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Abstract

Results from previous studies testing for under-reaction and overreaction in the commodity futures market are mixed and inconclusive. Using a data of more than 20 categories of future contacts ranging from agricultural, metal and energy, we have found significant evidence of under-reaction in food and agricultural commodities but not in the energy and metal sector. It is also found that those relatively inactive commodity future contracts tend to have a stronger tendency to under-react than commodity future contracts are very actively traded. The result also agrees with the behavioral hypothesis that under-reaction is caused by gradual incorporation of information among investors.

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Introduction

1. Background

After the proposal of efficient market hypothesis by Fama (1970), it is had been assumed that global financial markets, whether it is equity, foreign exchange, or commodity futures, are efficient. Prices in these markets, are supposed to reflect all of the current information and there is not supposed to be any method that could beat the market consistently.

Yet, later studies from other scholars have displayed proofs contrary to the EMH theory. As Shiller (1981) pointed out "We have seen the measure of stock price volatility over the past century appear to be far too high – five to thirteen times too high – to be attributed to new information about future real dividends." "The failure of efficient market model is thus so dramatic that it would seem impossible to attribute such things as data errors, price index problems, or changes in tax law." Such doubts in the efficient market hypothesis have pointed to the discovery of overreaction and under-reaction.

In the equity market, De Bondt and Thaler (1985) found that "loser" portfolios tend to earn about 25% more than "winner" portfolios 36 months after portfolio formation, which points towards the overreaction hypothesis. Later studies such as De Bondt and

Thaler (1987), John S and Howe (1986), Atkins and Dyl (1990), C.A., Costa (1994), David N. Dreman and Michael A. Berry (1995) have provided further proof for the existence of overreaction in the stock market.

In the Foreign Exchange Market, Goodheart (1988) has found that that in the short run, exchange rates tend to under-react to news, especially news of interest rate change. Larson and Madura (2001) have found that in the short run, currencies in emerging markets tend to overreact while currencies in industrial markets tend to under-react; they have also found that exchange rates have a tendency to under-react to defined economic and political news while overreact in days without the presence of such news.

Overreaction and under-reaction have nowadays been proved extensively. The psychological theory that provides grounding for these two phenomena includes representative heuristics, conservatism, self-attribution, disposition effect, gradual incorporation of private information and overconfidence in private information.

Academic researches have discovered the phenomenon of stock market under-reaction to a series of news events such as earning surprises, open market share repurchases, negative modification to analyst' forecasts and stock splits. In 1990, Shleifer and Summer proposed the investor sentiment/limited arbitrage hypothesis to explain under-reaction, they proposed that some one of the strategies arbitragers use is 'trend chasing': as noisy traders, they buy when the price goes up, in expectation of further price appreciation. They mentioned that sometime rational arbitragers also jump on the bandwagon created by noisy traders, buy when the price goes up and sell when price goes down. Another strategy of this sort is 'stop loss' orders, in which the investor sells after a prescribed level of loss regardless of future prospects. Behavior of investors in this model causes under-reaction, since investor's behavior intensifies and prolongs the rally or decline in the market.

Daniel et al (1998) proposed that under-reaction is induced by biased self-attribution of market participants. The self-attribution theory states that people tend to credit themselves for past success, and blame external factors for failure (Fischhoff (1982), Langer and Roth (1975), Miller and Ross (1975), Taylor and Brown (1988)); this cause the confidence of market participants who acted upon private information to grow when public information agrees with his information, but not to fall when public information contradicts with his information, which causes drift after public news announcements.

Barberis et al (1998) suggested that under-reaction is caused by conservatism of investors: investors might disregard the full information content of a public news announcement and still sling partially to their prior estimate of earnings. Conservatism is defined by (Edward (1968)) as the slow updating of models in face of a new evidence. Hong and Stein (1999) attributed under-reaction to the gradual incorporation of private information to market participants. Frazzini (2006), however, proposed that the disposition effect, which causes investors to ride losses and realized gains, causes under-reaction to news. In Frazzini's model, when good news comes out, investors have the tendency to sell the security in order to realize gains, which causes the securities to be traded below fundamental level; while when bad news com out, investors who are caught in a loss are reluctant to sell the securities, which causes a premium to the security price.

