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Exploring the Determinants of Agricultural Commodity Returns

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Abstract

This paper investigates the Granger causal relations between agricultural commodity returns and several potential determinants using a multivariate Vector Error Correction Model (VECM) and Impulse Response Functions (IRF). Agricultural commodities are critical for global food supply, and understanding their determinants is crucial for policymakers and investors. Results show that biofuel and fertilizer returns have a short-run predictive power over future agricultural commodity returns. We contribute to the existing body of literature by examining a comprehensive array of determinants. Our findings could help inform decision-makers in the agricultural sector and improve the investment processes for agricultural commodity investors.

Keywords: Agricultural commodities; Energy commodities; Granger causality; Vector Error Correction Model; VECM; Impulse Response Functions; IRF

JEL classification: C32; C53; G17; Q17

Introduction

In this paper, we explored the Granger causal relationships of agricultural commodity returns, focusing on the impact of the stock market, energy commodities, and macroeconomic variables. We conducted a multivariate Vector Error Correction Model (VECM) and Impulse Response Functions (IRF) to address the short-run and long-run deterministic effects on agricultural commodity returns. Since agricultural commodities are critical for global food supply, understanding their determinants is crucial for policymakers and investors (Nazlioglu and Soytas 2012). Therefore, the findings of our study could help inform decision-makers in the agricultural sector and potentially improve the investment processes for agricultural commodity investors.

The background of this study lies in the increased demand for commodity investments by financial institutions since the early 2000s due to the increased availability of index-tracking products. The indexation of commodities has facilitated financial speculation in commodity markets, leading to an increased correlation between asset classes (Tang and Xiong 2012; Cheng and Xiong 2014; Basak and Pavlova 2016). Furthermore, since commodity indices are composed partly of agricultural commodities, the development has concerned policymakers and investors since farmers and households depend on stable food prices (Bruno *et al.* 2017).

Therefore, the linkage between financial markets does not only apply to the broad commodity markets but also to agricultural commodity markets (Tadesse *et al.* 2014). Similar studies have extended the array of potential determinants to investigate the effects of variables such as the U.S. dollar, natural gas, biofuel, inflation, fertilizers, and crude oil (Nazlioglu and Soytas 2012; Nicola *et al.* 2016; Gnutzmann and Spiewanowski 2016; Baffes 2007; Elser *et al.* 2014; Taghizadeh-Hesary *et al.* 2019). However, as we will argue in this paper, the determinants of agricultural commodities might not be as many as the previous authors suggest.

This paper originates in the financial literature dating back to Granger (1969), who highlighted the problems of using contemporaneous values since causal effects are seldom instantaneous. Instead, such intertemporal dependencies could be better examined using the lagged values of one variable to predict the future value of another. On the contrary, the efficient market hypothesis states that lagged values should not have the power to predict future values since market participants should already have exploited market anomalies, and the effect of past values on future values would be diluted due to market efficiency (Fama 1970).

Contributing to this debate, a method for testing Granger causality was introduced by Sims (1980). The model is known as the Vector Autoregressive (VAR) model, which became a popular model for testing Granger causality. However, an issue of the VAR was that it solely measured the short-run causality and did not account for the long-run causal effects, which is the case when the endogenous variables are cointegrated. An augmented version of the VAR, the VECM, proposed a solution. The concept underlying the VECM is similar to the VAR, except that it incorporates the Error Correction Term (ECT) and first differences for all variables within the model. The addition of the ECT allows for interpreting the long-run relationships (Engle and Granger 1987).

While the model gained an additional feature, the increased complexity of the VECM made it challenging to establish and interpret the estimated short-run coefficients. The VECM could therefore be complemented with an IRF, which provides interpretability in the direction and persistence of the short-run effects from the determinants (Koop *et al.* 1996; Pesaran and Shin 1998).

Researchers within the agricultural commodity markets have adopted these models. Serra *et al.* (2011), Allen *et al.* (2018), Olagunju *et al.* (2021), Akram (2009) and Elser *et al.* (2014) showed that crude oil, biofuel, and natural gas are important in explaining agricultural commodity returns through their use in transportation costs, fertilizers, and other production inputs. Nazlioglu and Soytas (2012) further strengthened the findings that crude oil prices are important in explaining agricultural commodity prices.

Furthermore, Nazlioglu and Soytas (2012) and Adämmer and Bohl (2015) also found that the strength of the U.S. dollar can predict future agricultural commodity prices. The authors explained that the deterministic effect existed because most global commodity trades are conducted in U.S. dollars. Finally, the deterministic effects between equity and agricultural commodity markets were analyzed by Bruno *et al.* (2017). They found a deterministic effect from equity returns to agricultural commodity returns and that shocks in equity returns have enduring impacts on agricultural commodity returns.

To extend the current body of empirical research, we investigated the determinants of agricultural commodity returns using a VECM and IRFs. These models enabled us to analyze the short-term and long-term deterministic effects of multiple variables and the direction and persistence of these effects. To test the statistical significance of the VECM coefficients, a Wald test was conducted (Nazlioglu and Soytas 2012; Akram 2009; Taghizadeh-Hesary *et al.* 2019; Kapusuzoglu and Karacaer Ulusoy 2015). Inspired by Batten *et al.* (2017), the dataset was split into an in-sample dataset ranging from 2009 to 2021 and an out-of-sample dataset ranging from 2021 to 2023, where the latter was used to test the replicability of the reported results.

The results from our short-run causality analysis showed that biofuel returns had a deterministic short-run effect on future agricultural commodity returns. We also found that agricultural commodity returns had a deterministic short-run effect on future biofuel returns. Thus, the Granger causal effect between biofuel and agricultural commodities was bidirectional. Furthermore, we found a unidirectional short-run effect from fertilizer returns to agricultural commodity returns. The bidirectional and unidirectional effects were further examined, and we found that the effects were positive, had a minimal delay, and permanently impacted each other. On the other hand, the long-run causality analysis showed no statistically significant evidence, meaning that we could not conclude any long-run effects. Finally, the post-estimation tests showed mixed results.

This paper's primary contribution is its comprehensive approach to examining the determinants of agricultural commodity returns. Unlike previous researchers who studied a limited number of determinants, we compiled a more diverse range to provide a holistic outlook. The results can help policymakers to direct regulatory focus to mitigate price changes in agricultural commodities and assist investors in the agricultural sector in understanding the determinants and predictability of returns.

The rest of the paper is structured as follows. Section I. describes the model on which our study is based, while Section II. presents the specific method employed for our dataset. Section III. describe the dataset and data-collecting process, as well as the execution of the pre-estimation tests. Section IV. presents the estimation outputs, post-estimation outputs, and the interpretation of results. Finally, Section V. concludes the findings with relevant policy implications and suggestions for future research.

I. The Model

Inspired by the work of Nazlioglu and Soytas (2012), Zhang *et al.* (2010) and Olagunju *et al.* (2021), we employed a VECM rather than a VAR to examine our variables' short-run and long-run relationships. The decision was based on the Johansen cointegration test presented in Table II, which found evidence of cointegration among our variables. The VECM specifies which variables could predict future agricultural commodity returns and whether agricultural commodity returns could predict future returns of those variables. Our study was based on the following specification for the VECM:

$$\Delta \mathbf{Y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{p-1} \boldsymbol{\phi}_j \Delta \mathbf{Y}_{t-j} + \boldsymbol{\lambda} \mathrm{ECT}_{t-1} + \boldsymbol{\varepsilon}_t \tag{1}$$

Where $\Delta \mathbf{Y}_t$ is a vector containing the contemporaneous first differenced variables. $\boldsymbol{\alpha}$ is a vector with intercept parameters. $\boldsymbol{\phi}_j$ is a square matrix with the estimated coefficients for assessing short-run Granger causality. p is the optimal lag length and was determined through the lowest value of Akaike's information criterion (AIC) (Akaike 1974), the Hannan-Quinn information criterion (HQIC) (Hannan and Quinn 1979) and the Schwarz's Bayesian information criterion (SBIC) (Schwarz 1978).

