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COMMODITY FUTURES: WHAT DRIVES ASSET PRICES? CAUSALITY AND COINTEGRATION

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Contents

1	In	trodu	iction	4
2	Li	teratı	ıre Review	4
3	M	ethod	lology	5
4			nd Sources	
-	4.1		a Retrieval	
	4.2		ifying and Cleaning of Data	
	4.2		Missing Data	
	4.2	2.2	Outliers	
	4.3	Des	scription of Data	7
	4.3	3.1	Subsamples	7
	4.3	3.2	Stationarity	8
	4.3	3.3	Normality Test	8
		4.3.3.1	Box Plots	9
	,	4.3.3.2	•	
		4.3.3.3	•	
	4.4	Dat	abase Setup	11
5	Aı	nalys	is of Cointegration & Causality	12
	5.1	Coi	ntegration	12
	5.2	Cau	usality	12
6	Co	onclu	sion	13
7	Bi	blioa	raphy	14
8			dix	
•	8.1	•	pendix 1	
	8.2		pendix 2	
	8.3		pendix 3	
	8.4		pendix 4	
	8.5	• • •	pendix 5	
	8.6	• • •	pendix 6	
	8.7		pendix 7	
	8.8		pendix 8	
		• • •		
	8.9	Δnr	oendix 9	۸۲.

List of Figures

Figure 1: Selected Instruments	5
Figure 2: Descriptive Statistics of Subsamples	7
Figure 3: Box Plots	g
Figure 4: Histogram	10
Figure 5: SQLite database	11

1 Introduction

This paper aims to investigate the causal relationships and long-term equilibrium dynamics among a set of commodity futures through the lens of cointegration analysis and Granger causality testing.

2 Literature Review

Studies have shown that many economic time series follow a stochastic process and can be classified as non-stationary. The methods for the analysis of regression models and hypothesis tests require the use of stationary time series. If this requirement is ignored and non-stationary time series are used, there is a risk of spurious regressions (Winker, 2017, pp. 268-269). A common method for testing the null hypothesis of non-stationarity is the Augmented Dickey-Fuller unit root test (Winker, 2017, pp. 273-275; Acikalin & Basci, 2016, p. 569).

To avoid the difficulties resulting from spurious correlations, non-stationary time series can be differenced to make them stationary. A disadvantage of the analysis of differences is that information about long term dependencies get lost (Gerhards, 1994, p. 73).

It is often of interest to determine whether there are certain dependencies between non-stationary time series (Gerhards, 1994, p. 73). Cointegration occurs when two or more non-stationary variables exhibit a common long-term trend and do not drift away from each other (Kirchgässner, Wolters, & Hassler, 2023, p. 209). The time series therefore develop in parallel in the long term and the difference between the two time series remains the same over time, although both time series individually have a trend (Gerhards, 1994, p. 74).

The Granger Causality Test is used to find out whether a Time Series can help to predict another Time Series. It states that a variable X is Granger-causal for Y if, for a given amount of information up to time t-1, variable Y can be predicted better at time t than without the inclusion of variable X. The Granger causality test can apply in one direction or in both directions. The Times Series must also be stationary for Granger Causality (Granger, 1969, pp. 431-436)

This means that in case of non-stationary data, as described above, the time series must first be differentiated.

3 Methodology

For the analysis, 20 different commodity futures are analyzed and tested for causality and cointegration. As reference of the commodity futures, the first generic commodity future will be used. The analysis will be done mainly by using Python and SQL is used as support. The raw data for this is obtained from Refinitiv. For an additional control of the data, the data will be pulled via Excel on the one hand and directly via Python API interface on the other hand. Afterwards, the data has to be cleaned due to missing values. Then an SQL database is created for further processing. In this way, the data can be processed more easily and efficiently.

The first step of the main analysis is to test the stationarity of all time series in level and first difference. Thereafter, each asset is tested against each other for cointegration and granger causality. Both analyses are performed in Python using a loop to test all possible combinations. The respective results are saved and added to this work as a table.

4 Data and Sources

4.1 Data Retrieval

The data used in this paper is obtained from Refinitiv and covers a period of ten years, from 02.05.2013 to 01.05.2023. We focus on analyzing the daily closing prices of the 1st generic commodity futures for twenty different instruments.

```
Instrument
                                                                     Instrument Description
         CLc1 NYMEX Light Sweet Crude Oil (WTI) Electronic Energy Future Continuation 1
                                                      CBoT Corn Composite Commodity Future
                                     COMEX Gold Composite Commodity Future Continuation 1
         GCc1
         LCc1
                              CME Live Cattle Electronic Commodity Future Continuation 1
                     NYMEX Henry Hub Natural Gas Electronic Energy Future Continuation 1
         NGc1
                        ICE-US FCOJ-A Futures Electronic Commodity Future Continuation 1
                               NYMEX Palladium Electronic Commodity Future Continuation 1
         PAc1
         PI c1
                                NYMEX Platinum Electronic Commodity Future Continuation 1
                                                   COMEX Silver Composite Commodity Future
         SIc1
                                     CBoT Wheat Composite Commodity Future Continuation 1
          Wc1
        SOYc1
                     Johannesburg Stock Exchange Soybean Commodity Future Continuation 1
11
         HGc1
                                   COMEX Copper Composite Commodity Future Continuation 1
                  ICE-US Sugar No. 16 Futures Electronic Commodity Future Continuation 1
12
        SFSc1
                                  ICE Europe London Cocoa Commodity Future Continuation 1
13
        LCCc1
                                          ICE Europe Brent Crude Electronic Energy Future
15
                              NYMEX RBOB Gasoline Electronic Energy Future Continuation 1
16
         HOc1
                             NYMEX NY Harbor ULSD Electronic Energy Future Continuation 1
                                           SHFE Aluminium Commodity Future Continuation 1
SHFE Zinc Commodity Future Continuation 1
17
        SAFc1
18
                  NYMEX Chicago Ethanol (Platts) Electronic Energy Future Continuation 1,
```

Figure 1: Selected Instruments

To gather the data, two methods were employed: the Formula Builder in the Excel Add-in and the Eikon API. Both approaches utilized the same parameters, including the asset keys, daily intervals, and the "CLOSE" field for the specified time horizon as defined above.