Overreaction (De Bondt and Thaler 1985) was first found prior to under-reaction, and according to Kahneman and Tvesky, it was caused by representative heuristics: "In revising their beliefs, individuals tend to overweight recent information and underweight prior data; people seem to make predictions according to a simple matching rule: "The predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impression"". Such psychological bias causes investors to buy on previous gains in the market and sell on previous losses in the market, which cause the market to "overreact". This could also be a cause for market under-reaction in the short run.

Daniel et al (1998) suggested that overreaction is caused by investor's overconfidence in private information; overconfidence is a psychological phenomenon that has been found in miscellaneous studies from various fields, such as Oskamp (1965), Christensen-Szalanski and Bushyhead (1981), Kidd (1970), Wagenaar and Keren

(1986) etc. According to Einhorn (1980), overconfidence is more severe for diffuse tasks, which require judgment than for mechanical tasks, and more severe for tasks with delayed result feedback than for tasks that have immediate and conclusive outcome. According to Daniel et al (1998), making investment decision is a diffused task while the correctness of the decision is both lagged and unclear; thus people tend to be more overconfident in investment than in other fields.

While overreaction and under-reaction have been proved extensively in the equity market, there have been few papers studying overreaction and under-reaction in the commodity market. Whether these phenomena exist in the commodity market, and whether they are caused by the same psychological drivers as they did in the equity market remains unclear.

2. Literature review

a) Results

In this section, we seek to review important previous studies in the field of commodity futures overreaction and under-reaction, their procedure and the results that they have obtained. Previous studies testing for overreaction and under-reaction in the commodity futures market are scarce, among them, the methodologies employed are miscellaneous and results obtained are also mixed and inconclusive.

Stevenson and Bear (1970) found subtle results of overreaction in the commodity futures market. Stenvenson and Bear conducted a test of the random walk hypothesis on corn and soybean futures using price data of July futures from 1957 to 1968 and find a generally negative serial correlation coefficient of the close to close daily price difference with lag of 1 day. For lags of 5 days, the serial correlation coefficient is found to be mainly positive. Their study casts doubts on the application of the efficient market hypothesis in the commodity market.

Ma, Dare and Donaldson (1990) conducted a study on six agricultural commodities future contracts and two metal future contracts testing for rationality in this market. In their study, Ma, Dare and Donaldson used daily price changes to test for overreaction and under-reaction. A significant change in price is defined as a proxy for the occurrence of significant events, and similar to Stevenson and Bear, they used the difference between daily closing prices to account for daily price change. It is observed that after a significant abnormal price change has occurred, agricultural futures such as Coffee, Corn, Soybean meal, Wheat and Pork Bellies show significant price reversal on the next trading day, whereas the results for metal contacts, i.e. gold and silver appear to be mixed and insignificant.

Gay, Kale, Kolb and Noe (1994) studied the opening price of commodity futures subsequent to wall street journal headlines that describe the abnormal trading activities of a certain commodity in the previous day and found signs of under-reaction in the commodity future market. They selected Wall street journal headlines that only describe the trading activity of the previous day thus this news should contain only historical information and does not contribution to the current information set of this commodity, if market is efficient, there is supposed to be no significant cumulative return on the next trading day. Examples of news headlines that Gay et al use are as follows:

"Price of Cocoa Rises after Producers, Consumers Agree on Plan for Surplus" (WSJ, January 19 1988, p 56)

"Copper Prices Plunge 7.1 Cents to Close Below $1 a pound for the first time since 1988" (WSJ, January 28, 1988, p. 36)

All information contained in these headlines are already delivered to the investor on the previous trading day hence should have no impact for the opening price on the next day. Yet, by measuring the difference between the opening price of the second day and closing price of the previous day of the specific commodity described in the news headline, Gay, Kale, Kolb and Noe found that market tend to open higher when the report on the previous day express bullish sentiment and tend to open lower when the report on the previous day express bearish sentiment. The opening-price drift is found to be larger for bearish reports than for bullish reports.

