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Commodity Future Contracts Price Overreaction and Underreaction:

A Relative Empirical Study Of The Impact Of World Events

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Abstract

Using an event-based study methodology to identify which trading days are considered as event days within the sample period, commodity futures contracts prices and subsequently returns are tested for if their behaviour follows the overreaction, underreaction or efficient market hypothesis. Twelve contracts' prices are observed over two six-month time periods in 2020 and 2022 respectively, to empirically evaluate if the commodity futures market reacted due to the Covid-19 pandemic compared to the Ukraine-Russia War. Despite the strong assumptions and oversimplifications of the methodology, the empirical findings show that the efficient market hypothesis cannot be rejected in favour of the overreaction or underreaction hypothesis. Even though some contracts show evidence of underreaction or overreaction behaviour, these are considered more as isolated cases rather than a pattern. I conclude that there is insignificant and inconclusive evidence to claim that the commodities futures market reacted adversely when comparing the Covid-19 pandemic world event to the Ukraine-Russia War world event. Lastly, we find that extreme overreactions or underreactions provide the potential for profitable trading returns during both time periods.

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1 Introduction

The efficient market hypothesis states due to perfect information in the market, there should be no arbitrage opportunities for investors to exploit. This notion is considered one of the cornerstones of economics. However, academics and researchers have empirically found market anomalies, which are market circumstances whereby there is an opportunity to make an abnormal profit. De Bondt and Thaler (1985) conceptualized one such market anomaly as the "Overreaction Hypothesis". Their hypothesis states that investors overreact to unexpected recent news and subsequently relatively ignore the past financial performance of a stock which results in exaggerated price movements followed by large overcorrections. They find that equities which exhibit positive abnormal returns subsequently are followed by consecutive days of negative returns, whereas equities which exhibit negative abnormal returns are followed by consecutive days of positive returns. This paper aims to examine this hypothesis empirically for commodity futures contracts during financially and politically tumultuous times.

Commodities and their futures contracts are a relatively understudied topic in finance because of their innateness. However, they remain the 'building blocks' of every economy. The manner in which their markets behave is influenced by a multitude of factors and mechanisms that need to be first laid out as the foundation before delving into the research aims of this paper. Commodity spot prices for instance are influenced by a variety of tangible and intangible factors such as aggregate demand, aggregate supply, global commodity inventory and investors' sentiment and speculative demand. Commodity futures contract prices are affected by a few similar important factors, excluding the transaction cost of trading. They are dependent on the spot price of the underlying asset, the risk-free interest rate, interest income, the cost of carrying - which is the cost to physically store the commodity, the time till the contract expires and the convenience yield. Commodity futures contract prices over their outstanding lifetime fluctuate, however as the date of expiry of a futures contract nears, the contract price will naturally converge to the spot price at the expiration date. Thus, the greater the difference between the spot price and the futures contract price, the greater the arbitrage opportunity.

This paper in essence wants to examine the impact of the Ukraine war and the Covid-19 pandemic on commodity futures prices, which is done with caution as lockdown policies implemented by many countries globally heavily impact the supply chain networks as well as commodity imports and exports further distorting prices. Recent past literature has documented the reaction of commodity prices due to the Covid-19 pandemic, highlighting the importance of commodity markets to the global economy. Foreign exchange markets and import and export markets naturally also play a role in the functioning and behaviour of commodity futures markets, however, this will be ignored in this paper. The financial impact of the pandemic on stock markets has been extensively researched and documented, as well as the supply chain disruptions and forecasting growth rates, such as done by Nikolopoulos et al. (2021). Commodities and commodity futures prices historically have behaved in synchronization, however, due to the pandemic and the Ukraine War, certain supply chains were disrupted for certain commodities breaking the synchronization. For example, because of the Ukraine War and mainland Europe's dependency on Russian oil and gas supply through, for example, the Nord Stream pipeline between Russia and Germany, oil supply was suddenly cut off. More recent academic literature has also looked into Covid-19's impact on commodity and commodity futures markets (Adekoya et al. (2021), Lin et al. (2020)).

The World Bank report on "Commodity Markets Outlook" published in October 2020 and June 2022 both outlined significant price changes in the commodity markets due to the two major events. However, the price changes depends on the commodity type. For instance, energy commodities decreased in price in 2020 but increased in price in 2022, the former being because of reduced demand and the latter because of reduced supply. Contrastingly, agricultural commodities increased in price in 2020 and 2022, both because of reduced supply. Evidently, commodity prices and their overreactions due to major world events spill over into other industries, showing the importance of commodity markets and commodity security exchanges for the global economy.

This paper considers twelve commodity futures contracts' daily prices during the first two quarters of 2020 and 2022. The paper aims to find the impact of a world event such as the Ukraine-Russia War which broke out officially on the 24th of February 2022 on commodity future contract prices, as world events such as this impact global supply chains and influence to an extent all market forces and stakeholders. In order to contextualise these findings, the same analysis is parallelly carried out for the first two quarters of 2020 when the Covid-19 pandemic broke out officially - this is to relatively compare the market's response across different world events. The pandemic's analysis is used in absolute terms to evaluate its impact on the commodity futures market, but also to evaluate the commodity futures market's reaction due to the Ukraine-Russia War relative to another world event - the pandemic. I use end-of-day daily futures prices to examine if the market overreacted, underreacted or was efficient. An event-based methodology is used to identify event days where prices significantly changed. However, three different criteria are formulated to determine which days within the sample periods can be considered as event days. Hence, the explicit research question this paper attempts to answer is: *To what extent did the commodity futures market overreact or underreact due to the Ukraine-Russia War world event in 2022 relative to Covid-19 pandemic world event in 2022?*

The empirical results show little conclusive evidence, contrary to what was anticipated. Some futures contracts in either time period showed significant evidence of overreacting or underreacting. However, the lack of robustness of the methodology could be the cause of accumulating too few data points to gain significant results, however, this may be due to a too small data sample, to begin with. Subsequently, this research's main aim to find whether the Covid-19 pandemic as a world event caused a greater or lesser degree of overreaction or underreaction in the commodities futures market relative to the consequences of the Ukraine-Russia War.

The remainder of this paper is structured as follows. Section 2 reviews the existing literature on the overreaction hypothesis and commodity futures markets. Section 3 describes the data used in the study. Section 4 presents the methodological framework used. Section 5 presents and discusses the empirical results, while also evaluating the data set, methodology and the results themselves. Lastly, section 6 concludes the paper.

2 Literature review

Commodities have long been the backbone of most economies and price changes in these markets tend to have a trickle-down effect into equity markets and subsequently influence macroeconomic trends - yet these markets are relatively understudied. Kabundi and Zahid (2021) look at commodity price cycles, their commonalities and drivers from 1970 - 2019. Their most relevant findings are that global macroeconomic supply and demand shocks are the major drivers of commodity price volatility, accounting for about 60% of the variation. Furthermore, they find that commodity price cycles are highly synchronized across commodity categories - a result we could expect empirically.