The Error Correction Term (ECT_{t-1}) is a scalar derived from the residuals of a regression, as can be seen in Appendix Equation (A3). By estimating the $\boldsymbol{\lambda}$ coefficient of the ECT, we can determine how deviations from past equilibriums can explain future equilibriums. The $\boldsymbol{\lambda}$ coefficient is the speed of adjustment to long-run equilibrium. It measures how many percent of disequilibrium has been corrected until the following observation, meaning we could assess the long-run causality. Mathematical details regarding the ECT and the VAR augmentation process on which the VECM originates are found in Appendix A. The error term is the $\boldsymbol{\varepsilon}_t$.

We employed a Wald test to address the limited interpretability of the estimated short-run coefficients, which was similar to Nazlioglu and Soytas (2012). The Wald test was conducted to test whether the estimated coefficients are statistically different from zero and whether the variables impact agricultural commodity returns. The results provided evidence of unidirectional Granger causality between agricultural commodities and some of the tested variables. Therefore, those variables were further examined by imposing a Wald test in the opposite direction to test for evidence of bidirectional Granger causality.

Similar to Akram (2009), Taghizadeh-Hesary *et al.* (2019), Bruno *et al.* (2017) and Allen *et al.* (2018), we used IRFs as a complement to the VECM. The IRFs enabled us to further examine the direction and persistence of the significant Granger causal relationships found by the VECM. The IRFs were computed by imposing a one-time shock of a standard deviation of returns to the impulse variable while holding all other variables constant. Whether the standard deviation shock is daily, weekly, monthly, or annualized depends on the frequency of the data. To determine the direction and persistence of the effect, a graphical illustration was used to show the impact of the shock on the responding variable. The IRFs should include a time period long enough to capture the shock's full response.

II. Methodology

A. Vector Error Correction Model

Following Nazlioglu and Soytas (2012) and Olagunju *et al.* (2021), we converted all variables in our dataset through the natural logarithm to reduce the variation and heteroscedasticity. The lag length selection criteria illustrated an optimal lag length of two, as shown in Appendix Table B.II. Equipped with the knowledge that the optimal lag was two and the number of variables was nine; the VECM used for our study was specified as follows:

$$\Delta \mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\phi} \Delta \mathbf{Y}_{t-1} + \boldsymbol{\lambda} \mathrm{ECT}_{t-1} + \boldsymbol{\varepsilon}_t \tag{2}$$

In our study, $\Delta \mathbf{Y}_t$ refers to a $9x1$ vector that includes the contemporaneous logarithmic first differences of all the variables. This is equivalent to the continuously compounded returns. As a result, the findings were interpreted as returns. $\boldsymbol{\alpha}$ is a $9x1$ vector with intercept parameters. $\boldsymbol{\phi}_j$ is a $9x9$ matrix with the estimated coefficients used to assess the short-run Granger causality with the Wald test. $\Delta \mathbf{Y}_{t-1}$ is a $9x1$ vector consisting of the lagged logarithmic returns. The $\boldsymbol{\lambda}$ is a $9x1$ vector used to assess the long-run causality, and the $\boldsymbol{\varepsilon}_t$ is a $9x1$ vector containing the error terms (Engle and Granger 1987).

B. Impulse Response Functions

We employed IRFs on the significant Granger causal variables identified through the VECM estimation. The unidirectional IRFs were conducted to examine how agricultural commodity returns respond to a shock in the Granger causal variables. For bidirectional IRFs, we imposed a shock in agricultural commodity returns and observed the impact on the responding Granger causal variables. By observing the response through a sufficient number of months, we could conclude whether or not the effect is permanent or transitory (Koop *et al.* 1996; Pesaran and Shin 1998). The one-time shock was based on monthly observations due to the frequency of the data. Therefore, we have chosen a 10-month observation period to capture the full effect of the shocks.

The shocks were analyzed visually through graphs. Firstly, a shock was applied to each variable that Granger causes agricultural commodity returns. Secondly, bidirectional Granger causality was observed by applying a shock to agricultural commodity returns and observing the response in the variables that are Granger caused by agricultural commodity returns.

C. Pre-estimation tests

The VECM assumes stationarity, no residual autocorrelation, and normally distributed residuals (Brüggemann *et al.* 2006). We employed a unit root test to ensure compliance with the stationarity assumption. Further, we tested for residual autocorrelation and residual normality in the post-estimation section.

C.1 Johansen cointegration test

To determine if VECM was a suitable method for our dataset, we used the Johansen cointegration test to determine the existence of cointegration and the number of cointegrating relationships among our variables. To test the null hypothesis of no cointegration against the alternative hypothesis of cointegration, we used the trace statistics and maximum eigenvalue tests proposed by Johansen (1988) and Johansen (1991). The results of the Johansen cointegration test presented in Table II were used to decide between the VECM and the VAR correctly. The results were also used to correctly specify the VECM in Equation (2), where each cointegrating relationship should have one error correction term. The Johansen cointegration test was specified using the same optimal lag length used for the VECM estimation; see Appendix Table B.II.

C.2 Augmented Dickey-Fuller unit root test

To test if the stationarity assumption of our VECM was fulfilled and if spurious results were avoided, each variable was tested for the existence of unit roots. For this, we used the test introduced by Dickey and Fuller (1979), known as the Augmented Dickey-Fuller (ADF) test. For our study, the ADF was specified as follows:

$$\Delta Y_{i,t} = \alpha_i + \beta_i Y_{i,t-1} + \sum_{j=1}^{m} \gamma_j \Delta Y_{i,t-j} + \delta_i t + \varepsilon_{i,t} \tag{3}$$

Where i is each of our nine variables in logarithmic form. δ_i is the deterministic trend included if statistically significant at the 5% level. Including the deterministic trend affects which critical value was used to compare against our test statistic. m is the maximum lag length estimated for each i separately. The null hypothesis of the ADF was that β_i was equal to zero, and the alternative hypothesis was that β_i was not zero. Rejection at the 5% significance level as seen in Table III indicates that the time series contained no unit roots and were thus a stationary process that fulfilled the VECM stationarity assumption.

D. Post-estimation tests

D.1 Lagrange-multiplier & Jarque-Bera test

The reliability of our VECM results was assessed by testing if the assumptions of no residual autocorrelation and normally distributed residuals were fulfilled. We tested for residual autocorrelation with Lagrange-multiplier (LM) test as suggested by Brüggemann *et al.* (2006) and for residual normality with the Jarque-Bera test (Jarque and Bera 1987).

D.2 Out-of-sample VECM

Inspired by Batten *et al.* (2017), a 23-month out-of-sample VECM estimation was employed to assess the ability to replicate the in-sample results. For this purpose, the dataset was separated such that the in-sample period ranges between January 2009 and January 2021 and the out-of-sample ranges between February 2021 and January 2023. Although there is no exact way to determine the reliability of the post-estimation techniques mentioned above, these techniques could assist readers in drawing their conclusions about the reliability of our results.