Chen (1998) conducted yet another study testing for overreaction in the futures market. The contracts Chen used in his analysis include corn, soybeans, soybean meal, soybean oil, wheat, feeder cattle, live cattle, copper, gold, silver and cotton. Chen used three methods to measure overreaction: the average of the future price on the day after the event day, the opening price of the post-event day and the closing price of the post event day. The results found in three measures are different from each other, yet the level of significance is unable to provide sufficient basis for the overreaction and under-reaction hypothesis in three measures.

b) Previous Methodologies

In this section, we will compare and discuss the methodologies employed by former academic researchers to test for overreaction and under-reaction in commodity futures.

In order to define overreaction and under-reaction, first we need to define what level of reaction is considered normal, thus the amount of abnormal reaction could be measured. In the equity market, we usually measure the normal level of reaction using the CAPM model, yet in the commodity market; it is hard to price commodity futures. According to Fischer BLACK (1976):

$$E(\Delta\tilde{P}) = \beta^{*}[E(\tilde{R}_m) - R].$$

$$E(\Delta\tilde{P}) = 0, \quad \text{when} \quad \operatorname{cov}(\Delta\tilde{P}, \tilde{R}_m) = 0.$$

Where △P refers to the expected return of a future contract. BLACK also mentioned that beta could be approximately zero for many commodities. Thus, we might want to consider using the actual return to model for the abnormal return in the measurement of overreaction and under-reaction.

Stevenson and Bear (1970) measure the serial correlation of Corn and Soybean Future on the Chicago Board of Trade using a lag of 1 day, 2 days and 5 days respectively. Stevenson and Bear used the difference between the closing price of the previous day and the closing price of that day to measure the return for a day.

Ma, Dare and Donaldson (1990), used trading days that have statistically significant returns as proxies for significant events. The return of each future contract on the next trading day is thus measured to observe overreaction and under-reaction. To measure the abnormal component of price change, Ma used the Box and Jenkin's method of autoregressive integrated moving average (ARIMA) model to evaluate the expected component of commodity prices. The ARIMA model for each future contract in Ma et al's study is displayed in table 1.

The study done by Gay, Kale, Kolb and Noe (1994) used WSJ headlines that only delivers information regarding the price movement of a specific commodity future on the previous day as significant events. The opening price of that specific commodity future contract on the day of WSJ news is then compared with the closing price of the previous trading day as a proxy for abnormal return; as Gay, Kale, Kolb and Noe mentioned: "because future contracts require no net investment and should contain little, if any, risk premia over the short time intervals for which these tests are conducted, the expected change in future prices should be virtually nil."

Futures Contract	Sample Period	Number of Obs.	ARIMA Model	Chi-Square Lags: 6	12	18	Min. Days
Commodities Futures							
Com	Jan. 1977–Dec. 1987	2528	$R_t = -7.39E\text{-}05 + .0092\, R_{t-1} + \varepsilon_t$	7.84	15.97	25.75	3
Coffee	Jan. 1977–Dec. 1987	2514	$R_t = -.00022 - .0387\, R_{t-1} + \varepsilon_t$	15.86	21.03	31.87	72
Pork Bellies	Jan. 1977–Dec. 1987	2531	$R_t = -.0454 - .00003\, t = .1102\, R_{t-1} + .0585\, R_{t-10} + \varepsilon_t$	8.57	16.16	18.27	3
Soybean	Jan. 1977–Dec. 1987	2528	$R_t = -3.322E\text{-}06 - .0253\, R_{t-1} + \varepsilon_t$	8.39	18.83	25.01	6
Soymeal	Jan. 1977–Dec. 1987	2527	$R_t = -.00011 - .0123\, R_{t-1} + \varepsilon_t$	5.33	11.77	17.00	4
Wheat	Jan. 1977–Dec. 1987	2528	$R_t = .0001 - .0180\, R_{t-1} + \varepsilon_t$	5.54	12.65	24.42	26
Metal Futures							
Gold	Jan. 1975–July 1987	2899	$R_t + .1138 - .0001\, t = -.0719\, R_{t-1} - .0908\, R_{t-4}$ $+ .039\, R_{t-10} + .0592\, R_{t-12}$ $+ .0575\, R_{t-13} + \varepsilon_t$	4.05	6.61	24.09	9
Silver	Jan. 1975–July 1988	3149	$R_t + .0804 - .00004\, t = .0583\, R_{t-1} - .0569\, R_{t-4}$ $- .0602\, R_{t-5} + .0698\, R_{t-8}$ $+ .0498\, R_{t-12} + .0411\, R_{t-13} + \varepsilon_t$	1.35	4.40	18.13	13