Larson and Mardura (2003) also found that stock prices in the equity market had higher tendencies to move more drastically in the opposite direction, the more significant the initial price change after an event would be. If overreaction, as De Bondt and Thaler (1985) describe it, is an over-response to new and recent information and a simultaneous under-response to prior information - then underreaction is the under-response caused by the gradual diffusion of information into the market and therefore into the commodity price itself. This finding could reverse the reason that commodity spot prices, and by extension, commodity futures prices, behave similarly because it is commonly considered that commodity price directly influences most stock price behaviours to an extent. This is for two reasons: firstly, public firms that may produce commodities or secondly, public firms who use commodities as inputs to produce their goods or services. Larson and Mardura (2001) also find and prove empirically in another paper that the greater the initial price change on the event day, the greater uncertainty there is and the higher likelihood that the price reversal will be greater in magnitude.

A follow-up academic research paper by Bremer and Sweeney (1991) to De Bondt and Thaler (1985) considers significant event days as days where the price increases or decreases by at least 10% of a particular stock. They also find that after such an event day, the return of that stock is reversed for the following two days, which the authors claim to be inconsistent with the notion that market prices almost immediately incorporate all relevant information.

Moreover, they infer that because market prices adjust relatively slower than anticipated, the overreaction hypothesis consequently might not even be present.

Borgards et al. (2021) examine the intra-day price overreaction behaviour of 20 commodity futures across two sub-time periods, one pre-covid pandemic and one during the covid pandemic. Specifically, they look at data from 20th November 2019 to June 3rd 2020 - and as this is a similar period to what we are studying, our results can be gauged relative to this. Even though Borgards et al. (2021) look at intra-day data, whereas we will look at inter-day data, they find empirical evidence using a non-parametric approach confirming the presence of the overreaction hypothesis. They find that the magnitude of the overreactions was greater during the covid pandemic than in the pre-pandemic period. One of their main findings is that especially crude oil futures exhibited more negative overreactions than positive ones relative to the other commodities - a result we also expect to find.

Previous studies by Brown et al. (1988) and Ajayi and Mehdian (1994) have looked at the overreaction of equity indices in US and non-US markets, where they find that the impact of macroeconomic events or events that cause macroeconomic shocks are not reflected in stock prices. By extension, this result would imply that macroeconomic level events would not affect stock, security or other derivatives prices and would suggest this paper's aim to be obsolete. Furthermore, there are some studies which look more specifically at certain commodities and their futures contracts. For instance, contrastingly, Ma et al. (1990) find that agricultural futures prices historically tend to overreact to significant events in one direction. Whereas, Allen et al. (1994) found that commodity spot prices usually reverse after events causing significant price changes, which supports the overreaction hypothesis.

Even though we are using data from the Covid-19 pandemic time period as a reference point to evaluate the price behaviours of commodity futures contracts during the Ukraine War time period, the subsequent effects on price behaviour can be starkly different. The covid pandemic can be considered to an extent a natural disaster leading to economic distress, whereas the Ukraine war can be considered a politically driven event leading to economic distress. Larson and Madura (2001) find in their paper that political events are more likely to cause market overreaction than economic events in the foreign exchange market. They claim that this is because market participants would find it relatively harder to assess the consequences of political events than economic events. These findings can be extrapolated to the commodity futures market too and could provide some insight into what our analysis' results could show - that the degree of overreaction during 2022 would be greater than that in 2020.

Hsu et al. (2013) examine the overreaction and underreaction of commodity futures prices, whereby they split their research into finding evidence for three different hypotheses: the overreaction hypothesis, the underreaction hypothesis and the efficient market hypothesis. The efficient market hypothesis asserts that investors can correctly estimate price behaviour as new information comes to light. The overreaction hypothesis asserts that investors tend to overreact to new information causing prices to significantly change followed by a price reversal, where investors re-estimate futures prices. Lastly, the underreaction hypothesis contends that investors do not respond strongly enough to recently new information and subsequently revise their price estimations in the same direction. These three hypotheses will be tested for further on in this paper.

From the above-reviewed literature, we note that it is important to understand the impact of the Covid-19 pandemic and the Ukraine War on the commodity futures market. This study, therefore, extends knowledge on the effectiveness of the following methodology in this paper's context, where the commodity futures market is tested for overreaction in the first two quarters of 2020 and 2022 - a period which has not been comparatively studied yet in the existing literature.

3 Data

The data used in this study includes twelve different commodity futures contracts, of which seven belong to the energy commodities category and the other five belong to the agricultural commodities category, structured in a panel data set. In order to simplify our analysis, only futures contracts expiring in September of that year are considered, because it is the first contract whose price we can track throughout the six-month period. Using contracts with the shortest time to the maturity date, also known as front contracts, has also been done in previous studies, such as by Zhang et al. (2020).

As we are comparing the first half year's prices in 2022 with the first half year's prices in 2020, we obtain two sets of six months of price data for each contract, obtained from the Bloomberg Terminal Database, which is sourced from different exchanges like the Chicago Mercantile Exchange (CME). This study only considers end-of-day prices for two reasons: firstly, intraday prices fluctuate significantly and therefore reflect all intraday noise which causes short-term volatility, which may distort the underlying price trend. Secondly, closing prices reflect the value of the contract at expiration, which intra-day prices do not.

Table 1 below summarizes all the future contracts considered and the number of trading days where an end-of-day price was observed.

Table 1 - Commodity Futures Contract Observations Summary

Commodity Contract Name	2nd Jan - 30th Jun 2020	3rd Jan - 30th Jun 2022
CLU ; WTI CRUDE FUTURE SEP	125	125
COU ; BRENT CRUDE FUTURE SEP	128	127
QSU ; LOW SULFUR GASOIL SEP	128	128
XBU ; GASOLINE RBOB FUTURE SEP	125	125
HOU ; HEATING OIL NY HARB ULSD FUTURE SEP	125	125
NGU ; NATURAL GAS FUTURE SEP	125	125

FNU ; ICE NATURAL GAS FUTURE SEP	128	128
KCU ; COFFEE C FUTURE SEP	128	128
C U ; CORN FUTURE SEP	125	125
CTU ; ICE COTTON SEP	128	124
S U ; SOYBEAN FUTURE SEP	125	125
W U ; WHEAT FUTURE SEP	125	125

Note: The table reports the number of trading days where a closing price is observed for each considered commodity futures contract in the first 6 months of 2020 and the first 6 months of 2022.

Before diving into the actual results of the statistical analysis, an insightful precursor to the results would be observing the price changes of all commodity contracts over the two time periods, as shown in Figure 1 and 2 below.