III. Data, Cointegration & Stationarity tests

A. Data

The dataset used for this study consisted of agricultural commodities, the stock market, crude oil, the bond market, the U.S. dollar, biofuel, natural gas, fertilizers, and the consumer price index. All variables were denoted in U.S. dollars with a monthly frequency from January 2009 to January 2023, resulting in 169 observations. We separated the dataset to conduct the out-of-sample estimation described in Subsection D.2. The full-sample period ranged between January 2009 and January 2021, and the out-of-sample ranged between February 2021 and January 2023.

In line with Bruno *et al.* (2017), we used the Standard and Poor Goldman Sachs Commodity Indices (S&P GSCI), representing investment performance in the commodity markets. More specifically, we used the S&P GSCI Agriculture, S&P GSCI Crude Oil, S&P GSCI Natural Gas, and S&P GSCI Biofuel to represent the performance of agricultural commodities, crude oil, natural gas, and biofuel, respectively. The constituent parts of the S&P GSCI indices are weighted by the value of world production based on a five-year production average and are rebalanced annually (S&P Dow Jones Indices 2023).

Additionally, we used the S&P U.S. Aggregate Bond Index as a variable representing investment performance in the bond markets. The bond index is weighted by market value and rebalanced monthly. The S&P 500 price index was used to represent investment performance in the U.S. stock markets, and the U.S. Dollar Index as a variable for the strength of the U.S. dollar. The index measures the strength of the U.S. dollar to a basket of six foreign currencies with a fixed weight. All S&P variables and the U.S. Dollar Index were collected from Thomson Reuters (2023).

The Producer Price Index by Commodity: Chemicals and Allied Products: Mixed Fertilizers was used to represent fertilizer prices in the U.S. The index was collected from the U.S. Bureau of Labor Statistics (2023) and consisted primarily of nitrogen, phosphorus, and potassium prices. This index, therefore, reflects the prices for the most common fertilizers used to produce agricultural commodities.

Table I: Descriptive statistics of annualized data in percentages (2009-2023)

	Agriculture	S&P 500	Crude oil	Bonds	USD	Biofuel	Natural gas	Fertilizers	CPI
Mean	3.0	10.3	4.2	-0.5	1.7	3.7	-1.6	2.1	2.5
Minimum	-22.1	-19.4	-45.9	-15.0	-9.9	-26.7	-32.1	-19.9	-0.2
Maximum	44.5	29.6	77.9	5.5	12.8	45.9	59.3	38.6	7.6
Std. Dev.	20.9	15.4	38.4	3.9	7.6	20.8	49.7	5.9	0.9

Table I shows the descriptive statistics of the dataset. Crude oil and natural gas exhibited the most considerable fluctuations, as seen by the standard deviations and minimum and maximum returns. Bonds and CPI illustrated minor fluctuations. The S&P 500 had the highest mean return during the full sample, while natural gas had the lowest mean return.

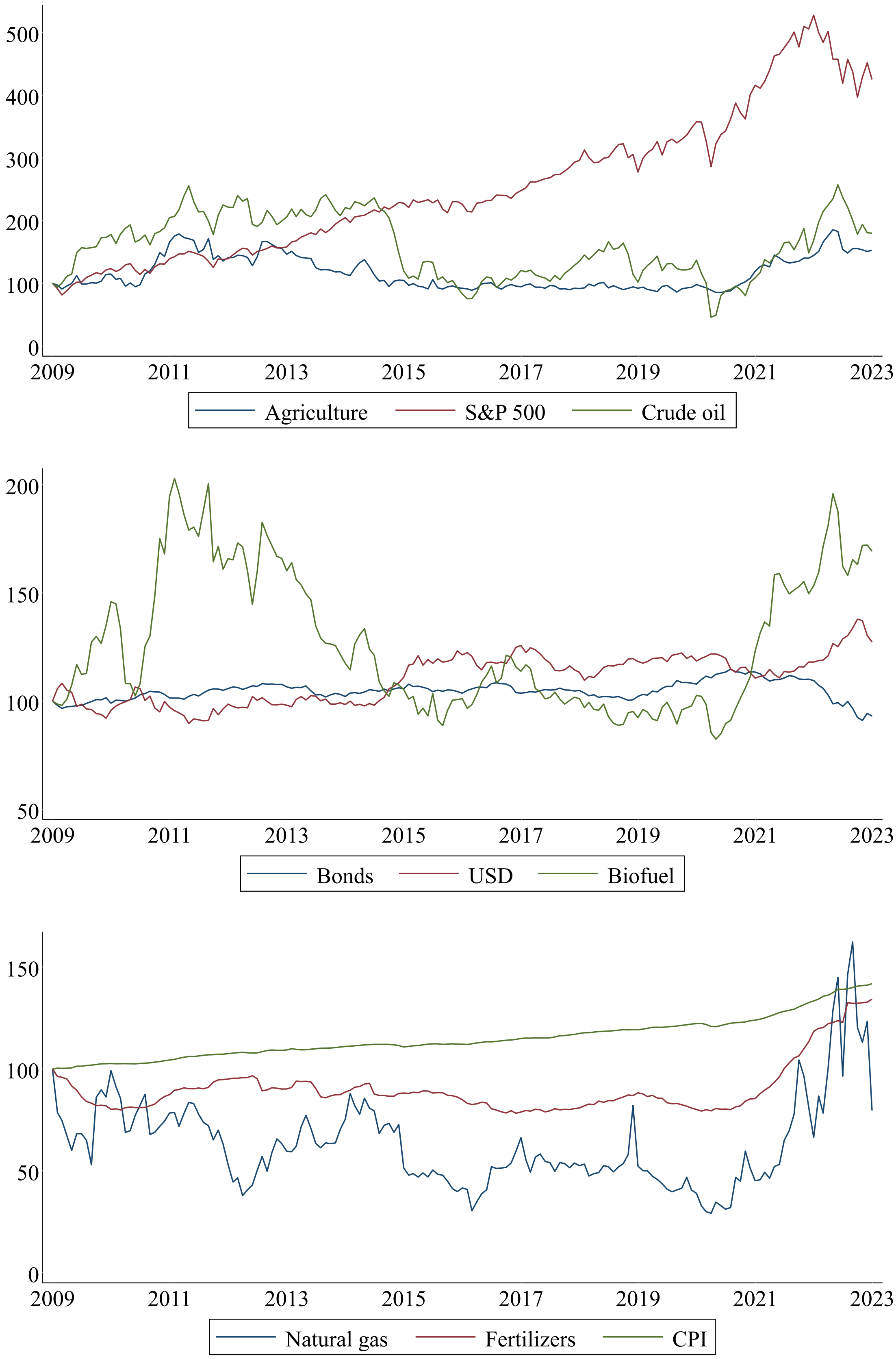

Figure 1: Indexed prices starting at 100. Note the difference in scales.

Figure 1 graphically illustrates the historical price developments of our variables. We could verify the fluctuating nature of crude oil and natural gas prices as illustrated in Table I. Additionally, biofuel prices have been experiencing considerable price fluctuations. Bonds and natural gas ended at a lower price than in 2009, indicating a negative mean return as confirmed by Table I. S&P 500 has been increasing the most during the full sample period.

B. Johansen cointegration test

Table II: Johansen cointegration test

	Trace statistics			Maximum eigenvalue		
Cointegrating rank	Trace statistics	5% critical value	Reject null	Max. eigenvalue	5% critical value	Reject null
0	211.3	192.9	Yes	62.9	57.1	Yes
1	148.5	156.0	No	47.5	51.4	No
2	100.9	124.2	No	40.2	45.3	No
3	60.8	94.2	No	21.4	39.4	No
4	39.4	68.5	No	14.8	33.5	No
5	24.6	47.2	No	13.4	27.1	No
6	11.2	29.7	No	8.7	21.0	No
7	2.5	15.4	No	2.5	14.1	No
8	0.0	3.8	No	0.0	3.8	No

Note: Variables included: agriculture, S&P 500, crude oil, bonds, USD, biofuel, natural gas, fertilizers, and CPI. All variables are in logarithmic form. Lags: 2 in accordance with AIC, see Appendix Table B.II.