Table 1

Study by Chen (1998) also used significant price changes as event days, and measured the price change on the next trading day to test for overreaction and under-reaction. Chen used the difference between the average price of day 1 and the closing price of the event day (day0) to measure the return for day 1, and used the difference between the closing price of event day and day -1 to define days with a significant return. The average price of day 1 is calculated using the average of the opening, closing, high and low for that day. Chen also used the actual daily movement of the future price as a proxy for abnormal movement in prices.

Data and Methodology

1. Data

The data employed in this study includes 26 categories of commodity future contracts, among them fifteen are food and agricultural commodities, three are metal contracts and eight belong to energy commodities. Table 2 is a summary of all the future contracts studied in the data and the number of observations for each future contract.

Name of Future Contract	NO. of Observation
Food and Agricultural	
CBOT Soybean Oil Crude BO	12883
LIFFE Coffee, Robusta (10 Tonne) LQ	4926
CME Cattle Feeder(Average) FC	9768
CBOT Wheat No. 2 Soft Red W-	12886
WCE Canola No. 1 WC	8961
CBOT Soybean Meal 48% Protein SM	12884
CME Hogs, Lean Average IowaS Minn LH	11213
ICE Coffee C Columbia KC	9511
KCBT Wheat No. 2 Hard Winter KW	10245
CME Cattle Live Choice Average LC	11528
CBOT Soybeans No. 1 Yellow S-	12884
TYCOM Rubber #3 YR	4336
ICE Cotton 1-1 16 CT	12809
LIFFE Sugar #5, White LW	5150
LIFFE Cocoa #7 LO	6123
Metals	
Nymex Copper High Grade HG	12816
Nymex Gold GC	8955
NYMEX Silver SI	11823

Energy	
NYMEX Crude Oil WTI CL	6875
NyMEX Heating Oil HO	7973
NYMEX Crude Oil Brent NB	5359
TYCOM Kerosene IO	2734
ICE Gas-Oil-Petroleum LF	6145
NYMEX Gasoline, Blendstock RB	2668
Tocom Gasoline IN	2734
NYMEX Natural Gas, Henry Hub NG	5114

Table 2 Summary of Commodity Future Contracts

2. *Methodology*

In this paper, we seek to test for overreaction and under-reaction by measuring the return of a future contract on the next day following a significant increase or decrease in price has occurred in the previous day. According to Gay, Kale, Kolb and Noe (1994), "future contracts require no net investment and should contain little, if any, risk premia over the short time intervals for which these tests are conducted, the expected change in future prices should be virtually nil." Thus we assume for the one to two days of period in which our test is conducted, the abnormal return of a commodity future contract is equal to its actual return. Also, return characteristics measured using the actual return has better trading implications, since it is extremely difficult to construct an accurate model for pricing of commodity futures.

Similar to Stevenson and Bear (1970), we measure the daily return of a commodity contract using the price difference between the closing price of the contract on that day and the closing price of the previous day. We didn't use the method of Chen (1998), e.g. the difference between the next day's average price and the closing price of the event day because future prices contain lots noises at the high and low point and a daily average computed based on the daily high low is interfered by such noise; the use of average price to measure overreaction and under-reaction also has little real world trading implications. We have used the difference between closing prices as we believe the daily settlement price of a certain contract, is the most accurate reflection of investors expectation of the value of that specific commodity.