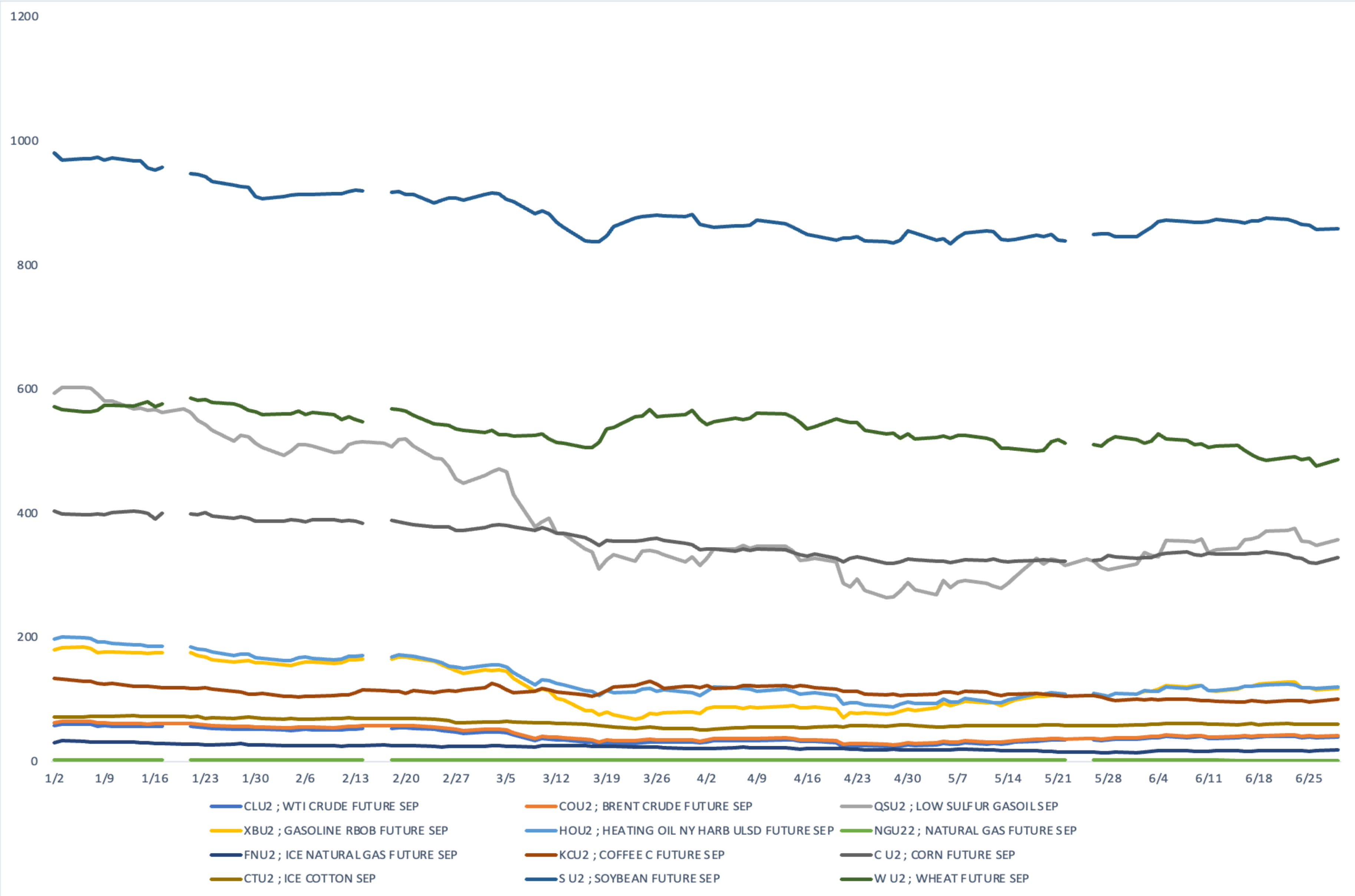

Figure 1 - 2020 Commodity Futures Contract prices January to June

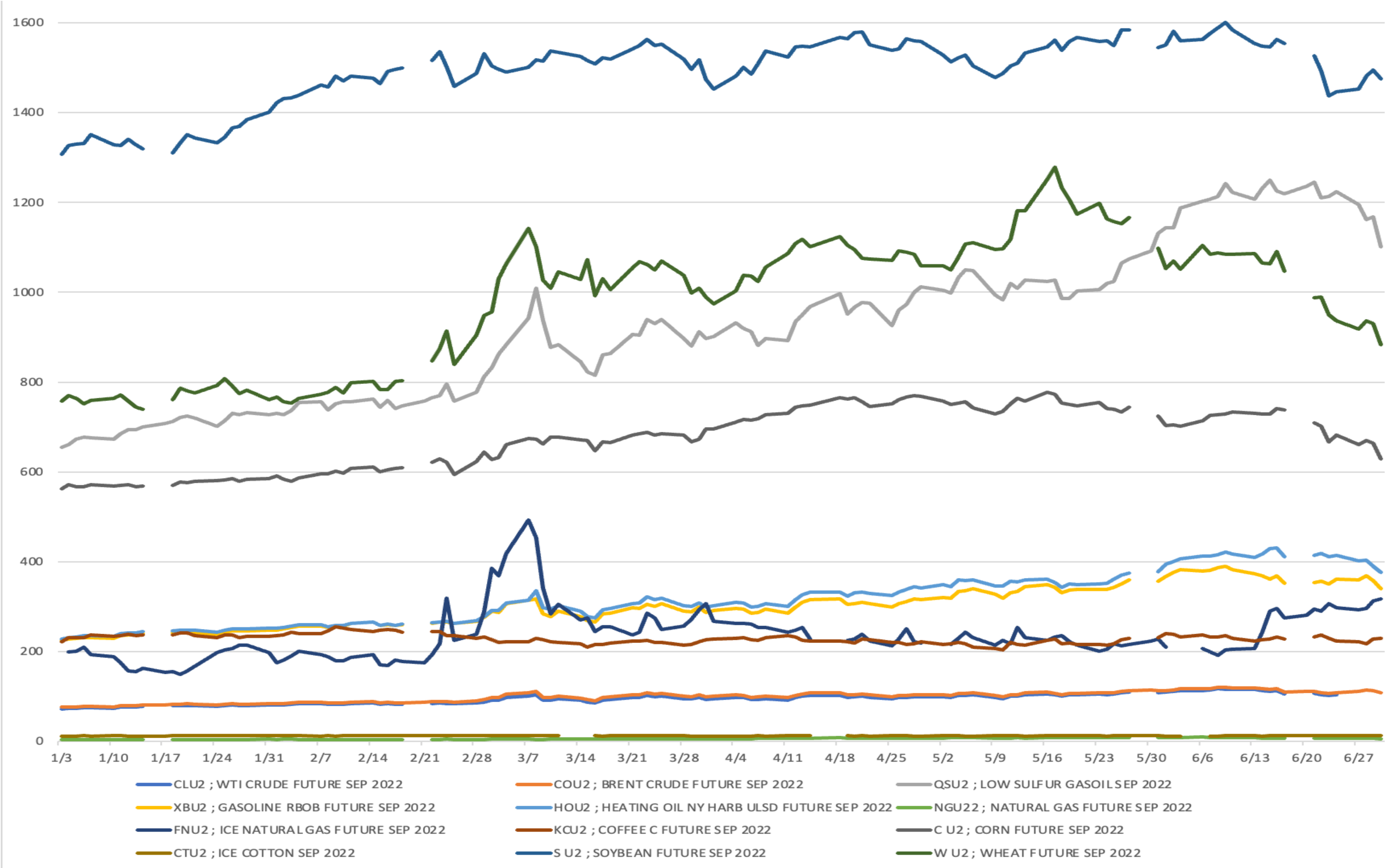

Figure 2 - 2022 Commodity Futures Contract prices January to June

It must be noticed that even though for instance the price time series of the coffee and natural gas futures contract seem fully flat over time - that this is only relative to the price fluctuations of the other contracts, which are of greater magnitude.

Noticeably there are gaps in the figures which is because some contracts are not traded on certain days. Surprisingly, contract prices do not seem to have an average upward or downward trend over the six-month period in 2020, despite the official declaration of the Covid-19 pandemic. Contrastingly, in Figure 2 all contract prices have had an increasing underlying trend. However, the most obvious observation is that around the middle of February most contract prices dip before subsequently substantially rising rapidly. This extreme fluctuation coincides with the official declaration of the Ukraine War by Russia and is premature visual evidence for the overreaction hypothesis. Strikingly, the prices in this period were far more volatile than in 2020. These visual patterns already raise the question of whether the commodity futures market did indeed overreact to the Ukraine War and underreact to the announcement of the Covid-19 pandemic. Or, they may be caused by real shocks to the supply and demand of the commodities and the surrounding tangible infrastructures.

Table 2 and Table 3 below summarize the descriptive statistics of the data set. It is observable that in both time periods, there were no extreme outliers that caused the level of kurtosis to be significantly high - all futures prices can be considered reasonably normally distributed. Another striking observation is that the mean daily returns of all the contracts in the 2020 sample period are negative, whereas in the 2022 sample period they are all positive. The fact that in the 2020 sample period they are negative could be preliminary evidence supporting the overreaction hypothesis, as by definition the overreaction hypothesis stipulates that a large positive return is followed by a return reversal, where negative returns are observed. Contrastingly, the fact that the average daily returns in the 2022 sample period are positive could be preliminary evidence rejecting the overreaction hypothesis in favour for the underreaction or efficient market hypothesis. It is also noticeable that energy commodity futures have higher standard deviations, hence are more volatile, compared to agricultural commodity futures - even though the cause and consequent market forces of the two events were different.