The results from the Johansen cointegration test are presented in Table II. The trace statistics and maximum eigenvalue were higher than the 5% critical value at the cointegration rank zero, which implied rejection of that null hypothesis. The null hypotheses at cointegration rank one to eight could not be rejected at the 5% significance level. This means that the Johansen cointegration test found evidence of one cointegrating relationship. As a result, the VECM in Equation (2) was specified with one error correction term.

C. Augmented Dickey-Fuller unit root test

Table III: Augmented Dickey-Fuller unit root test

		Logarithmic levels			First differences		
	Lags	Test statistic	5% critical value	Reject null	Test statistic	5% critical value	Reject null
Agriculture	1	-1.8	-2.9	No	-8.4	-2.9	Yes
S&P 500	3	-4.3	-3.4	Yes	-7.1	-2.9	Yes
Crude oil	3	-3.2	-3.4	No	-7.2	-2.9	Yes
Bonds	1	-1.4	-2.9	No	-8.3	-2.9	Yes
USD	1	-1.3	-2.9	No	-8.0	-2.9	Yes
Biofuel	2	-2.9	-3.4	No	-6.6	-2.9	Yes
Natural gas	1	-3.6	-3.4	Yes	-9.2	-2.9	Yes
Fertilizers	4	-2.5	-2.9	No	-4.6	-2.9	Yes
CPI	2	-2.5	-3.4	No	-5.0	-2.9	Yes

Note: AIC, SBIC, and HQIC were used to indicate optimal lag length, see Appendix Table B.I. The critical values are -3.4 if the deterministic trend (δ_i) was statistically significant at the 5% level and -2.9 if it was not statistically significant.

Table III presents the results of the ADF test specified in Equation (3) on the logarithmic prices and the logarithmic first differenced prices. In the logarithmic form, the test statistics were not sufficient to uniformly reject the null hypotheses for all variables at the 5% significance level. Hence, all variables were not stationary in the logarithmic form. However, the null hypotheses were rejected for all variables after first differencing the variables, implying stationarity at the first difference form. Thereby, the variables were suited for further empirical estimation.

IV. Calibration & Estimation

A. VECM & Granger causality estimation

To examine the Granger causal relationships of agricultural commodity returns, we estimated the VECM. Detailed VECM outputs are presented in Appendix Table C.V. The speed of adjustment ($\boldsymbol{\lambda}$) to long-run equilibrium was not statistically significant for agricultural commodity returns, meaning there was no evidence of any long-run relationships.

The existing literature has not drawn a uniform conclusion in this regard. Zhang *et al.* (2010) and Kapusuzoglu and Karacaer Ulusoy (2015) failed to find evidence of long-run relationships between oil prices and agricultural commodities. However, Nazlioglu and Soytas (2012) found that oil prices and the U.S. dollar have a long-run relationship with agricultural commodities. There has been limited research in the existing empirical literature concerning the long-term connections between agricultural commodities and our included variables. Hence, it was not possible to make an extensive comparison of our long-term results with previous studies.

Table IV: In-sample Granger causality test based on VECM

	Null hypothesis: Does not Granger cause	P-value	Reject null
Panel A: Unidirectional Granger causality			
	S&P 500 $\rightarrow$ Agriculture	.642	No
	Crude oil $\rightarrow$ Agriculture	.603	No
	Bonds $\rightarrow$ Agriculture	.933	No
	USD $\rightarrow$ Agriculture	.682	No
	Biofuel $\rightarrow$ Agriculture	.022	Yes
	Natural gas $\rightarrow$ Agriculture	.964	No
	Fertilizers $\rightarrow$ Agriculture	.023	Yes
	CPI $\rightarrow$ Agriculture	.267	No
Panel B: Bidirectional Granger causality			
	Agriculture $\rightarrow$ Biofuel	.006	Yes
	Agriculture $\rightarrow$ Fertilizers	.190	No

Note: The in-sample consists of 144 monthly observations spanning from 2009 to 2021.

The short-run Granger causal relationships were investigated using the Wald tests presented in Table IV. The results in panel A show that biofuel returns Granger caused agricultural commodity returns, meaning that the lagged biofuel returns had a predictive power over the coming month's agricultural commodity returns. This interdependency between biofuel and agricultural commodities was consistent with the findings from Nicola *et al.* (2016) and Allen *et al.* (2018). They argue that the relationship existed because biofuel production primarily consists of maize and soybean oil production inputs. Therefore, biofuel returns were anticipated to be interconnected to agricultural commodity returns.

Panel B in Table IV show statistical evidence that agricultural commodity returns Granger cause biofuel returns. Therefore, our findings showed that the Granger causal relations are bidirectional between biofuel and agricultural commodity returns. The existence of a bidirectional relationship between biofuel and agricultural commodities is in line with the findings by Serra *et al.* (2011).

Fertilizer returns Granger caused agricultural commodity return as seen in Panel A in Table IV. Similar results were found by Baffes (2007) and Nazlioglu (2011), and could be further supported since fertilizers are an essential input in the production of agricultural commodities and generally account for 44% of agricultural production cost (Gnutzmann and Spiewanowski 2016).

We could not find statistically significant evidence that S&P 500, crude oil, bonds, U.S. dollar, natural gas, or CPI Granger caused agricultural commodity returns. In contrast to our results, Bruno *et al.* (2017) found a relationship between the S&P 500 and agricultural commodities. Allen *et al.* (2018), Taghizadeh-Hesary *et al.* (2019) and Nazlioglu and Soytas (2012) found a relationship between crude oil and agricultural commodities. According to research conducted by Nazlioglu and Soytas (2012) and Adämmer and Bohl (2015), agricultural commodities are affected by the strength of the U.S. dollar. Additionally, Taghizadeh-Hesary *et al.* (2019) found a relationship between inflation and agricultural commodities. There has been a lack of extensive research on bonds and natural gas in relation to agricultural commodities, resulting in limited empirical data and conclusive findings.

To summarize our VECM findings, we discovered that out of the four energy commodities we researched, biofuel and fertilizers had a Granger causal relationship with agricultural commodity returns. However, we found no such linkages between crude oil and natural gas. It is important, however, to interpret these results with caution as the test had an R-squared of 8.9%. This could imply that the model has limited explanatory power, which means that the included variables only account for a minor portion of the returns.

B. IRF estimation

The IRFs presented in Figure 2 were based on the significant Granger causal relationships found in panel A in Table IV and illustrate the response during a 10-month period. The first graph in Figure 2 shows that a one-time positive shock in biofuel returns resulted in a positive response in agricultural commodity returns. The response in agricultural commodity returns sharply increased from month zero to month one, which continued to increase slightly until month four, when the response reached stable levels. Moreover, the effect was permanent and did not return to the pre-shock levels. This meant that a sharp increase in biofuel returns led to a permanent increase in agricultural commodity returns, where most of the increase was observed during the first month.

In the second graph of Figure 2, there was a similar response where a sudden increase in fertilizer returns led to a positive impact on agricultural commodity returns. Again, the response was immediate, significantly rising from month zero to month one. The increase continued for six months before reaching permanent and stable levels.