During the comparison of the two datasets, we observed that the data obtained through the Eikon API did not contain any NaN values as those dates were excluded. For that reason, we dropped the NaN values in the excel data to enable comparability. By employing the method .info() in pandas we identified that the data format in the two data differs in some asset classes. However, by utilizing the method .describe() in pandas, we confirmed that the values were identical (see Appendix 1).

4.2 Verifying and Cleaning of Data

4.2.1 Missing Data

In the data cleaning process, we initially examined the samples (plots see Appendix 2) and observed a significant number of days with more than 50% missing values, which coincided with public holidays in the USA. Additionally, we identified missing values for assets traded in Shanghai due to public holidays in China. Consequently, we proceeded by excluding these data points. As a result of the cleaning process, the initial sample, consisting of 2601 trading days, was reduced to 2357 trading days for each asset.

Furthermore, we encountered additional randomly missing dates across certain asset classes. To address this issue, we applied the method .ffill() in pandas. This method allowed us to replace the NaN values in each selected row with the values from the previous row, ensuring a consistent and continuous dataset.

4.2.2 Outliers

To identify and address outliers, we employed a methodology that involved calculating the moving average and standard deviation for each asset class. Any data points that fell outside a certain threshold were identified as outliers. Subsequently, these outliers were replaced with the corresponding moving average value, effectively smoothing the data and reducing the impact of extreme values. The plots of clean data are found in the Appendix 3.

4.3 Description of Data

4.3.1 Subsamples

After cleaning the data, we divided the set into five subsamples, each representing a two-year interval. To gain insights into the data distribution within each subsample, we employed the method .describe() to generate descriptive statistics.

	Price 1st generic Commodity Future		Full S 013-05-02 -	2023-05-02		2013-05-02 - 2015-05-01	2015-05-02 - 2017-05-01	2017-05-02 - 2019-05-01	2019-05-02 - 2021-05-01	2021-05-02 - 2023-05-02
		Mean	Std.	Min	Max	Mean	Mean	Mean	Mean	
CLc1	NYMEX Light Sweet Crude Oil (WTI) Electronic Energy Future Continuation 1	64,81	22,27	10,01	123,70	88,34	46,38	58,69	48,63	84,05
Cc1	CBoT Corn Composite Commodity Future	439,04	121,19		818,25	445,37	364,51	364,28	404,94	653,24
GCc1	COMEX Gold Composite Commodity Future Continuation 1	1431,65	258,81	1050,80	2051,50	1275,75			1663,46	1820,55
LCc1	CME Live Cattle Electronic Commodity Future Continuation 1	126,09	17,35	84,80	171,00	144,01	126,60		109,08	139,96
NGc1	NYMEX Henry Hub Natural Gas Electronic Energy Future Continuation 1	3,41	1,42	1,55	9,68	3,84	2,64	3,01	2,31	5,11
OJc1	ICE-US FCOJ-A Futures Electronic Commodity Future Continuation 1	140,46	27,49	91,25	232,85	140,98	155,36	142,79	109,39	171,25
PAc1	NYMEX Palladium Electronic Commodity Future Continuation 1	1309,27	681,94	469,90	2979,90	773,89	650,81	1051,34	2029,60	2083,85
PLc1	NYMEX Platinum Electronic Commodity Future Continuation 1	1036,86	200,31	595,90	1543,60	1369,81	988,77	891,75	931,57	997,70
Slc1	COMEX Silver Composite Commodity Future	18,88	3,67	11,74	29,40	19,42	16,55	15,98	20,20	22,96
Wc1	CBoT Wheat Composite Commodity Future Continuation 1	573,94	151,27	361,00	1425,25	601,72	457,32	473,52	550,26	811,49
SOYc1	Johannesburg Stock Exchange Soybean Commodity Future Continuation 1	6233,50	1557,62	4145,00	11113,00	5468,11	6049,08	4638,26	6871,59	8643,40
HGc1	COMEX Copper Composite Commodity Future Continuation 1	3,05	0,67	1,94	4,93	3,09	2,34	2,90	2,95	4,14
SFSc1	ICE-US Sugar No. 16 Futures Electronic Commodity Future Continuation 1	27,49	4,39	18,48	38,62	22,89	27,05	26,04	27,21	36,05
LCCc1	ICE Europe London Cocoa Commodity Future Continuation 1	1821,37	233,42	1326,00	2577,00	1835,32	2097,31	1615,22	1793,24	1812,44
LCOc1	ICE Europe Brent Crude Electronic Energy Future	69,67	23,38	19,33	127.98	95,31	49,01	64.95	53,08	88,16
RBc1	NYMEX RBOB Gasoline Electronic Energy Future Continuation 1	1,97	0,64	0,41	4.28	2,53	1,51	1,79	1,48	2.65
HOc1	NYMEX NY Harbor ULSD Electronic Energy Future Continuation 1	2,10	0,75	0,61	5,14	2,69	1,48	1,94	1,56	2,98
SAFc1	SHFE Aluminium Commodity Future Continuation 1	14829.72	2723.04	9825.00	24330.00	13747,36	12386.82	14394.23	14518,16	19745.88
SZNc1	SHFE Zinc Commodity Future Continuation 1	19680,96	3990,79	12275.00	28690.00	15539,48	16914,90	23457,48	19054,90	23979,61
CUUc1	NYMEX Chicago Ethanol (Platts) Electronic Energy Future Continuation 1	1,76	0,49	0,83	3,45	2,10	1,52	1,39	1,42	2,47
	# of data points		22	82		472	471	475	472	467
			Scale Std.	LOWEST	HIGHEST	Scale Rows	LOWEST	HIGHEST		

Figure 2: Descriptive Statistics of Subsamples

Following the analysis, the data was exported to Excel and consolidated, as depicted in Table 2 above.