Table 2 - Descriptive statistics of daily futures returns from January to June 2020

Future Contract	Mean	Median	Std. Dev.	Max.	Min.	Skewness	Kurtosis
CLU2 ; WTI CRUDE FUTURE SEP	-0.19%	0.06%	4.94%	16.93%	-21.48%	-1.03	6.07
COU2 ; BRENT CRUDE FUTURE SEP	-0.25%	-0.14%	4.06%	10.72%	-20.30%	-1.28	6.51
QSU2 ; LOW SULFUR GASOIL SEP	-0.34%	-0.25%	3.32%	9.91%	-12.09%	-0.26	2.00
XBU2 ; GASOLINE RBOB FUTURE SEP	-0.23%	0.15%	4.45%	12.10%	-17.95%	-1.15	4.35
HOU2 ; HEATING OIL NY HARB ULSD FUTURE SEP	-0.34%	-0.54%	3.42%	8.09%	-13.99%	-0.38	2.61
NGU22 ; NATURAL GAS FUTURE SEP	-0.16%	-0.22%	2.54%	9.28%	-6.44%	0.73	1.69
FNU2 ; ICE NATURAL GAS FUTURE SEP	-0.35%	-0.92%	3.21%	11.47%	-8.75%	0.66	1.39
KCU2 ; COFFEE C FUTURE SEP	-0.19%	-0.41%	2.26%	5.66%	-5.90%	0.20	0.10
C U2 ; CORN FUTURE SEP	-0.13%	-0.17%	1.05%	3.88%	-2.60%	0.50	1.62
CTU2 ; ICE COTTON SEP	-0.11%	0.03%	1.62%	4.90%	-5.45%	-0.17	1.07
S U2 ; SOYBEAN FUTURE SEP	-0.09%	-0.07%	0.75%	2.18%	-2.53%	-0.09	1.52
W U2 ; WHEAT FUTURE SEP	-0.11%	-0.23%	1.24%	4.13%	-2.60%	0.73	1.25

Note: From the observations in Table 1, daily future contract returns are calculated. This table reports the descriptive statistics of those returns for the 2020 time period, including the mean, median, standard deviation, maximum return, minimum return, skewness and kurtosis of the 12 chosen commodity future contracts.

Table 3 - Descriptive statistics of daily futures returns for January to June 2022

Future Contract	Mean	Median	Std. Dev.	Max.	Min.	Skewness	Kurtosis
CLU2 ; WTI CRUDE FUTURE SEP	0.32%	0.58%	2.78%	8.01%	-11.79%	-0.67	2.76
COU2 ; BRENT CRUDE FUTURE SEP	0.32%	0.53%	2.72%	8.06%	-12.69%	-0.82	3.92
QSU2 ; LOW SULFUR GASOIL SEP	0.44%	0.63%	2.53%	7.09%	-7.06%	-0.41	0.79
XBU2 ; GASOLINE RBOB	0.37%	0.59%	2.47%	6.83%	-10.74%	-0.75	2.88

FUTURE SEP							
HOU2 ; HEATING OIL NY HARB ULSD FUTURE SEP	0.43%	0.56%	2.42%	6.69%	-11.28%	-0.81	4.01
NGU22 ; NATURAL GAS FUTURE SEP	0.40%	0.71%	4.55%	9.55%	-16.96%	-1.09	2.34
FNU2 ; ICE NATURAL GAS FUTURE SEP	0.78%	0.42%	9.32%	47.41%	-29.74%	1.08	6.06
KCU2 ; COFFEE C FUTURE SEP	0.05%	0.07%	2.06%	7.85%	-4.20%	0.55	0.82
C U2 ; CORN FUTURE SEP	0.10%	0.26%	1.68%	4.71%	-5.31%	-0.41	1.53
CTU2 ; ICE COTTON SEP	0.02%	0.05%	0.71%	1.98%	-3.01%	-0.81	3.20
S U2 ; SOYBEAN FUTURE SEP	0.11%	0.25%	1.26%	2.93%	-3.77%	-0.51	-0.02
W U2 ; WHEAT FUTURE SEP	0.17%	0.00%	2.92%	7.85%	-8.21%	0.03	0.68

Note: From the observations in Table 1, daily future contract returns are calculated. This table reports the descriptive statistics of those returns for the 2022 time period, including the mean, median, standard deviation, maximum return, minimum return, skewness and kurtosis of the 12 chosen commodity future contracts.