The positive and persistent response in agricultural commodity returns from shocks in biofuel returns as seen in Figure 2 is in line with the findings from (Taghizadeh-Hesary *et al.* 2019). The authors also found a positive and persistent response in agricultural commodity prices from shocks in crude oil prices. Our VECM estimations in Table IV did not show statistically significant evidence of crude oil Granger causality. However, the authors argued that crude oil affects agricultural commodity prices through the production of fertilizers. Figure 2 shows that fertilizer returns positively and persistently impacted agricultural commodity returns. Therefore, the results of our IRFs in Figure 2 were similar to, but not equal to, the IRF results of (Taghizadeh-Hesary *et al.* 2019).

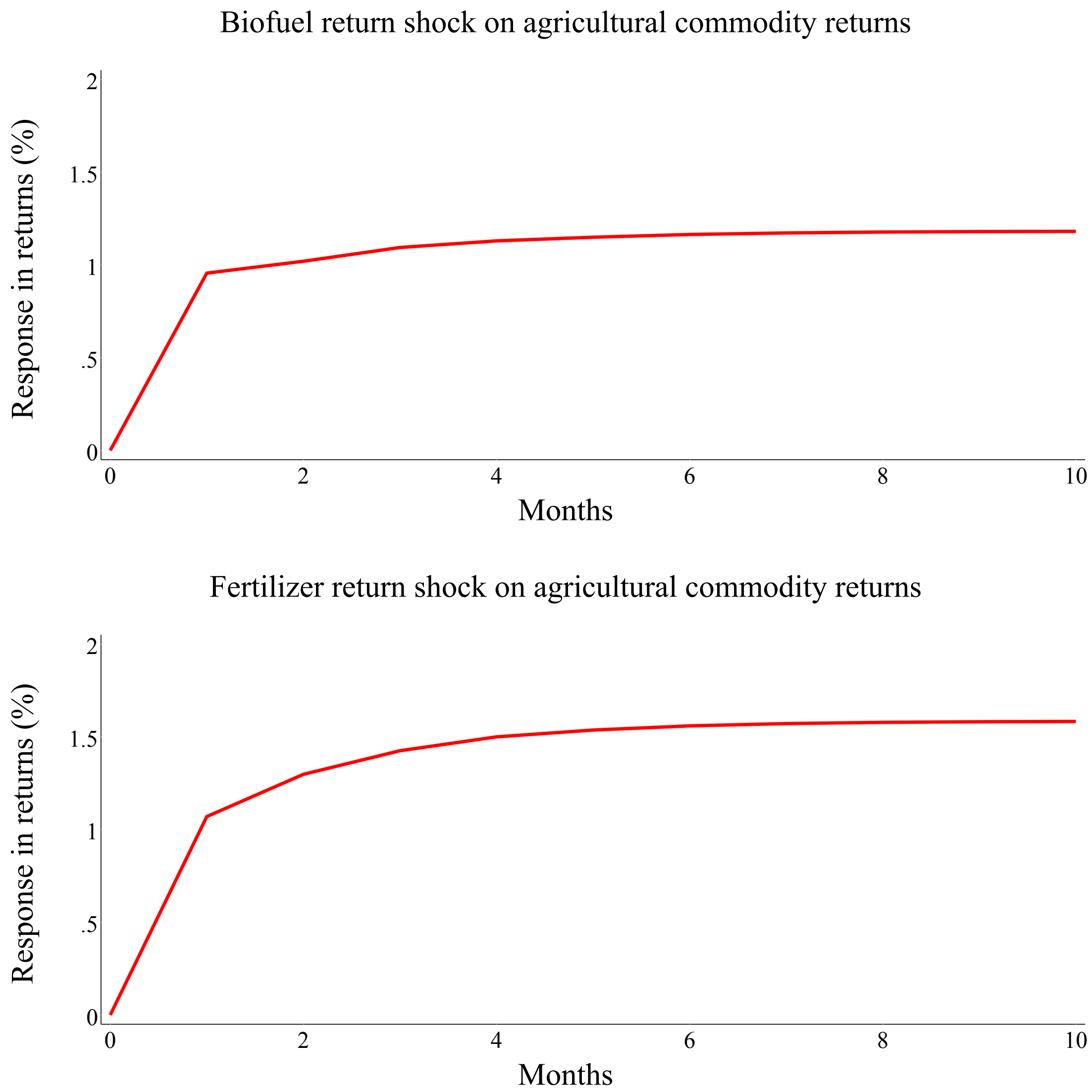

Figure 2: IRF. Monthly response of agricultural commodity returns from a one-time shock in biofuel and fertilizer returns

The IRF in Figure 3 further investigates the bidirectional Granger causal relationship found in panel B in Table IV through imposing a one-time positive shock in agricultural commodity returns. Biofuel returns responded with an immediate increase starting from month zero, where the response fluctuated slightly until month four. Afterward, the response sustained post-shock levels throughout the rest of the period. This means that a sharp increase in agricultural commodity returns led to a permanent and immediate increase in biofuel returns.

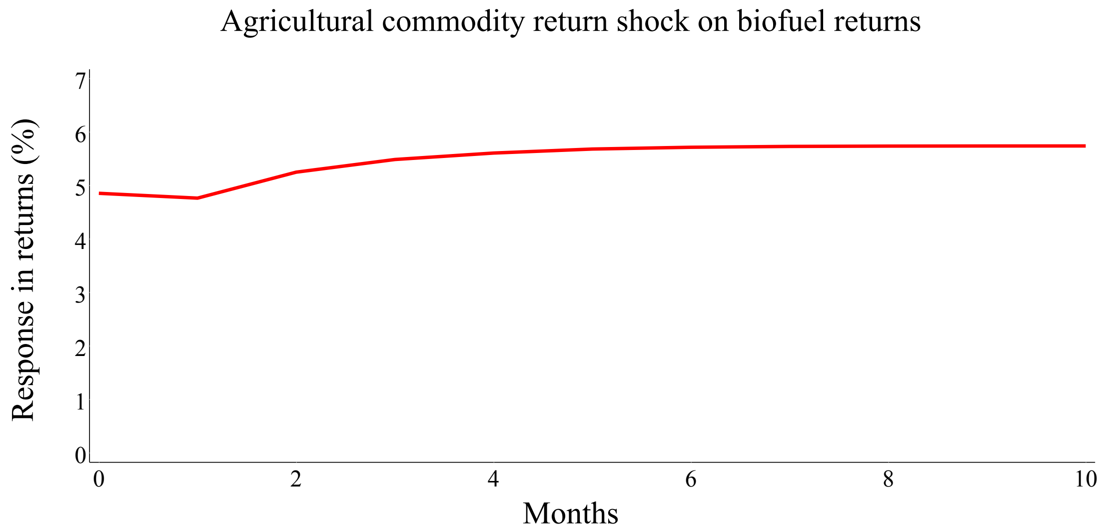

Figure 3: IRF. Monthly response of biofuel returns from a one-time shock in agricultural commodity returns

The results presented in Figure 2 and Figure 3 verified the significant relationships found in Table IV. The IRFs also suggested that the relationships are positive, the latency of response is minimal, and the responses had a persistent impact.

C. Post-estimation tests

Table V: Lagrange-multiplier test

Lag	Null hypothesis	P-value	Reject null
1	No residual autocorrelation at lag 1	.142	No
2	No residual autocorrelation at lag 2	.520	No

Note: The LM tests for residual autocorrelation in each lag order used for the VECM specification.