This table provides information on the number of observations, mean, standard deviation, minimum, and maximum price for each asset throughout the entire period. Additionally, it presents the average market price of each asset during different time periods. The standard deviations of each asset within the entire sample were visualized using a colour scale, ranging from green (indicating the lowest standard deviation) to red (representing the highest standard deviation). Additionally, the means of each asset in every subsample were also color-coded, with lighter shades denoting lower prices and darker shades indicating higher prices.

It becomes evident that the commodities Soybean, Aluminium and Zinc show the highest standard deviation in the full sample. This might result from lower volumes in this asset classes. Furthermore, once can notice that the prices in the last subsample are almost without exception the highest. From May 2015 till May 2019 the prices were usually the lowest. This downward pressure on commodity prices might be connected to several factors such as oversupply, reduced demand from emerging economies, and a stronger US Dollar.

4.3.2 Stationarity

Variables of economic time series are often non-stationary, they follow a trend and have cycles. A method to make variables of time series stationary is a first difference change.

We analyzed whether the time series are stationary or not. In a first step, we plotted the cleaned data (see appendix 2). At first glance, it seems that the time series have a unit root. Afterwards, we performed the Augmented Dickey-Fuller (ADF) test with a null and alternative hypothesis to test if the time series are stationary:

 H_0 : Nonstationary time series

 H_1 : Stationary time series

The null hypothesis can be rejected if the p-value is less than α . We use a 95% confidence interval, which means that the alpha is 5%. We tested stationary of commodity futures on both level and first differences, using up to 2 lags.

The ADF tests computed with one and two lags at price level show in both cases high p-values over 20% (see appendix 4). The null hypothesis can't be rejected. Therefore, it can be assumed that the time series have a unit root at price level.

The ADF test computed with one and two lags at first differences (absolute returns) show in both cases p-values of 0% (see appendix 4) The null hypothesis can be rejected. It can be assumed that the time series at first differences are stationary.

4.3.3 Normality Test

Normality tests check if a dataset follows a normal distribution and calculate the probability of the underlying random variable being normally distributed.

To tests if the data is normal distributed we are using to different types of normality test:

- Visual method Box Plots
- Visual method Histogram
- Statistical method Shapiro-Wilk test

4.3.3.1 Box Plots

The shape of a box plot can indicate whether a statistical dataset is normally distributed or skewed. If the median is positioned in the middle of the box and the whiskers are approximately equal on both sides of the box, it indicates a symmetric distribution.

In the table below 6 examples are shown, the others can be seen in the appendix 5. In most cases a non-symmetrical distribution can be recognized. In the case of LCc1, for example, one would have to look more closely. For this reason, another visual method will be used in the next chapter.

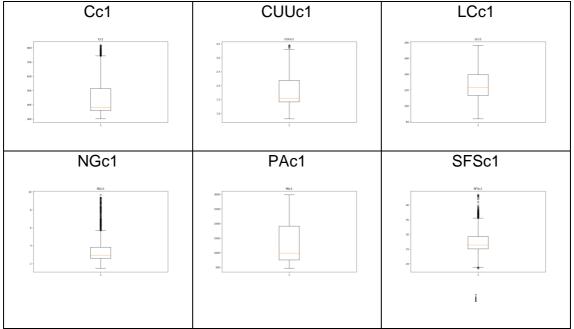


Figure 3: Box Plots

4.3.3.2 Histogram

The histogram is used to represent frequency distributions for statistical data. In a normal distribution, the distribution is Bell-shaped.

We again created a histogram for all assets and manually checked for a normal distribution. All histograms have been archived in the appendix 6. As in the previous chapter, most of the time series can be classified as not normally distributed. This time one can also guess at LCCc1 that it is not normally distributed. But to be sure, we apply a statistical method for the control.

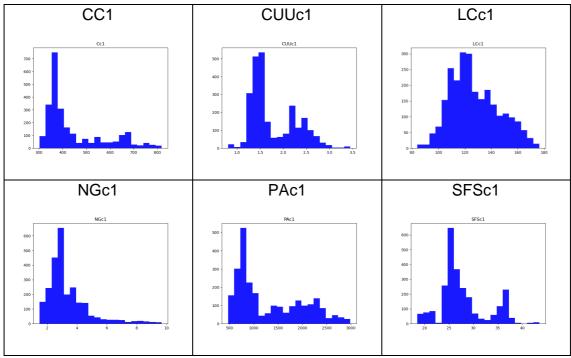


Figure 4: Histogram

4.3.3.3 Shapiro-Wilk Test

The Shapiro-Wilk test is a statistical Method for checking if Data is normal distributed. This is being done by testing the zero hypothesis that data is normally distributed.

For the Shapiro-Wilk test, we formulate following two hypotheses:

 H_0 : The sample comes from a normal distribution

 H_1 : The sample is not coming from a normal distribution

To test the hypothesis, we use a 95% confidence interval, which means that the alpha is 5%.