4 Methodology

To test for over or underreaction in the prices of all the contracts, we will look at the returns of each contract based on the end-of-day closing prices. Returns are calculated by taking the percentage difference of day T's closing price relative to day T-1's closing price. Trading days with positive returns are considered bullish days and trading days with negative returns are considered bearish days. Table 4 below summarises for each contract how many bullish and bearish trading days were observed for each time period.

Table 4 - Summary of bullish or bearish trading days

	2020		2022	
Commodity Contract Name	**Bearish Days**	**Bullish Days**	**Bearish Days**	**Bullish Days**
CLU ; WTI CRUDE FUTURE SEP	60	64	50	74
COU ; BRENT CRUDE FUTURE SEP	67	60	50	77
QSU ; LOW SULFUR GASOIL SEP	71	56	48	79
XBU ; GASOLINE RBOB FUTURE SEP	59	65	44	80
HOU ; HEATING OIL NY HARB ULSD FUTURE SEP	71	53	43	81
NGU ; NATURAL GAS FUTURE SEP	66	58	50	74
FNU ; ICE NATURAL GAS FUTURE SEP	74	53	61	66
KCU ; COFFEE C FUTURE SEP	69	58	63	64
C U ; CORN FUTURE SEP	71	53	54	70
CTU ; ICE COTTON SEP	62	65	58	65
S U ; SOYBEAN FUTURE SEP	70	54	54	70
W U ; WHEAT FUTURE SEP	71	53	63	61

Note: This table reports the number of trading days with positive futures contract returns, known as bullish days, and the number of trading days with negative future contract returns, known as bearish days in both the 2020 and 2022 time periods.

Table 4 shows a clear pattern that both the energy and agricultural commodity contracts have the same price movements. In the first half of 2020, most commodity contracts experienced more bearish days than bullish days. Contrastingly, in the first half of 2022, most contracts experienced significantly more bullish than bearish days.

To test for market over- or underreaction, we first must define a benchmark which helps to categorize whether prices and therefore absolute daily returns, have abnormally increased or normally changed. We thus set up three scenarios, each using a different benchmarking criterium to determine the spread of days with abnormal or normal returns which would mark the start of the overreaction hypothesis time cycle. Breemer and Sweeney (1991) use a greater than 10% absolute return as a benchmark to determine days where a significant price change occurs due to an event, and hence the start of an overreaction or undereaction time period. Bogards et al. (2021) term an overreaction as a large log price change between two turning points. Sturm (2016) considered these two turning turning points as the beginning and end of the overreaction, as different overreactions may take different lengths of time. These turning points are price levels which are proxies at which investor sentiment change. Bogards et al. (2021) go on to use the non-parametric Mann-Whitney-U test to test for the overreaction hypothesis, but more specifically see if the first price change is similarly distributed as the price reversal.

1. The futures contract's absolute daily return is greater than the standard deviation (volatility) of the last 10 trading days' returns (τ).
2. The futures contract's daily return is greater than *twice* the standard deviation (volatility) of the last 10 trading days' returns (τ).
3. The futures contract's daily return is greater than the expected rate of return based on the Capital Asset Pricing Model (CAPM): $E(R_i) = R_f + \boldsymbol{\beta}*(E(R_M) - R_f)$

Regarding criterium 3, to simplify calculating the expected return of each contract, we calculate one fixed expected return to be used as a benchmark for each trading day across each six month period. This is for two reasons, firstly, the risk-free rate is relatively fixed and stable over the six-month periods we are considering. Secondly, the beta of a commodity contract is also relatively fixed and stable across half a year, as six months can be considered the relative short run. Although the majority of the academic literature argues that the beta of commodities is near zero, empirically we have found that it is not - moreover, it varies considerably amongst different contracts during different time periods. Beta's of commodities that can be argued to be the backbone of economies such as Crude, Brent

Crude, Gasoline and Wheat have much higher beta's, albeit less than 1 still. Whereas, the rest of the commodities' beta's are between 0 and 0.2. Contrastingly, the beta's of most commodities in the 2022 time period were negative. The beta in this analysis is calculated for each contract in each time period by dividing the standard deviation of that futures contract's returns over the six-month period by the standard deviation of the returns of SPDR S&P 500 ETF Trust Fund (SPY), also based on its closing price, as it is the general consensus that this ETF well represents the overall financial market's status. This quotient is then multiplied by the correlation coefficient of the contract's returns and the SPY's returns. Likewise, it can also be calculated by $\beta = cov(R_i , R_M) / var(R_M)$. The risk-free rate considered here is the average of the 10 Year US Treasury rate over six months in 2020 and 2022 respectively. Lastly, the expected market return is calculated by taking the daily cumulative market return of the SPDR S&P 500 ETF Trust Fund over each six-month period.

Table 5 below summarizes for each contract how many trading days saw abnormal or normal returns based on the three different criteria scenarios for each time period.

Table 5 - Summary of return type in three different scenarios

Commodity Contract Name	2020						2022					
	Scenario 1		Scenario 2		Scenario 3		Scenario 1		Scenario 2		Scenario 3	
	Normal Rerturns	Abnormal Rerturns	Normal Rerturns	Abnormal Rerturns	Normal Rerturns	Abnormal Rerturns	Normal Rerturns	Abnormal Rerturns	Normal Rerturns	Abnormal Rerturns	Normal Rerturns	Abnormal Rerturns
CLU ; WTI CRUDE FUTURE SEP	79	44	116	7	12	112	76	47	114	9	111	13
COU ; BRENT CRUDE FUTURE SEP	85	41	116	10	18	109	117	9	124	2	119	8
QSU ; LOW SULFUR GASOIL SEP	83	43	117	9	47	80	75	51	121	5	113	14
XBU ; GASOLINE RBOB FUTURE SEP	86	37	114	9	10	114	73	50	115	8	90	34
HOU ; HEATING OIL NY HARB ULSD FUTURE SEP	86	37	114	9	27	97	72	51	114	9	100	24
NGU ; NATURAL GAS FUTURE SEP	79	44	113	10	65	59	75	48	116	7	15	109

FNU ; ICE NATURAL GAS FUTURE SEP	80	46	119	7	76	51	98	28	120	6	125	2
KCU ; COFFEE C FUTURE SEP	85	41	120	6	84	43	81	45	117	9	96	31
C U ; CORN FUTURE SEP	86	37	115	8	86	38	78	45	111	12	124	0
CTU ; ICE COTTON SEP	82	44	117	9	38	89	83	39	113	9	123	0
S U ; SOYBEAN FUTURE SEP	84	39	115	8	104	20	75	48	117	6	122	2
W U ; WHEAT FUTURE SEP	83	40	117	6	103	21	83	40	113	10	124	0

Note: This table reports the number of trading days in each scenario in each year's time period where normal and abnormal returns are observed based on the different scenario's criteria for each futures contract.