Table V presents the residual autocorrelation tests for both lags used in the VECM estimation. We could not reject the null hypotheses since the p-values were above the 5% significance level. Consequently, we found no residual autocorrelation for the two lag orders. Thus, the results from the LM test concluded that the VECM was not biased by residual autocorrelation.

Table VI: Jarque-Bera test

Null hypothesis: Residuals are normally distributed	P-value	Reject null
Agriculture	.001	Yes
S&P 500	.000	Yes
Crude oil	.000	Yes
Bonds	.171	No
USD	.188	No
Biofuel	.003	Yes
Natural gas	.000	Yes
Fertilizers	.000	Yes
CPI	.688	No
All	.000	Yes

Note: The Jarque-Bera tests if the residuals from each estimated VECM equation are normally distributed.

Table VI shows the Jarque-Bera residual normality tests based on the estimated VECM equations. The null hypothesis of normally distributed residuals was rejected at the 5% level for the VECM equations agriculture, S&P 500, crude oil, biofuel, natural gas, and fertilizers. In addition, the joint residual normality test was also rejected. As a result, the

VECM does not fulfill the normality assumption.

Table VII: Out-of-sample Granger causality test based on VECM

	Null hypothesis: Does not Granger cause	P-value	Reject null
Panel A: Unidirectional Granger causality			
	S&P 500 → Agriculture	.650	No
	Crude oil → Agriculture	.952	No
	Bonds → Agriculture	.399	No
	USD → Agriculture	.268	No
	Biofuel → Agriculture	.600	No
	Natural gas → Agriculture	.399	No
	Fertilizers → Agriculture	.913	No
	CPI → Agriculture	.636	No

Note: The out-of-sample consists of 23 monthly observations spanning from 2021 to 2023.

The out-of-sample estimation in Table VII failed to find significant Granger causal relationships between the investigated variables and agricultural commodity returns. Moreover, the out-of-sample dataset found evidence of unit roots in the first differenced variables, as noted in Appendix Table C.III, and thus suffered from non-stationarity. Additionally, the out-of-sample Johansen cointegration test in Appendix Table C.IV did not provide interpretable results. Therefore, we discard the out-of-sample results as not reliable.

V. Conclusion

In this paper, we investigated the Granger causal relationships of agricultural commodity returns, focusing on the impact of the stock market, energy commodities, and macroeconomic variables. We employed a VECM and IRFs on monthly returns and found unidirectional and bidirectional Granger causalities.

Firstly, we found a positive and persistent bidirectional Granger causality between biofuel returns and agricultural commodity returns. An explanation might be that agricultural commodities are essential to biofuel production. Hence, increased agricultural commodity prices have to be compensated by biofuel producers through higher prices. On the other hand, the inverse linkage could be explained that increased biofuel prices create economic incentives for biofuel producers to increase production; hence the demand and price for agricultural commodities increase.

Secondly, we found a positive and persistent unidirectional Granger causality flowing from fertilizer returns to agricultural commodity returns, implying that the production cost of agricultural commodities increases as the price of fertilizer increases. The findings are not unexpected since biofuel and fertilizers are closely related in the agricultural commodity production chain.

On the other hand, most existing literature found evidence of a linkage between the stock market, crude oil, and USD strength to agricultural commodities. However, this contradicts our findings since we did not find any significant Granger causality between these variables and agricultural commodity returns. A potential explanation for why our results differ from other authors could be linked to the specific time period chosen for analysis. It could also be because we used an aggregated agricultural commodity index that might neglect individual agricultural commodities' dependencies.

Our post-estimation tests showed mixed results. The VECM assumption of no residual autocorrelation was fulfilled according to the LM test, but the residual normality assumption was not fulfilled according to the Jarque-Bera test. Additionally, the 23 months out-of-sample dataset proved insufficient to provide reliable VECM results. A likely reason is that the number of observations was too few. Future researchers who want to employ an out-of-sample VAR or VECM could learn from our attempt that more observations might be required.

This paper's findings are important to investors in the agricultural sector and policymakers. First, the knowledge of Granger causality allows investors to use information from the biofuel and fertilizer markets to predict future agricultural commodity prices. Additionally, the lack of Granger causality can potentially highlight diversification benefits for investors since they are not intertemporally dependent on each other. Finally, policymakers can mitigate price changes in agricultural commodities by directing regulatory focus to biofuel and fertilizer markets.

We find three limitations of our study; firstly, since an agricultural commodity index is used, it might neglect idiosyncratic factors specific to separate commodities within the index. Secondly, the employed model lacks the ability to interpret the magnitude of the short-run Granger causalities. Thirdly, the post-estimation tests of our study showed mixed results, and the VECM illustrated an R-square of 8.9%, whereby each reader should draw their own conclusions about the validity of our results.

Future research could further examine the link between biofuel and fertilizers to agricultural commodities. We believe a more in-depth analysis could be done by splitting the fertilizers into the most commonly used fertilizers; nitrogen, phosphate, and potassium. Additionally, future studies could examine the predictability of farmland prices which would have policy implications for real estate investors, banks, and farmers.

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Andreas Blidberg & Ludwig Skans. Gothenburg, May, 2023.

A Appendix

We utilized Overleaf and LaTeX to write this thesis, as well as to create tables and equations. The statistical software STATA version SE 17.0 was used to handle, clean, and transform our dataset. STATA was also used to conduct statistical tests and to create graphs.

A.1 VECM

The VECM used in this paper was based on a VAR, which estimates one equation for each variable. For each equation, the value of the dependent variable is estimated by the lagged variables. The base model VAR for our study was specified as:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{p} \boldsymbol{\phi}_j \mathbf{Y}_{t-j} + \boldsymbol{\varepsilon}_t \tag{A1}$$

Where $\mathbf{Y}_t$ is a vector of logarithmic variables. $\boldsymbol{\alpha}$ is a vector with intercept parameters. $\boldsymbol{\phi}_j$ is a square matrix with the coefficients used to assess short-run causality. Since our Johansen cointegration tests in Table II showed evidence of one cointegrating relationship among our variables, we augmented the VAR with an additional vector:

$$\boldsymbol{\lambda}\mathrm{ECT}_{t-1} \tag{A2}$$

Where $\boldsymbol{\lambda}$ is the speed of adjustment to long-run equilibrium and ECT_{t-1} is computed as the OLS regression error:

$$\mathrm{ECT}_{t-1} = Y_{1,t-1} - \alpha - \sum_{j=1}^{i-1} \beta_j Y_{j+1,t-1} \tag{A3}$$

Where i is the number of variables. If the variables are far apart but share a common trend, they would be expected to draw closer to each other over time, and thus the error will be *corrected*, as the name - Error Correction Term suggests. The speed of adjustment term $\boldsymbol{\lambda}$ assesses the long-run causal relationships but must be statistically significant to add interpretational value. After adding the $\boldsymbol{\lambda}\mathrm{ECT}_{t-1}$ vector and first differencing operators, we ended up with the VECM specified in Equation (1):

$$\Delta\mathbf{Y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{p-1} \boldsymbol{\phi}_j \Delta\mathbf{Y}_{t-j} + \boldsymbol{\lambda}\mathrm{ECT}_{t-1} + \boldsymbol{\varepsilon}_t \tag{A4}$$

B Appendix - In-sample VECM estimation

B.1 Appendix – Optimal lag length for ADF

Appendix Table B.I: Lag length selection criteria in each separate variable for ADF