In order to simplify our analysis, we are only using price data from the newest commodity contract available. For example, CBOT Soybean meal 48% Protein 1975 January contract expires at 14 Jan 1975, but the 1975 February contract starts trading at 17 Dec 1974, so starting from 17 Dec 1974, we will use the price data of 1975 Feb contract in our analysis. Since there is a significant spread between contracts of different months, the return data for the first trading day of each new contract is highly diluted. In order to control for this dilution of data, we consider the return for the first trading day of each monthly contract as 0.

We define event days as days in which the price of a commodity contract has increased or decreased significantly. For a certain trading day, we calculate the standard deviation of the return of the past 200 trading days, which we call τ. Three types of event days are defined:

1. Days in which the absolute value of the daily return is greater than τ.
2. Days that satisfy situation (a), while at the same time, the cumulative return of the past 5 trading days is also greater than the 5-day τ of the past 200 trading days.
3. Days in which the absolute value of the daily return is greater than two times of τ.

For each future contract, each event day is categorized as days that represent bullish events and days that represent bearish events. The cumulative average return of bearish events and bullish events are calculated for scenario 1 to scenario 3 respectively. The number of bullish and bearish event observations for each scenario is displayed in table 3 below.

	Scenario 1		Scenario 2		Scenario 3	
	bullish obs	bearish obs	bullish obs	bearish obs	bullish obs	bearish obs
CBOT Soybean Oil Crude BO	1683	1548	425	266	436	289
LIFFE Coffee, Robusta (10 Tonne) LQ	518	478	131	75	154	136
CME Cattle Feeder(Average) FC	1168	1037	250	229	162	171
CBOT Wheat No. 2 Soft Red W-	1522	1525	351	234	314	265
WCE Canola No. 1 WC	1065	1018	257	175	271	226
CBOT Soybean Meal 48% Protein SM	1547	1308	395	208	419	290
CME Hogs, Lean Average LH	903	792	156	111	46	52
ICE Coffee C Columbia KC	1043	1023	242	156	273	249
KCBT Wheat No. 2 Hard Winter KW	1273	1138	327	161	304	235
CME Cattle Live Choice Average LC	1291	1168	258	230	124	138
CBOT Soybeans No. 1 Yellow S-	1592	1438	435	238	429	383
TYCOM Rubber #3 YR	504	470	121	83	96	128

ICE Cotton 1-1 16 CT	1342	1343	242	258	269	271
LIFFE Sugar #5, White LW	567	479	128	99	128	108
LIFFE Cocoa #7 LO	710	694	151	96	168	148
Nymex Copper High Grade HG	1693	1480	421	228	383	328
Nymex Gold GC	1120	1001	231	181	266	259
NYMEX Silver SI	1429	1333	325	202	372	364
NYMEX Crude Oil WTI CL	895	849	156	147	180	171
NyMEX Heating Oil HO	945	866	186	123	203	186
NYMEX Crude Oil Brent NB	720	655	142	114	156	131
TYCOM Kerosene IO	344	267	85	61	63	51
ICE Gas-Oil-Petroleum LF	755	673	162	120	165	144
NYMEX Gasoline, Blendstock RB	310	290	46	44	47	52
Tocom Gasoline IN	292	284	67	61	36	51
NYMEX Natural Gas, Henry Hub NG	515	483	129	94	120	109

Table 3

After we have made sufficient adjustments to the data itself, we will then measure the price reaction of different future contracts to the scenarios and events mentioned in table 3. We will discuss our results as three sectors of commodity futures respectively: e.g. food and agricultural, metals and energy.

Consider the event day as day 0, if the cumulative average daily return at day t + 1 for bullish events is both economically and statistically significantly positive, while the cumulative average daily return at day t+1 for bearish events is both economically and statistically significantly negative, it means this sector of commodity under-reacts to significant price changes.

If the cumulative average daily return at day t + 1 for bullish events is both economically and statistically significantly negative, while the cumulative average daily return at day t+1 for bearish events is both economically and statistically significantly positive, it means this sector of commodity overreacts to significant price changes.