The Shapiro-Wilk test confirms our finding from the Box Plots and the Histograms as all p-values are smaller than 5%. Therefore, the zero hypothesis can be rejected, meaning that data is not normal distributed.

This was to be expected since stock market prices are usually not normally distributed. Performance figures are excluded from this statement.

4.4 Database Setup

As a database allows simple handling and a clear structuring of the data, the clean data is loaded into a database in SQLite. We established a connection between Python and SQLite and created a table named ASSET_PRICES using a timestamp as the primary key and the different asset classes as columns with data type FLOAT. Afterwards we imported the data exported by Refinitiv via Excel into the SQL database.

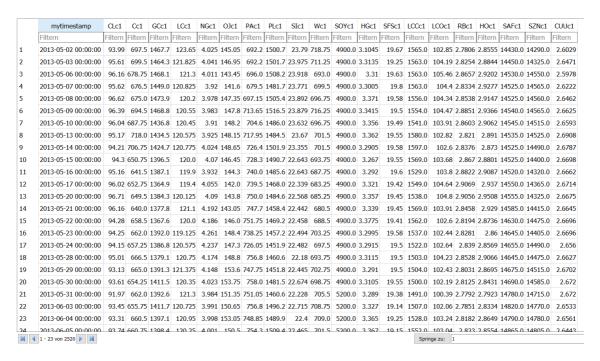


Figure 5: SQLite database

After the analysis, we uploaded the results of the cointegration and causality tests into new tables – RESULTS_COINTEGRATION_1, RESULTS_COINTEGRATION_2 and RESULTS_CAUSALITY – in the same database (see appendix 9)

5 Analysis of Cointegration & Causality

5.1 Cointegration

The commodity futures at price level could be classified as nonstationary using

the ADF test. To find out whether two commodity futures time series share a

common long-run trend, have a long-run equilibrium and do not drift away from

each other, they were tested for cointegration with a confidence interval of 95%

and an alpha level of 5%:

 H_0 : No Cointegration

 H_1 : Cointegration

The test for cointegration was performed with one and two lags. The matrix with

the calculated P-values as well as the visualizations can be found in appendix 7.

The commodity future pairs with a P-value of less than 5% are highlighted in

green. Using a lag of 1, 63 of the 380 null hypotheses could be rejected.

Therefore, with an alpha level of 5%, 63 commodity future pairs can be assumed

to be cointegrated. The test with a lag of 2 showed similar results and 62

commodity future pairs could be assumed to be cointegrated.

5.2 Causality

As already mentioned in chapter 5.1 Cointegration, the data are not stationary.

For this reason, the time series must be differenced. Thereafter, we check again

with the ADF test whether the data are stationary.

For the Granger Causality Test, we compare all variables with each other. For

this we use a confidence interval of 95% and an alpha level of 5%. The hypothesis

for the Granger Causality Test is as follows:

 H_0 : No Granger Causality

 H_1 : Granger Causality

The matrix with all the P-values can be seen in the appendix 8. Of all these, 104

cases with a P-value of less than 5% are marked in red in the table. This means,

that the hypothesis for these cases can be rejected as there is a Granger

Causality relation in place for them.

12

6 Conclusion

Like many financial time series, the twenty commodity futures analyzed follow stochastic trends, have cycles and are therefore non-stationary.

If non-stationary time series are used for the analysis of regression models, there is a risk of spurious regressions. With the first difference, the twenty time series analyzed became stationary and the risk of spurious regressions could be minimized. A disadvantage of the analysis of the first difference is that information about long-term dependencies gets lost.

The cointegration test was used to examine whether the individual pairs of the non-stationary commodity futures time series at the price level show a common long-term trend and do not move away from each other. Out of the 380 regressions analyzed with a lag of 1, 63 pairs were cointegrated. The result with a lag of 2 remained almost identical with 62 cointegrated pairs.

The Granger Causality Test indicated which variables can be used to predict future changes in other variables. Since the data for the Granger Causality Test should always be stationary, market prices must always be differentiated first. In the end, out of a total of 400 combinations, only 104 combinations showed a Granger Causality. Only the commodities PAc1 and PLc1 are not useful for predictions in any combination. All others can be used for at least one other commodity.