We consider days with abnormal returns as event days. If the event day is a bullish day and is considered as day t, and if the cumulative average daily return on days t+1 is positive and statistically significant, while the cumulative average daily return on days t+1 is negative for bearish event days, then there is evidence that those commodity futures contracts underreact to significant price changes. If the cumulative average daily return on days t+1 are statistically significantly negative after a bullish event day, while the cumulative average daily return on days t+1 are statistically significantly positive after bearish event days, there is evidence that those commodity futures contracts overreaction to significant price changes. Naturally, it would make sense to also test for days t+2 and t+3 after the event day to see if there indeed is a price reversal, but that was out of the scope of this paper.

There is no private information available for investors to exploit in the commodity futures market, as is in equity markets. Nonetheless, there remains a certain amount of private information held by people working in that specific industry for a short period of time before it spills over to the public. For example, if because of the Ukraine War water supply was cut off to wheat farms in the Ukrainian countryside, the public will understand that this will reduce wheat supply and thus raise its price on the commodity spot markets. But the exact extent to which supply is reduced, only the local farmers will know first. Larson and Madura

(2003) look at a 3-day post event returns as a proxy to see the rate at which private information diffuses into the market. However, due to the volatile nature of the time periods, we assume that private information diffuses much faster into the public market and only take 1 day.

For each commodity contract in both time periods we look at each scenario separately. First, we consider scenario 1, where event days are considered to exhibit abnormal returns. In scenario 1, abnormal returns are determined if the daily return of that day is greater than the standard deviation of the previous 10 days' daily returns. We look at bullish and bearish event days separately - using this criteria, the event day's return is regressed on the the next day's return using White robust Standard errors, while satisfying all other OLS assumptions are held. The estimated regression beta, if significant, can be interpreted as following: if the estimator is positive after a bullish event day, there is evidence for that specific commodity future contract in that time period on average has underreacted. If the estimator is negative after a bullish event day, there is evidence for that specific commodity futures contracts in that time period on average has overreacted. If the estimator is positive after a bearish event day, there is evidence for that specific commodity futures contract in that time period on average has overreacted. Lastly, if the estimator is negative after a bearish event day, there is evidence for that specific commodity futures contract in that time period to have underreacted. Naturally, the more days after the event day that the returns move in the respective directions, the stronger the evidence for over or underreaction. Besides the sign of the regression coefficients, if significant, the coefficient's magnitude simultanesouly also provide evidence for Larson and Madura's (2001) hypothesis: the larger the initial price change, the greater tendency for a greater price reversal. Besides looking at regression estimates, a simple average next-day-post-event-day returns is also calculated. This methodology is also repeated for scenario 2 and 3.

A common misunderstanding in testing for market overreactions outlined in academic literature is that within a certain time period, there can be multiple event days where prices significantly changed. Testing for overreaction during the Ukraine War for instance does not neccessarliy mean that only the first day of the invasion is considered an event day and subsequently the market only reacts to that. During the time periods considered in this paper, there are many event days - days in which the market exhibits abnormal returns which could be due to new pieces of information coming to the market or other shocks to market forces for instance.

5 Results and Discussion

The results of the regressions overall offer little convincing evidence for over or underreaction of all commodity futures. There are some results however which were significant and provided evidence for over and underreaction, but this would be considered weak evidence as the majority of results were inconclusive. Tables 6 to 9 below summarize the results of the regressions run for scenarios 1 and 3. Regressions for scenario 2 were not conducted because that criterion resulted in too few event days with abnormal returns in both 2020 and 2022 which would lead to misleading results, despite some regression estimates being significant.

Table 6 - Scenario 1 regression results for 2020

Futures Contract	Next Day Return of Bullish Events	P-value	Average Next Day Return	Observa-tions	Next Day Return of Bearish Events	P-value	Average Next Day Return	Observ-ations
CLU2 ; WTI CRUDE FUTURE SEP	-0.52	0.19	-0.60%	20	-0.31	0.17	-0.94%	24
COU2 ; BRENT CRUDE FUTURE SEP	-0.32	0.34	-0.31%	15	-0.21	0.32	-0.80%	26
QSU2 ; LOW SULFUR GASOIL SEP	-0.45*	0.07	-0.70%	16	-0.09	0.63	-1.27%	27
XBU2 ; GASOLINE RBOB FUTURE SEP	-0.43	0.18	0.80%	14	-0.31	0.10	-0.78%	23
HOU2 ; HEATING OIL NY HARB ULSD FUTURE SEP	-0.29	0.30	-0.70%	16	-0.18	0.28	-1.04%	21
NGU22 ; NATURAL GAS FUTURE SEP	-0.03	0.86	0.66%	19	0.04	0.64	0.13%	25
FNU2 ; ICE NATURAL GAS FUTURE SEP	0.26	0.25	0.70%	19	-0.12*	0.07	0.21%	27
KCU2 ; COFFEE C FUTURE SEP	0.09	0.50	-0.86%	16	-0.08	0.50	0.17%	25
C U2 ; CORN FUTURE SEP	0.26**	0.02	-0.65%	14	-0.03	0.74	-0.15%	22
CTU2 ; ICE COTTON	0.10	0.41	0.05%	19	-0.11	0.27	0.21%	24

SEP								
S U2 ; SOYBEAN FUTURE SEP	0.12	0.56	-0.39%	15	-0.12	0.41	0.21%	23
W U2 ; WHEAT FUTURE SEP	0.07	0.69	-0.27%	14	-0.03	0.81	-0.15%	26

*Note: ** p < 0.05 ; * p < 0.10 ;* This table reports the regression results when the next day post-event-day return is regressed on the event day's return itself in scenario 1 for each commodity futures contract. In the first column, the regression's beta estimate is reported for bullish event days. In the second column, the regression coefficient's p-value is reported. In the third column, the sample's average next day's return is reported. In the fourth column, the number of observations is reported. In the fifth column, the regression's beta estimate is reported for bearish event days. In the sixth column, that regression coefficient's p-value is reported. In the seventh column, the sample's average next day's return is reported. In the eighth column, the number of observations is reported.