	Lag	AIC	HQIC	SBIC
Agriculture				
	0	-.33	-.32	-.31
	1	-2.77*	-2.75*	-2.72*
	2	-2.75	-2.73	-2.69
	3	-2.74	-2.71	-2.66
	4	-2.73	-2.68	-2.62
S&P 500				
	0	.84	.85	.86
	1	-3.56	-3.54*	-3.52*
	2	-3.55	-3.52	-3.49
	3	-3.56*	-3.53	-3.48
	4	-3.55	-3.51	-3.45
Crude oil				
	0	.74	.75	.76
	1	-1.44	-1.42	-1.40*
	2	-1.46	-1.43*	-1.40
	3	-1.46*	-1.43	-1.38
	4	-1.45	-1.41	-1.35
Bonds				
	0	-4.04	-4.03	-4.02
	1	-6.57*	-6.56*	-6.53*
	2	-6.56	-6.53	-6.50
	3	-6.55	-6.52	-6.47
	4	-6.56	-6.52	-6.46
USD				
	0	-1.81	-1.80	-1.79
	1	-4.84*	-4.82*	-4.79*
	2	-4.82	-4.80	-4.76
	3	-4.83	-4.79	-4.74
	4	-4.81	-4.77	-4.71
Biofuel				
	0	-.07	-.06	-.05
	1	-2.76	-2.75	-2.72*
	2	-2.77*	-2.75*	-2.71
	3	-2.76	-2.73	-2.68
	4	-2.75	-2.70	-2.64
Natural gas				
	0	.25	.259	.271
	1	-1.40*	-1.38*	-1.36*
	2	-1.39	-1.36	-1.33
	3	-1.38	-1.34	-1.29
	4	-1.36	-1.32	-1.26
Fertilizers				
	0	-2.92	-2.91	-2.90
	1	-5.56	-5.58	-5.56
	2	-5.71	-5.68*	-5.65*
	3	-5.70	-5.67	-5.62
	4	-5.71*	-5.67	-5.61
CPI				
	0	-2.93	-2.92	-9.53*
	1	-9.40	-9.39	-9.36
	2	-9.55	-9.53	-9.49*
	3	-9.56	-9.53	-9.48
	4	-9.57*	-9.53*	-9.47

Note: * = optimal lag. All variables are in logarithmic form.

B.2 Optimal lag length for Johansen cointegration and VECM

Appendix Table B.II: Lag length selection criteria for Johansen cointegration and VECM

Lag	AIC	HQIC	SBIC
0	-22.80	-22.72	-22.61
1	-41.23	-40.46^{*}	-39.34^{*}
2	-41.41^{*}	-39.95	-37.83
3	-41.00	-38.86	-35.73
4	-40.83	-38.00	-33.86

Note: * = optimal lag. Variables included: agriculture, S&P 500, crude oil, bonds, USD, biofuel, natural gas, fertilizers, and CPI. All variables are in logarithmic form.

B.3 Appendix - Full in-sample VECM outputs

Appendix Table B.III: In-sample VECM outputs

	Short-run causality									Long-run causality
	AG	SP	CL	BND	USD	BF	NG	FRT	CPI	ECT
λ	.020	.085*	.435*	-.002	-.043*	.101*	-.227*	-.013	.004*	-
	(.634)	(.004)	(.000)	(.712)	(.003)	(.014)	(.008)	(.171)	(.014)	
AG_{t-1}	-.393*	-.075	-.239	-.021	.118*	-.431*	-.323	.049	-.004	1
	(.016)	(.505)	(.374)	(.399)	(.030)	(.006)	(.317)	(.190)	(.451)	
SP_{t-1}	-.072	.014	.822*	-.030	.042	.071	-.205	-.018	.001	-.774*
	(.642)	(.892)	(.001)	(.194)	(.422)	(.634)	(.504)	(.618)	(.823)	(.002)
CL_{t-1}	.005	.003	-.032	.000	.013	.000	-.149	-.026	.002	-.442*
	(.933)	(.947)	(.750)	(.993)	(.512)	(.998)	(.221)	(.064)	(.232)	(.000)
BND_{t-1}	.292	.434	.599	-.044	-.202	.499	-.696	-.034	.002	.239
	(.603)	(.261)	(.519)	(.599)	(.284)	(.356)	(.532)	(.792)	(.931)	(.748)
USD_{t-1}	-.121	-.084	.618	-.073	.013	.073	.290	.038	.001	.418
	(.682)	(.679)	(.206)	(.100)	(.892)	(.798)	(.620)	(.574)	(.958)	(.334)
BF_{t-1}	.374*	-.001	-.224	.024	-.048	.469*	.399	-.019	.006	-.758*
	(.022)	(.993)	(.406)	(.326)	(.384)	(.003)	(.217)	(.622)	(.250)	(.000)
NG_{t-1}	.002	-.052	-.084	.000	.012	-.028	-.063	.008	-.001	.414*
	(.964)	(.075)	(.231)	(.984)	(.399)	(.493)	(.456)	(.435)	(.527)	(.000)
FRT_{t-1}	.783*	.360	.501	-.045	.015	.709*	1.007	.298*	.000	.154
	(.023)	(.129)	(.380)	(.382)	(.898)	(.033)	(.141)	(.000)	(.994)	(.639)
CPI_{t-1}	3.339	2.458	20.726*	-.930*	-3.282*	4.041	8.542	1.574*	.290*	4.079*
	(.267)	(.234)	(.000)	(.040)	(.001)	(.163)	(.152)	(.023)	(.004)	(.009)
Intercept	-.001	.011*	-.015	.003*	.003	.000	-.025	-.003*	.001*	-21.934
	(.880)	(.023)	(.198)	(.015)	(.256)	(.971)	(.073)	(.043)	(.000)	
R-square	.089	.161	.337	.088	.184	.143	.104	.176	.453	-

Note: * = significance at the 5% level. Values inside parentheses are the p-values. The term λ measures the speed of adjustment to equilibrium. Abbreviations: AG = agriculture, SP = S&P 500, CL = crude oil, BND = bonds, BF = biofuel, NG = natural gas, FRT = fertilizers.

C Appendix - Out-of-sample VECM estimation

C.1 Appendix – Optimal lag length for ADF

Appendix Table C.I: Lag length selection criteria in each separate variable for ADF

	Lag	AIC	HQIC	SBIC
Agriculture				
	0	-1.73	-1.72	-1.68
	1	-2.92	-2.90	-2.82*
	2	-2.95*	-2.92*	-2.80
	3	-2.87	-2.83	-2.67
	4	-2.78	-2.73	-2.53
S&P 500				
	0	-2.28	-2.27	-2.23
	1	-2.85*	-2.83*	-2.75*
	2	-2.82	-2.80	-2.67
	3	-2.74	-2.70	-2.54
	4	-2.71	-2.66	-2.46
Crude oil				
	0	-.75	-.74	-.70
	1	-1.76*	-1.74*	-1.66*
	2	-1.66	-1.63	-1.51
	3	-1.56	-1.52	-1.36
	4	-1.53	-1.48	-1.28
Bonds				
	0	-2.39	-2.38	-2.34
	1	-4.84*	-4.82*	-4.74*
	2	-4.74	-4.71	-4.59
	3	-4.68	-4.65	-4.49
	4	-4.66	-4.62	-4.41
USD				
	0	-2.52	-2.51	-2.47
	1	-4.71*	-4.69*	-4.61*
	2	-4.68	-4.65	-4.53
	3	-4.58	-4.54	-4.38
	4	-4.49	-4.45	-4.25
Biofuel				
	0	-2.26	-2.25	-2.21
	1	-3.09	-3.07	-2.99*
	2	-3.13*	-3.11*	-2.99
	3	-3.07	-3.03	-2.87
	4	-3.00	-2.95	-2.75
Natural gas				
	0	.51	.52	.56
	1	-.13*	-.11*	-.03*
	2	-.05	-.02	.10
	3	.02	.06	.22
	4	.01	.15	.35
Fertilizers				
	0	-1.63	-1.62	-1.58
	1	-5.08*	-5.06*	-4.98*
	2	-5.04	-5.01	-4.89
	3	-4.96	-4.92	-4.76
	4	-4.94	-4.89	-4.69
CPI				
	0	-3.77	-3.76	-3.72
	1	-8.69*	-8.67*	-8.59*
	2	-8.60	-8.57	-8.45
	3	-8.53	-8.49	-8.33
	4	-8.50	-8.45	-8.25

Note: * = optimal lag. All variables are in logarithmic form.