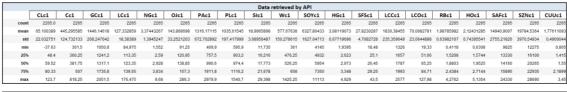
7 Bibliography

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8 Appendix

8.1 Appendix 1

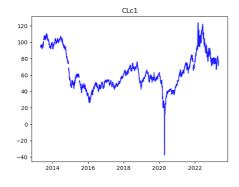
Comparison of data sets

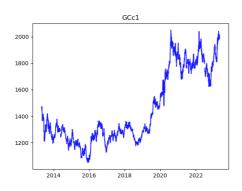


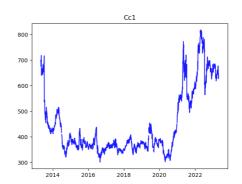
	Data retrieved by Formula Builder																			
	CLc1	Cc1	GCc1	LCc1	NGc1	OJc1	PAc1	PLc1	Slc1	Wc1	SOYc1	HGc1	SFSc1	LCCc1	LCOc1	RBc1	HOc1	SAFc1	SZNc1	CUUc1
count	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265
mean	65,1003885	445,295585	1446,14618	127,332859	3,37443267	143,868698	1316,17115	1035,61545	18,9965898	577,67638	6327,80433	3,08119073	27,8230287	1830,38455	70,0082781	1,98785982	2,12431285	14940,9007	19784,5364	1,77611093
std	22,0327512	124,732133	268,247042	18,38389	1,3945247	33,2521203	672,702892	197,417999	3,68956487	150,278615	1627,04713	0,67719696	4,7082728	235,359649	23,0644888	0,63982107	0,74395541	2755,21826	3970,54934	0,4900044
min	-37,63	301,5	1050,8	84,975	1,552	91,25	469,9	595,9	11,735	361	4145	1,9395	18,48	1326	19,33	0,4118	0,6308	9825	12275	0,805
25%	48,4	360,25	1241,2	113,35	2,59	120,95	757,5	903,2	16,216	476,25	4932	2,623	25,1	1657	51,66	1,5208	1,5744	13330	16100	1,415
50%	59,52	381,75	1317,1	123,35	2,928	138,85	990,6	974,4	17,773	526,25	5954	2,973	26,45	1787	65,25	1,8803	1,9525	14160	20265	1,55
75%	80,33	507	1735,8	139,55	3,834	157,3	1911,8	1116,2	21,678	658	7350	3,348	29,25	1993	84,71	2,4384	2,7144	15895	22935	2,1899
max	123,7	818,25	2051,5	176,475	9,68	286,3	2979,9	1540,7	29,398	1425,25	11113	4,929	43,5	2577	127,98	4,2762	5,1354	24330	28690	3,45