Since commodity prices have changed dramatically from the 1950s to nowadays, for example, gold price nowadays is almost 8 times of that in the 1970s, when calculating daily returns for day t +1, using absolute return in our analysis will dilute our results towards to patterns of recent years. We need to transfer the absolute return of contracts to percentage return using the following formula:

Percentage return = Absolute return / closing price of future contract at event day

In the commodity futures market, there is no so-called “private information” as in the stock market; yet certain information are indeed “private” in the sense that only people who are within the related industry would be able to know these information so precisely as to make an investment decision. For example, while the information that there is a drought in China, Henan Province could be known to all, only the farmers on site would have a precise idea regarding how severe rice plantation has been affected; while the information that high oil price has reduced petrol consumption from cars is public, only staffs working in the petrol stations would know exactly how severe has demand for petrol been influenced.

Larson and Mardura (2003) used the 3-days abnormal return proceeding the event day as a proxy for the amount of private information leakage; considering the slower diffusing of information in the commodity market, we use the 5-day return before the event day as a proxy for the amount of “private” information that is incorporated among investors. If under-reaction is due to the gradual incorporation of these information, the phenomenon of under-reaction, if any, should become less significant in scenario 2 compared to in scenario 1. If overreaction is detected, and if overreaction in the commodity market is indeed due to investors’ overconfidence in private information, the degree of overreaction should also be more severe in scenario 2 than in scenario 1 since more private information has been incorporated into investors.

Larson and Mardura (2003) also mentioned: “The Tendency for a reversal is expected to be stronger when the initial price change is more extreme.” If overreaction or under-reaction is indeed caused by over-response to information or gradual diffusion of information, when the initial price change is larger, either the market has over-responded to in a greater manner (overreaction) or more information would have been diffused into the market (under-reaction). Thus, return data in scenarios 3 is expected to demonstrate weaker forms of under-reaction or stronger forms of overreaction in general compared to scenario 1.

Results and Discussions

Results for Scenario 1 are displayed in table 4 below: we are able to find strong evidence of under-reaction for food and agricultural commodities in general, but not for metals and energy commodities. In the food and agricultural group, we have found strong under-reaction for all contracts except ICE Cotton, Liffe Cocoa and Liffe Sugar NO. 5; among them, results for Feeder Cattle and Live Cattle are strongest in terms of statistical significance, while results for Liffe Coffee and TOCOM Rubber exhibit the largest magnitude of under-reaction. In the metals group, we were able to find slight evidence of overreaction in Comex Gold, however both the degree of reaction and statistical significance were not great; results for copper and silver revealed neither overreaction nor under-reaction. In the energy group, results appear to be diffused, TOCOM Kerosene, TOCOM Gasoline and ICE Gasoil showed some signs of under-reaction, while results from the rest of the products appeared random.

The reason for overreaction to be spotted mostly only in the food and agricultural group might be due to that financial markets for metal and energy are generally more active and developed than that of food and agricultural commodities. Highly developed financial markets attract more players and attention, hence the market becomes more "efficient" to information; while in less developed financial markets, diffusion of information would be slower and hence the gradual incorporation of information causes these markets to under-react. The fact that we find stronger sign of under-reaction in Liffee Coffee compared to ICE Coffee supports this hypothesis, as we know Coffee contract listed on ICE is more active than the one listed on Liffe; the meat commodities, which are found to show strongest evidence of under-reaction, happen to be less active compared to the other agricultural commodities as well. In the energy market, the three contracts that are found to show some signs of under-reaction are also relatively non-mainstream contracts compared to the rest of the energy contracts studied in this paper. Another reason causing the food and agricultural commodities to act differently from metal and energy commodities could be that the percentage of non-commercial players in Metals and Energy far exceeds that in the food and agricultural sector. Non-commercial players such as hedge funds are more sensitive to certain information than commercial players and hence speed up the process of incorporation of information in these markets. This assumption is in line with our result that meat commodities show stronger sign of under-reaction than agricultural commodity contracts in general, as there are less non-commercial players in the meat commodity contracts.