Table 7 - Scenario 1 regression results for 2022

Futures Contract	Next Day Return of Bullish Events	P-value	Average Next Day Return	Observa -tions	Next Day Return of Bearish Events	P-value	Average Next Day Return	Observa -tions
CLU2 ; WTI CRUDE FUTURE SEP	0.16	0.30	0.69%	29	0.21	0.25	1.03%	17
COU2 ; BRENT CRUDE FUTURE SEP	0.26	0.24	0.44%	7	0.07	-	1.42%	2
QSU2 ; LOW SULFUR GASOIL SEP	-0.04	0.81	0.44%	33	0.21	0.30	0.28%	17
XBU2 ; GASOLINE RBOB FUTURE SEP	0.13	0.21	0.51%	32	0.22	0.32	0.37%	17
HOU2 ; HEATING OIL NY HARB ULSD FUTURE SEP	-0.12	0.40	0.54%	35	0.83	0.18	0.63%	15
NGU22 ; NATURAL GAS FUTURE SEP	-0.14	0.20	0.30%	29	-0.06	0.69	0.42%	18
FNU2 ; ICE NATURAL GAS FUTURE SEP	-0.26	0.20	5.88%	16	-0.11	0.82	-2.31%	12
KCU2 ; COFFEE C FUTURE SEP	-0.07	0.76	-0.12%	21	-0.01	0.86	-0.01%	24
C U2 ; CORN FUTURE SEP	0.22	0.32	0.09%	26	-0.25**	0.02	0.39%	18
CTU2 ; ICE COTTON	-0.05	0.57	-0.07%	21	0.32	0.14	0.32%	17

SEP								
S U2 ; SOYBEAN FUTURE SEP	-0.03	0.68	0.07%	28	0.02	0.86	-0.40%	19
W U2 ; WHEAT FUTURE SEP	0.03	0.77	0.24%	22	-0.24	0.11	-0.58%	17

*Note: ** p < 0.05 ; * p < 0.10 ;* This table reports the regression results when the next day post-event-day return is regressed on the event day's return itself in scenario 1 for each commodity futures contract. In the first column, the regression's beta estimate is reported for bullish event days. In the second column, the regression coefficient's p-value is reported. In the third column, the sample's average next day's return is reported. In the fourth column, the number of observations is reported. In the fifth column, the regression's beta estimate is reported for bearish event days. In the sixth column, that regression coefficient's p-value is reported. In the seventh column, the sample's average next day's return is reported. In the eighth column, the number of observations is reported.

Table 8 - Scenario 2 regression results for 2020

Futures contract	Next Day Return of Bullish Events	P-value	Average Next Day Return	Observa-tions	Next Day Return of Bearish Events	P-value	Average Next Day Return	Observa-tions
CLU2 ; WTI CRUDE FUTURE SEP	-0.16	0.30	0.16%	64	-0.01	0.79	-0.81%	47
COU2 ; BRENT CRUDE FUTURE SEP	-0.10	0.44	0.39%	60	0.02	0.68	-1.16%	48
QSU2 ; LOW SULFUR GASOIL SEP	-0.09	0.39	0.02%	55	-0.01	0.61	-0.93%	24
XBU2 ; GASOLINE RBOB FUTURE SEP	0.06	0.51	0.13%	64	-0.01	0.78	-0.79%	49
HOU2 ; HEATING OIL NY HARB ULSD FUTURE SEP	-0.11	0.35	-0.08%	52	0.01	0.74	-0.43%	44
NGU22 ; NATURAL GAS FUTURE SEP	0.12	0.24	-0.20%	57	-	-	-	-
FNU2 ; ICE NATURAL GAS FUTURE SEP	0.12	0.39	-0.09%	58	-	-	-	-
KCU2 ; COFFEE C FUTURE SEP	0.04	0.65	0.27%	42	-	-	-	-
C U2 ; CORN FUTURE SEP	0.19	0.22	0.00%	37	-	-	-	-
CTU2 ; ICE COTTON	0.08	0.25	-0.09%	64	0.03	0.41	0.12%	24

SEP								
S U2 ; SOYBEAN FUTURE SEP	0.12	0.35	0.26%	19	-	-	-	-
W U2 ; WHEAT FUTURE SEP	0.09	0.41	-0.07%	20	-	-	-	-

*Note: ** p < 0.05 ; * p < 0.10 ;* This table reports the regression results when the next day post-event-day return is regressed on the event day's return itself in scenario 1 for each commodity futures contract. In the first column, the regression's beta estimate is reported for bullish event days. In the second column, the regression coefficient's p-value is reported. In the third column, the sample's average next day's return is reported. In the fourth column, the number of observations is reported. In the fifth column, the regression's beta estimate is reported for bearish event days. In the sixth column, that regression coefficient's p-value is reported. In the seventh column, the sample's average next day's return is reported. In the eighth column, the number of observations is reported.

Table 9 - Scenario 2 regression results for 2022

Futures contract	Next Day Return of Bullish Events	P-value	Average Next Day Return	Observ-ations	Next Day Return of Bearish Events	P-value	Average Next Day Return	Observat-ions
CLU2 ; WTI CRUDE FUTURE SEP	-	-	-	-	0.29*	0.06	-0.17%	13
COU2 ; BRENT CRUDE FUTURE SEP	0.58**	0.04	0.66%	8	-	-	-	-
QSU2 ; LOW SULFUR GASOIL SEP	-0.05	0.79	0.52%		-	-	-	-
XBU2 ; GASOLINE RBOB FUTURE SEP	0.09	0.23	-0.03%	34	-	-	-	-
HOU2 ; HEATING OIL NY HARB ULSD FUTURE SEP	-0.12	0.23	0.26%	24	-	-	-	-
NGU22 ; NATURAL GAS FUTURE SEP	-0.09	0.22	0.83%	74	0.02	0.60	0	35
FNU2 ; ICE NATURAL GAS FUTURE SEP	-	-	-	-	-	-	-	-
KCU2 ; COFFEE C FUTURE SEP	-0.02	0.91	-0.14%	31	-	-	-	-
C U2 ; CORN FUTURE SEP	-	-	-	-	-	-	-	-
CTU2 ; ICE COTTON	-	-	-	-	-	-	-	-

SEP								
S U2 ; SOYBEAN FUTURE SEP	-	-	-	-	-	-	-	-
W U2 ; WHEAT FUTURE SEP	-	-	-	-	-	-	-	-

*Note: ** p < 0.05 ; * p < 0.10 ;* This table reports the regression results when the next day post-event-day return is regressed on the event day's return itself in scenario 1 for each commodity futures contract. In the first column, the regression's beta estimate is reported for bullish event days. In the second column, the regression coefficient's p-value is reported. In the third column, the sample's average next day's return is reported. In the fourth column, the number of observations is reported. In the fifth column, the regression's beta estimate is reported for bearish event days. In the sixth column, that regression coefficient's p-value is reported. In the seventh column, the sample's average next day's return is reported. In the eighth column, the number of observations is reported.