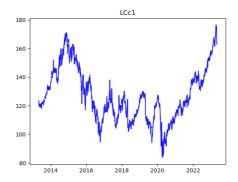
8.2 Appendix 2

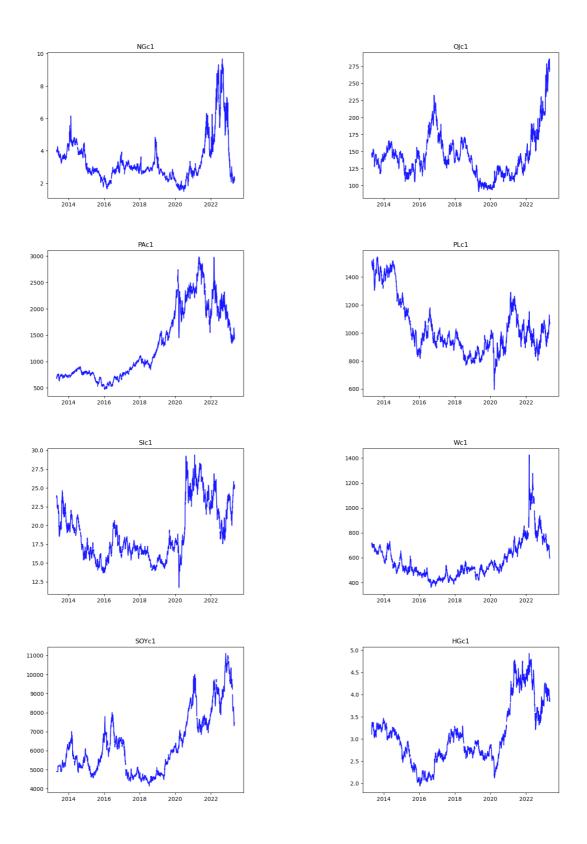
Plots original data

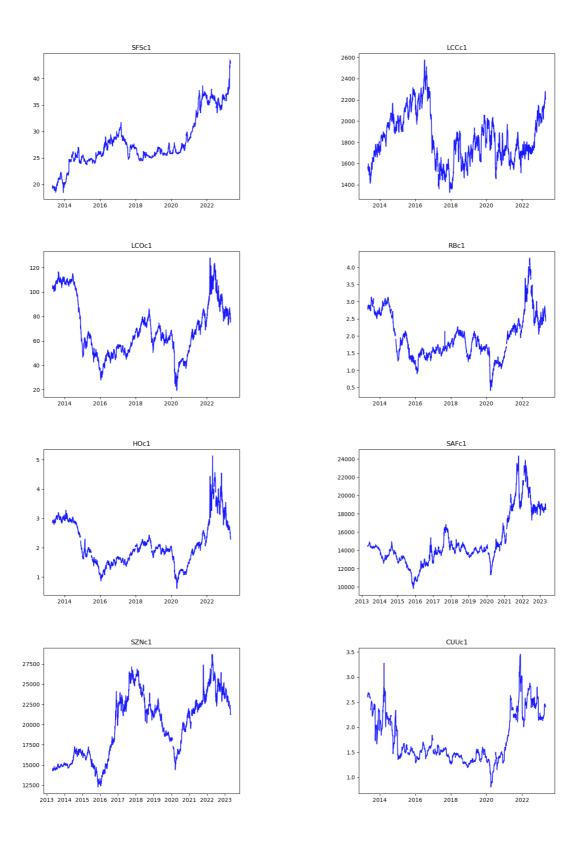






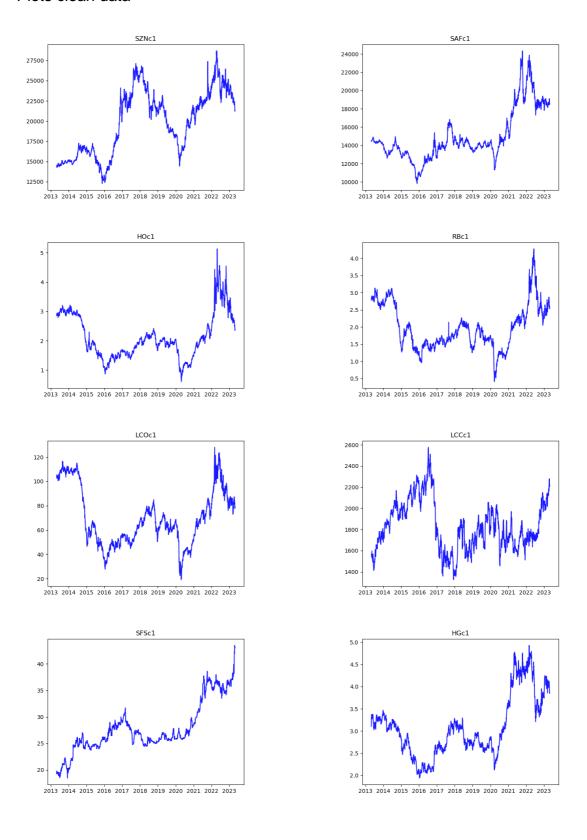


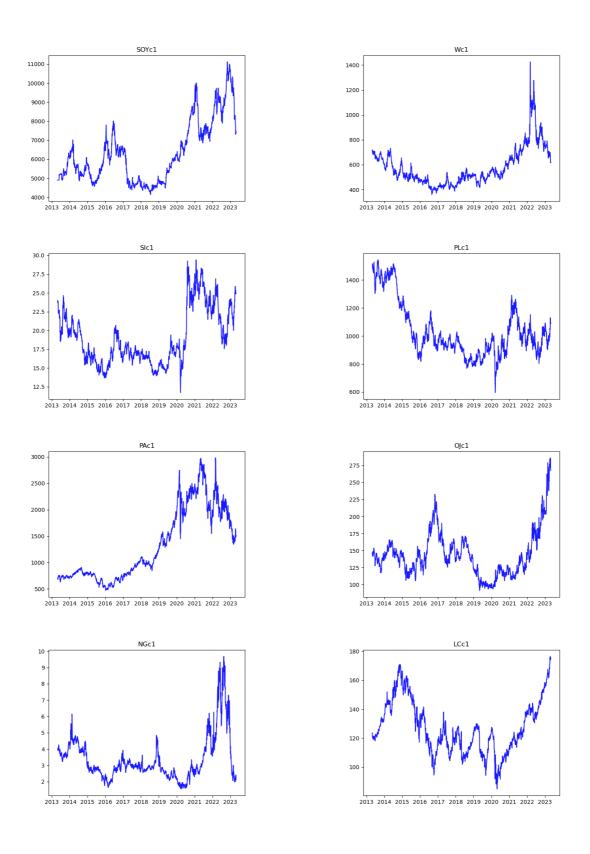




8.3 Appendix 3

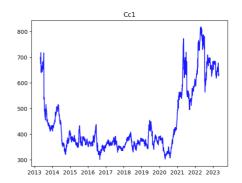
Plots clean data













8.4 Appendix 4

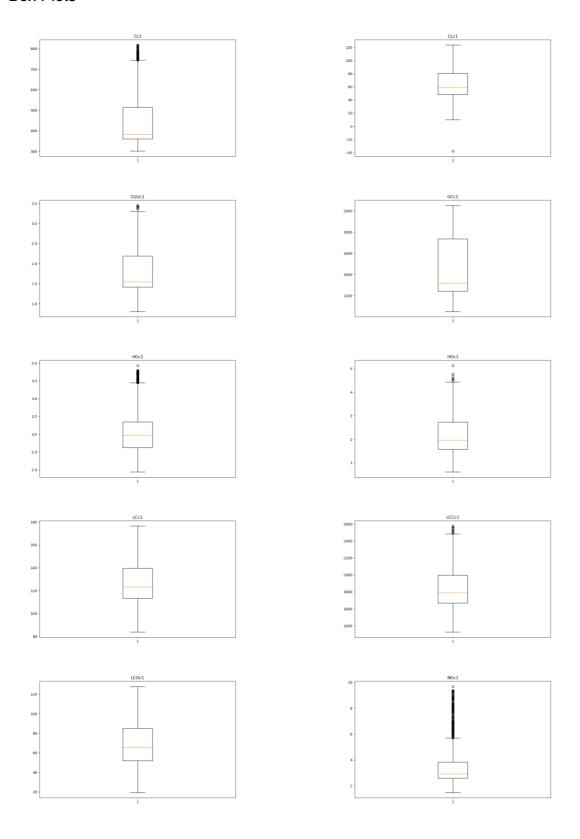
ADF-Test Prices (Level)

