
	(0.00957)	(0.01284)	(0.00749)	(0.01500)	(0.01711)	(0.01663)	(0.01179)	(0.01343)
	[0.30236]	[-0.14776]	[0.67193]	[-0.23217]	[1.52355]	[-0.28910]	[0.09324]	[0.32575]

D(OILBRE(-2))	0.017998	0.012166	0.000930	-0.016054	0.022819	-0.011055	0.027659	0.007156
	(0.00956)	(0.01283)	(0.00749)	(0.01500)	(0.01710)	(0.01662)	(0.01179)	(0.01342)
	[1.88186]	[0.94816]	[0.12428]	[-1.07063]	[1.33431]	[-0.66502]	[2.34693]	[0.53327]
D(TIN(-1))	-0.015984	0.000384	-0.010356	0.018594	-0.002974	-0.014628	0.026911	-0.023913
	(0.01519)	(0.02038)	(0.01189)	(0.02382)	(0.02717)	(0.02641)	(0.01872)	(0.02132)
	[-1.05204]	[0.01883]	[-0.87078]	[0.78052]	[-0.10948]	[-0.55392]	[1.43736]	[-1.12164]
D(TIN(-2))	0.036550	0.041391	-0.004629	0.028539	0.013703	0.009521	-0.019717	0.034286
	(0.01517)	(0.02035)	(0.01187)	(0.02378)	(0.02712)	(0.02636)	(0.01869)	(0.02128)
	[2.40970]	[2.03402]	[-0.38991]	[1.20000]	[0.50523]	[0.36114]	[-1.05487]	[1.61093]
D(ZINC(-1))	-0.038152	-0.033849	0.006143	-0.034604	0.014784	-0.052062	0.000980	-0.004591
	(0.01686)	(0.02262)	(0.01320)	(0.02643)	(0.03014)	(0.02930)	(0.02077)	(0.02365)
	[-2.26314]	[-1.49667]	[0.46551]	[-1.30920]	[0.49043]	[-1.77683]	[0.04719]	[-0.19407]
D(ZINC(-2))	0.006383	0.000752	0.005221	0.015483	0.005020	-0.023285	-0.003259	-0.020356
	(0.01686)	(0.02261)	(0.01320)	(0.02643)	(0.03014)	(0.02930)	(0.02077)	(0.02365)
	[0.37867]	[0.03327]	[0.39565]	[0.58582]	[0.16655]	[-0.79475]	[-0.15688]	[-0.86063]
R-squared	0.015803	0.011804	0.013950	0.011311	0.005046	0.006048	0.008771	0.010773
Adj. R-squared	0.011759	0.007743	0.009899	0.007248	0.000958	0.001964	0.004698	0.006709
Sum sq. resids	0.662271	1.191975	0.405804	1.628088	2.117604	2.000695	1.005637	1.303935
S.E. equation	0.013041	0.017496	0.010208	0.020448	0.023320	0.022667	0.016070	0.018299
F-statistic	3.907755	2.907074	3.443158	2.784200	1.234272	1.480941	2.153419	2.650539
Log likelihood	11431.37	10282.14	12389.18	9672.422	9158.362	9269.416	10614.55	10106.58
Akaike AIC	-5.837058	-5.249366	-6.326862	-4.937572	-4.674693	-4.731483	-5.419356	-5.159591
Schwarz SC	-5.809797	-5.222106	-6.299601	-4.910311	-4.647432	-4.704223	-5.392096	-5.132331
Mean dependent	5.93E-05	0.000254	0.000275	0.000340	0.000312	0.000387	0.000293	0.000213
S.D. dependent	0.013119	0.017564	0.010259	0.020522	0.023331	0.022689	0.016108	0.018361
Determinant resid covariance (dof adj.)			3.91E-30					
Determinant resid covariance			3.78E-30					
Log likelihood			88086.99					
Akaike information criterion			-44.97162					
Schwarz criterion			-44.73910					

X. Table 23: VEC Granger Causality/Block Exogeneity Wald Tests without restriction

No restrictions								
Ex.\End. Variable:	**D(Alum)**	**D(Copper)**	**D(Gold)**	**D(Lead)**	**D(Nickel)**	**D(Oil)**	**D(Tin)**	**D(Zinc)**
D(Aluminum)		0.1761	**0.0409****	0.7390	0.5865	**0.0139****	0.5281	0.6028
D(Copper)	**0.0130****		**0.0166****	**0.0679***	0.1888	0.4585	**0.0598***	**0.0133****
D(Gold)	0.4613	**0.0057****		0.7976	0.9936	0.8530	0.7412	**0.0599***
D(Lead)	0.6138	0.9223	0.1170		0.3147	0.2498	0.3912	0.1653
D(Nickel)	0.7236	0.9125	0.9759	0.9683		0.5712	**0.0006****	0.4683
D(Oil)	0.1592	0.6508	0.7896	0.5333	0.1416		**0.0760***	0.8213
D(Tin)	**0.0352****	0.1301	0.6161	0.3650	0.8773	0.8059		0.1545
D(Zinc)	**0.0801***	0.3366	0.8068	0.3708	0.8724	0.1550	0.9870	
All	**0.0027****	**0.0174****	**0.0000****	0.1025	0.2638	0.2266	**0.0090****	**0.0303****

Note: * and ** denote significance at the 10% and 5% levels, respectively

Y. Table 24: VEC Granger Causality/Block Exogeneity Wald Tests with restrictions: α (Nickel)=0, α (Tin)=0 and β(Aluminum)=1

Restriction: A(Nickel)=0, A(Tin)=0, B(Aluminum)=1								
Ex.\End. Variable:	**D(Alum)**	**D(Copper)**	**D(Gold)**	**D(Lead)**	**D(Nickel)**	**D(Oil)**	**D(Tin)**	**D(Zinc)**
D(Aluminum)		0.1891	**0.0418****	0.7134	0.5638	**0.0174****	0.4530	0.5965
D(Copper)	**0.0103****		**0.0178****	**0.0675***	0.2091	0.4602	**0.0830***	**0.0116****
D(Gold)	0.3949	**0.0061****		0.8270	0.9943	0.8579	0.7375	**0.0656***
D(Lead)	0.6711	0.8581	**0.0975***		0.3274	0.2265	0.3510	0.1351
D(Nickel)	0.6863	0.9356	0.9870	0.9598		0.5125	**0.0005****	0.5297
D(Oil)	0.1632	0.6304	0.7922	0.5496	0.1303		**0.0635***	0.8236
D(Tin)	**0.0337****	0.1260	0.6282	0.3495	0.8762	0.8079		0.1529
D(Zinc)	**0.0732***	0.3263	0.8263	0.3635	0.8728	0.1456	0.9868	
All	**0.0024****	**0.0168****	**0.0000****	0.1059	0.2668	0.2072	**0.0081****	**0.0310****

Note: * and ** denote significance at the 10% and 5% levels, respectively