Table 6 shows relatively weak evidence for the overreaction of the QSU2 contract on bullish days, as it is only significant at the 10% significance level. This is because the regression estimate is negative, which is interpreted as the next day's return after a bullish event day being negative, implying the that contract's price has overreacted according to the overreaction hypothesis. There is also weak evidence for underreaction of the FNU2 contract on bearish days, as it is only significant at the 10% significance level. There is however strong evidence for underreaction of the C U2 contract on bullish days, as it is significant at the 5% significance level. Table 7 only shows strong evidence at the 5% significance level for underreaction for the C U2 contract in 2022. Overall, evaluating the results for 2020 and 2022 if we consider event days as per scenario 1's criteria, the results are inconclusive. This is because the majority of the regression results are insignificant. Even though some results are significant, these can be interpreted as sporadic contextless significant results and hence the actual outliers. Therefore, we cannot reject the general hypothesis that any of the commodity futures contracts individually, or as a whole representing the energy commodity futures or agricultural commodity futures market have over or underreacted. This does not however directly imply that the efficient market hypothesis is accepted. Lastly, due to the inconclusive nature of the results, we cannot comment on the relative comparison of the 2020 versus 2022 results and comment on whether the Ukraine War caused more market volatility compared to the Covid-19 pandemic.

Evaluating the results from considering event days as per scenario 3’s criteria yield no significant results to support the overreaction or underreaction hypotheses in 2020, as shown in Table 8. Table 9, presenting the results for the 2022 time period, show evidence for the overreaction of the CLU2 contract at the 10% significance level on bearish event days. There is also strong evidence at the 5% significance level for the underreaction of the COU2 contract after bullish event days.

The simplification of this paper’s analysis and methodology might be a contributing factor to the inconclusive nature of the results. For example, the length of the two time periods may be too short to yield enough observations under each event day criterium. Looking back, testing for over or underreaction is not based on one event date. An overreaction, for instance, starts with defining an event day, which can be done according to many criteria, and then testing the sign and magnitude of the following days’ returns.

However, the criteria used to define event days may not be the most accurate either. Criteria 1, which defines an event day as if its return is greater than the standard deviation of the past 10 trading days’ returns. This only captures the recent past and based on that, defines days with abnormal returns. The longer the backward time horizon is, the fewer event days and hence observations we would have. Having a shorter backward time horizon would lead to too many event days, which would be misleading for interpretation. This was the issue with criteria 2 - it led to too few observations because the threshold to define events days was set too high. In general, some criteria for certain contracts lead to too few observations leading to insignificant regression results, if not, no regression estimate at all. Lastly, criteria 3, where an event day was considered if that day's return was greater than the return computed using the CAPM. There is little academic literature on using CAPM to estimate commodity futures returns, however when we look deeper into the assumption of the CAPM, then certain assumptions are different from when using the CAPM for equities. For example, to calculate the market return, the S&P 500 index fund is used as a fund which reasonable captures and represents market behaviour. However, the S&P 500 index fund includes equities and past academic literature has proven that the commodity market and the commodity futures market do not necessarily always behave in sync with the stock market. A more relevant and reasonable proxy to calculate market return from might have been a commodity futures index, such as the Bloomberg Commodity Index (BCOM), which tracks the price of a basket of commodity futures. Another assumption while using the CAPM which may be problematic is that the risk-free rate was fixed over each time period as we took the return of a long-run US treasury security, whereas other academic literature uses short-run US treasury returns - the issue being that it is more volatile in nature. The last variable that comes with a significant assumption in the CAPM is the commodity futures contract's beta. This paper's methodology empirically calculates the beta of each contract separately, however, for example, Westgaard & Steen (2017) mention in their paper that commodities and their futures contracts have a generally historical long-term low correlation with stocks, and by extension the stock market, and hence low beta's. They mention that in the short-term, however, commodity beta's can be more volatile due to demand and supply shocks for the underlying commodity. The calculated short-term empirical beta's were not near zero, a result which is reasonable and sound.

To give our results more context, we can compare them to the results of Borgards et al (2021), who test for overreaction for 20 commodity futures contracts during the Covid-19 pandemic using intra-day prices, however. They find conclusive significant evidence for price overreaction for all their contracts, and that the magnitude and frequency of the overreactions are greater during the pandemic compared to the pre-pandemic period. We also find that the frequency of abnormal returns (only according to criterium 1) is greater in the 2020 time period compared to the 2022 time period. Borgards et al (2021) also find that agricultural and metals commodity contracts overreact to a lesser extent compared to energy contracts - a result anticipated and supported by past literature.

Gao et al. (2019) create a dynamic futures pricing model to analyze different investors' sentiments. One of their results which stands out is that they find that in periods of market crashes, which the Covid-19 pandemic and the Ukraine War could be considered to an extent, the number of short-term investors decreases and the market becomes more efficient as regulators introduce policies to reduce short-term investments. This finding is interesting with respect to the overreaction hypothesis during market crashes because it is expected that due to the higher volatility in the market in the short run, more short-term investors would be attracted to make abnormal profits through short-term arbitrage opportunities and market inefficiencies. However, on the other hand, the results could be considered consistent with this studies results - that the market actually becomes more efficient and thus shows fewer signs of extreme price behaviours.

6 Conclusion

This paper studies 12 commodity future contracts' (from the agricultural and energy commodities sectors) price behaviour in the first half of 2020 and 2022, where the impact of the Covid-19 pandemic and the Ukraine War respectively are tested for the overreaction, underreaction or efficient market hypothesis. End-of-day prices are used to identify days with abnormal returns, marked as event days, after which the returns of the following day are tested for return reversal. Our main findings are inconclusive, as the regression results show insignificant estimates, and thus we cannot reject the efficient market hypothesis in favour of the over or underreaction hypothesis - despite some commodity futures contracts showing significant results for over or under-reaction. Therefore, we cannot conclude that during the Ukraine War, commodity futures overreaction any more or less significantly than commodity futures during the Covid-19 period. In fact, we can deduce that in general across the two commodity futures classes, the markets behaved in similar ways and prices reflected all available information and thus showed signs of an efficient market. This can be attributed to a too small sample size or a non-linear relationship between the event day's returns and the next day's returns. Furthermore, another possible reason for the lack of significant results would be because of the oversimplification and lack of robustness of the methodology. Firstly, in hindsight, a longer time horizon could have been used. Secondly, pre-reviewed existing literature looked at the two or three days proceeding the event day and tested them for signs of price reversal and thus overreaction. However, this methodological framework only considered the following day's returns after the event day. Thirdly, the criteria to determine event days came with strong assumptions. Our results naturally are consistent with some existing literature which say that during times of financial crises, markets indeed become more efficient. But, simultaneously, our results also are inconsistent with other similar literature, which indicate that during the pandemic period, commodities empirically showed more negative overreactions than positive ones.

The findings of this paper have somewhat useful empirical implications for investors, policymakers and portfolio managers when they would like to benefit from positive abnormal returns from commodity futures trading, especially during tumultuous financial periods caused by world events.

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