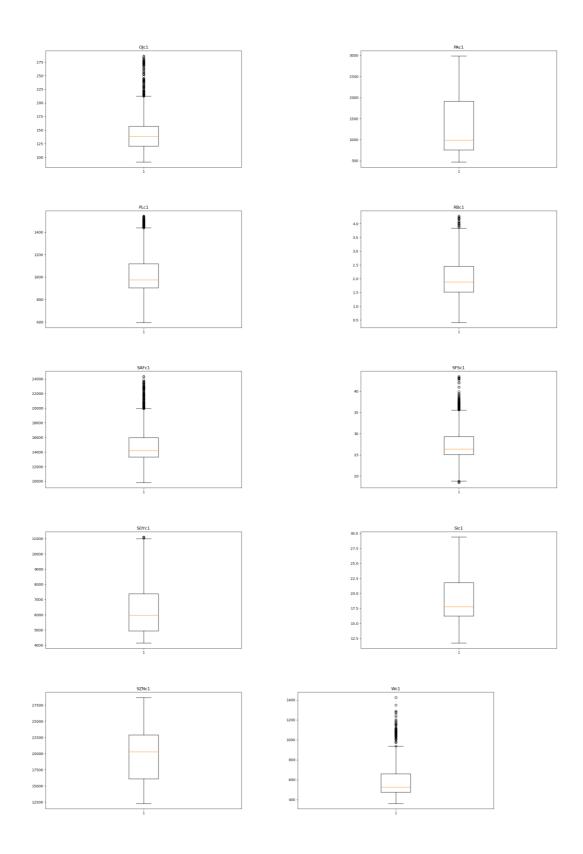
ADF-Test Absolute Returns

```
Number of lags used: 1
                                                 Number of lags used: 1
ADF P-Val for Prices (Level)
                                                 ADF P-Val for Absolute Returns (1st Difference)
CLc1: 0.34
                                                 CLc1 : 0.00
Cc1: 0.42
                                                 Cc1: 0.00
GCc1 : 0.86
                                                 GCc1 : 0.00
LCc1: 0.83
                                                 LCc1 : 0.00
NGc1: 0.21
                                                 NGc1: 0.00
OJc1: 0.79
                                                 0Jc1: 0.00
PAc1: 0.52
                                                 PAc1 : 0.00
PLc1: 0.28
                                                 PLc1: 0.00
SIc1: 0.55
Wc1: 0.39
                                                 SIc1 : 0.00
                                                 Wc1: 0.00
S0Yc1: 0.70
                                                 S0Yc1: 0.00
                                                 HGc1: 0.00
SFSc1: 0.00
HGc1 : 0.67
SFSc1: 0.99
LCCc1: 0.71
                                                 LCCc1 : 0.00
LCOc1: 0.32
                                                 LCOc1: 0.00
RBc1 : 0.40
                                                 RBc1 : 0.00
H0c1: 0.33
                                                 H0c1: 0.00
SAFc1: 0.73
                                                 SAFc1 : 0.00
                                                 SZNc1 : 0.00
CUUc1 : 0.00
SZNc1: 0.73
CUUc1: 0.38
Number of lags used: 2
                                                 Number of lags used: 2
ADF P-Val for Prices (Level)
                                                 ADF P-Val for Absolute Returns (1st Difference)
CLc1: 0.34
                                                 CLc1: 0.00
Cc1: 0.45
                                                 Cc1: 0.00
GCc1: 0.86
                                                 GCc1: 0.00
LCc1: 0.84
                                                 LCc1 : 0.00
NGc1: 0.23
                                                 NGc1: 0.00
OJc1 : 0.81
PAc1 : 0.53
                                                 OJc1 : 0.00
                                                 PAc1: 0.00
PLc1: 0.28
                                                 PLc1: 0.00
SIc1: 0.55
                                                 SIc1 : 0.00
                                                 Wc1 : 0.00
S0Yc1 : 0.00
Wc1: 0.39
S0Yc1: 0.69
HGc1: 0.67
                                                 HGc1 : 0.00
SFSc1: 0.99
                                                 SFSc1 : 0.00
LCCc1: 0.71
                                                 LCCc1 : 0.00
LCOc1: 0.31
                                                 LCOc1 : 0.00
RBc1: 0.39
                                                 RBc1: 0.00
H0c1: 0.33
                                                 H0c1: 0.00
SAFc1: 0.75
                                                 SAFc1: 0.00
                                                 SZNc1 : 0.00
SZNc1: 0.75
CUUc1: 0.40
                                                 CUUc1 : 0.00
```