C.2 Augmented Dickey-Fuller test

Appendix Table C.II: Augmented Dickey-Fuller (ADF) unit root test

		Logarithmic levels			First differences		
	Lags	Test statistic	5% critical value	Reject null	Test statistic	5% critical value	Reject null
Agriculture	2	-2.0	-3.0	No	-3.2	-3.0	Yes
S&P 500	1	-2.3	-3.6	No	-4.0	-3.0	Yes
Crude oil	1	-1.0	-3.0	No	-3.3	-3.0	Yes
Bonds	1	-2.1	-3.6	No	-3.4	-3.0	Yes
USD	1	-1.1	-3.0	No	-2.5	-3.0	No
Biofuel	2	-2.8	-3.0	No	-3.8	-3.0	Yes
Natural gas	1	-1.8	-3.0	No	-3.8	-3.0	Yes
Fertilizers	1	-2.2	-3.0	No	-3.9	-3.6	Yes
CPI	1	-1.6	-3.0	No	-3.0	-3.0	No

Note: AIC, SBIC, and HQIC were used to indicate optimal lag length. The critical values are -3.6 if the deterministic trend (δ_i) was statistically significant at the 5% level and -3.0 if it was not statistically significant.

Appendix Table C.II shows that the null hypothesis of unit root cannot be rejected in biofuel and CPI in the first differences, indicating a non-stationarity problem.

C.3 Optimal lag length for Johansen cointegration and VECM

Appendix Table C.III: Lag length selection criteria for Johansen cointegration and VECM

Lag	AIC	HQIC	SBIC
0	-35.48	-35.41	-35.03
1	-83.93	-83.32	-79.48
2	-519.76	-518.65	-511.75
3	-569.97	-567.87	-560.96
4	-564.90	-563.79	-556.89
5	-575.67	-574.57	-567.66
6	-579.31^{*}	-578.20^{*}	-571.30^{*}

Note: * = optimal lag. Variables included: agriculture, S&P 500, crude oil, bonds, USD, biofuel, natural gas, fertilizers, and CPI. All variables are in logarithmic form.

C.4 Johansen cointegration test

Appendix Table C.IV: Johansen cointegration test

	Trace statistics			Maximum eigenvalue		
Cointegrating rank	Trace statistics	5% critical value	Reject null	Max. eigenvalue	5% critical value	Reject null
0	-	192.9	No	-	57.1	No
1	-	156.0	No	737.7	51.4	Yes
2	-	124.2	No	-	45.3	No
3	-	94.2	No	-	39.4	No
4	-	68.5	No	-	33.5	No
5	-	47.2	No	-	27.1	No
6	-	29.7	No	-	21.0	No
7	-	15.4	No	-	14.1	No
8	-	3.8	No	-	3.8	No

Note: Variables included: agriculture, S&P 500, crude oil, bonds, USD, biofuel, natural gas, fertilizers, and CPI. All variables are in logarithmic form. Lags specified: 6.

When estimating the Johansen cointegration for our out-of-sample dataset in Appendix table C.IV, STATA automatically removed three lags because of collinearity. This is problematic because it is not in accordance with the optimal lag length. Consequently, the outputs in Appendix Table C.IV were not interpretable and thus failed to correctly identify potential cointegrating relationships among our variables.

The following section presents the full out-of-sample VECM outputs. However, because of the non-stationarity problem and failure to correctly test for cointegration, we deem the results of our out-of-sample estimation unreliable. Nevertheless, to be transparent, we estimated the out-of-sample VECM with the same specification as the in-sample VECM. The results are presented in Appendix Table C.V.

C.5 Full out-of-sample VECM outputs

Appendix Table C.V: In-sample VECM outputs

	Short-run causality									Long-run causality
	AG	SP	CL	BND	USD	BF	NG	FRT	CPI	ECT
λ	1.21	.317	-.837	.115	-.266	.170	-4.063	-.020	.125*	-
	(.385)	(.762)	(.707)	(.673)	(.529)	(.901)	(.365)	(.955)	(.012)	
AG_{t-1}	-.381	-.359	.012	4.084	3.000	1.102	-.232	-.166	-3.987	1
	(.804)	(.650)	(.952)	(.399)	(.268)	(.547)	(.399)	(.913)	(.636)	
SP_{t-1}	-1.421	-.435	.112	3.402	2.581	1.674	-.253	-.346	3.931	.328
	(.218)	(.463)	(.458)	(.349)	(.204)	(.223)	(.221)	(.761)	(.533)	(.375)
CL_{t-1}	-.304	-.755	-.265	-3.335	-2.459	.537	.088	2.920	7.453	.522
	(.902)	(.551)	(.411)	(.668)	(.571)	(.855)	(.841)	(.229)	(.580)	(.670)
BND_{t-1}	-.773*	-.001	.0477	1.246	.880	.780*	-.072	-.406	2.648	-4.34*
	(.010)	(.951)	(.223)	(.188)	(.096)	(.029)	(.179)	(.170)	(.107)	(.003)
USD_{t-1}	.693	.078	-.010	-2.158	-1.304	-.972	.100	.757	-1.158	-3.101*
	(.137)	(.745)	(.866)	(.142)	(.112)	(.080)	(.229)	(.100)	(.650)	(.009)
BF_{t-1}	.424	.192	-.070	-.209	.954	-.037	-.063	.424	-5.879	-1.521*
	(.777)	(.803)	(.720)	(.965)	(.718)	(.984)	(.814)	(.774)	(.474)	(.000)
NG_{t-1}	.561	1.021	.511	-12.176	-1.641	-1.017	.273	6.439	-25.261	.238*
	(.910)	(.688)	(.429)	(.435)	(.851)	(.863)	(.758)	(.187)	(.351)	(.000)
FRT_{t-1}	-.209	-.125	.035	1.002	.604	.240	-.060	-.071	.075	2.096*
	(.599)	(.542)	(.503)	(.425)	(.389)	(.613)	(.397)	(.857)	(.973)	(.001)
CPI_{t-1}	-.094	-.065*	.004	.388*	.213*	.154*	-.0198*	-.003	.165	-9.522*
	(.088)	(.022)	(.598)	(.026)	(.029)	(.020)	(.046)	(.953)	(.585)	(.000)
Intercept	.219	-.011	-.077	-.015	-.003	.024	.022	.025	.004	74.195
	(.712)	(.800)	(.416)	(.194)	(.886)	(.678)	(.907)	(.109)	(.070)	
R-square	.292	.551	.330	.776	.551	.320	.491	.761	.923	-

Note: * = significance at the 5% level. Values inside parentheses are the p-values. The term λ measures the speed of adjustment to equilibrium. Abbreviations: AG = agriculture, SP = S&P 500, CL = crude oil, BND = bonds, BF = biofuel, NG = natural gas, FRT = fertilizers.

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