8.5 Appendix 5

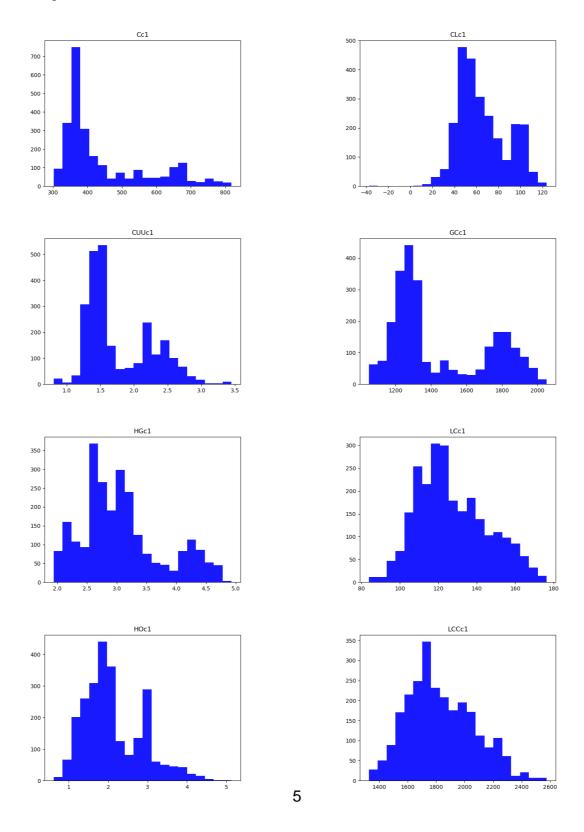
Box Plots

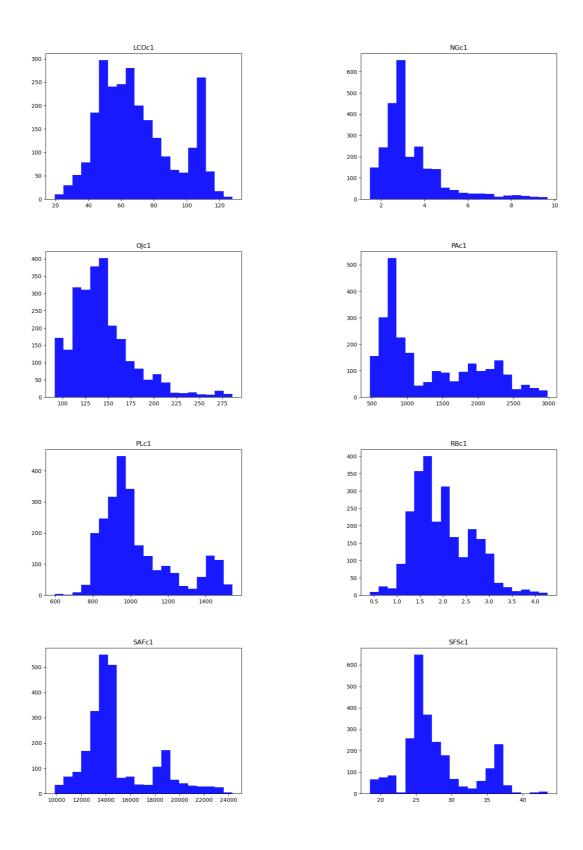


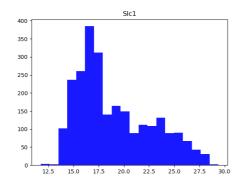


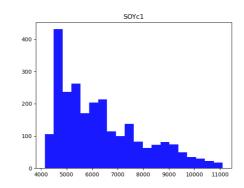
8.6 Appendix 6

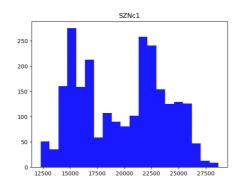
Histograms

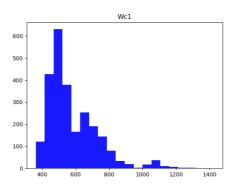










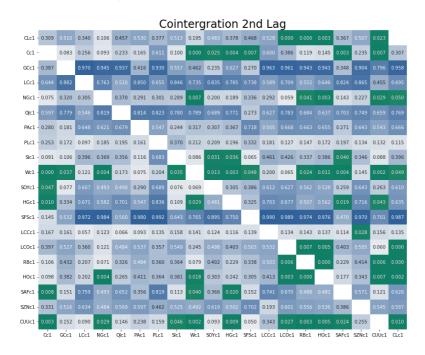


8.7 Appendix 7

Cointegration

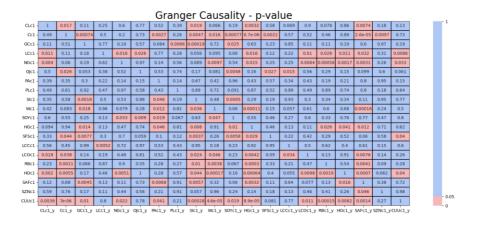
total number of regressions conducted: 760 total number of identified cointegrations using only ECM Library: 125

Cointergration 1st Lag CLc1 - 0.309 0.510 0.340 0.069 0.457 0.530 0.377 0.513 0.195 0.483 0.332 0.468 0.52 0930 0.557 0.542 0.276 0.627 0.270 0.600 0.386 0.655 0.846 0.735 0.835 0.735 0.083 0.256 0.093 0.233 0.165 0.611 0.007 0.132 0.110 0.224 0.212 0.814 0.823 0.780 0.789 0.689 0.771 0.273 0.547 0.208 0.272 0.307 0.367 0.370 0.212 0.209 0.196 0.332 0.181 0.127 0.147 0.172 0.197 0.134 0.132 0.115 Sic1 - 0.091 0.106 0.396 0.369 0.356 0.116 0.120 0.006 0.244 0.086 0.289 0.067 0.169 0.269 0.107 0.101 0.631 0.493 0.520 0.326 0.715 0.076 0.097 0.334 0.671 0.493 0.701 0.547 0.836 0.109 0.048 0.325 - 0.167 0.161 0.057 0.123 0.066 0.093 0.135 0.158 0.141 0.124 0.116 0.139 LCOc1 - 0.397 0.527 0.360 0.082 0.484 0.537 0.357 0.549 0.245 0.498 0.317 0.503 RBc1 - 0.106 0.432 0.207 HOc1 - 0.052 0.344 0.202 0.001 0.229 0.366 0.315 0.342 0.018 0.274 0.153 0.269 0.364 0.177 0.314 0.008 0.151 0.705 0.405 0.593 0.356 0.768 0.113 0.040 0.314 0.009 0.108 0.68 0.471 0.089 0.6 0.153 0.001 0.114 0.082 0.011 0.103 0.183 0.159 0.046 0.002 0.068 0.009 0.033 Cc1 GCc1 LCc1 NGc1 Ojc1 PAc1 PLc1 Sic1 Wc1 SOYc1 HGc1 SFSc1 LCCc1 LCOc1 RBc1 HOc1 SAFc1 SZNc1 CUUc1 CLc1



8.8 Appendix 8

Granger Causality



8.9 Appendix 9

Table RESULTS_COINTEGRATION_1

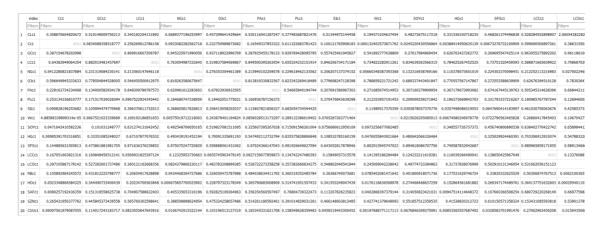


Table RESULTS_COINTEGRATION_2

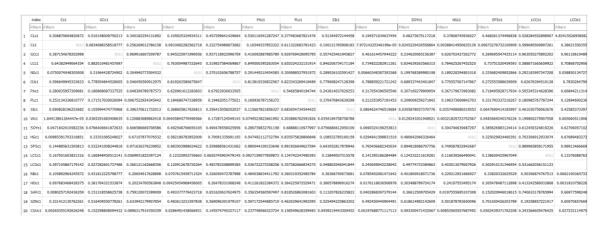


Table RESULTS CAUSALITY