Scenario 1						
	Next day Return of Bullish Events	t value	obs	Next day Return of Bearish Events	t value	obs
Food and Agriculture						
CBOT Soybean Oil Crude BO	0.21%	4.5	1683	-0.06%	-1.35	1548
LIFFE Coffee, Robusta (10 Tonne) LQ	0.39%	3.43	518	-0.27%	-2.36	478
CME Cattle Feeder(Average) FC	0.18%	6.36	1168	-0.12%	-3.38	1037
CBOT Wheat No. 2 Soft Red W-	0.09%	1.88	1522	-0.08%	-2	1525
WCE Canola No. 1 WC	0.09%	1.94	1065	-0.23%	-5.09	1018
CBOT Soybean Meal 48% Protein SM	0.24%	4.19	1547	-0.09%	-1.24	1308
CME Hogs, Lean Average LH	0.18%	3.22	903	-0.08%	-1	792
ICE Coffee C Columbia KC	0.13%	1.35	1043	-0.04%	-0.51	1023
KCBT Wheat No. 2 Hard Winter KW	0.20%	3.72	1273	-0.10%	-2.02	1138
CME Cattle Live Choice Average LC	0.21%	7.16	1291	-0.11%	-3.14	1168
CBOT Soybeans No. 1 Yellow S-	0.15%	3.14	1592	-0.12%	-2.36	1438
TYCOM Rubber #3 YR	0.27%	2.61	504	-0.32%	-2.53	470
ICE Cotton 1-1 16 CT	0.00%	-0.03	1342	-0.06%	-1.35	1343
LIFFE Sugar #5, White LW	0.04%	0.6	567	0.03%	0.32	479
LIFFE Cocoa #7 LO	0.04%	0.59	710	-0.03%	-0.35	694
Metals						
Nymex Copper High Grade HG	0.04%	0.75	1693	0.04%	0.71	1480
Nymex Gold GC	-0.05%	-1.04	1120	0.06%	1.4	1001
NYMEX Silver SI	0.02%	0.29	1429	-0.01%	-0.17	1333
Energy						
NYMEX Crude Oil WTI CL	-0.07%	-0.79	895	-0.08%	-0.92	849
NyMEX Heating Oil HO	-0.02%	-0.28	945	0.04%	0.5	866
NYMEX Crude Oil Brent NB	0.00%	0	720	0.05%	0.54	655
TYCOM Kerosene IO	0.34%	3.85	344	-0.16%	-1.32	267
ICE Gas-Oil-Petroleum LF	0.15%	1.74	755	-0.12%	-1.27	673
NYMEX Gasoline, Blendstock RB	-0.05%	-0.35	310	0.06%	0.36	290
Tocom Gasoline IN	0.14%	1.33	292	-0.08%	-0.75	284
NYMEX Natural Gas, Henry Hub NG	-0.03%	-0.17	515	-0.25%	-1.6	483

Table 4

Results for Scenario 2 are displayed in table 5 below. In the food and agricultural group, most agricultural commodities that used to show clear sign of under-reaction in Scenario 1 are no longer showing sufficient evidence for under-reaction. Results for some agricultural products are random, while some others still exhibit signs of under-reaction without sufficient statistical significance; Canola is the only product that still shows clear signs of under-reaction in Scenario 2. All meats commodities, in the meantime, continue to show evidence of under-reaction, with a weaker statistical significance compared to Scenario 1. Results have also become more random in the metal and energy group. In general, under-reaction has become weaker in Scenario 2.

This result corresponds with our prior hypothesis that under-reaction in Scenario 2 is supposed to be weaker than that in Scenario 1. Due to the amount of information that has already been diffused and reflected in the market during the previous 5 days, less information to be incorporated in to the market causes weaker under-reaction. Meat Commodities are still showing stronger levels of under-reaction compared to other contract categories, since meat markets are less developed than other commodity markets.

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Scenario 2						
	Next day Return of Bullish Events	t value	obs	Next day Return of Bearish Events	t value	obs
Food and Agriculture						
CBOT Soybean Oil Crude BO	**0.16%**	**1.55**	**425**	**-0.06%**	**-0.42**	**266**
LIFFE Coffee, Robusta (10 Tonne) LQ	**0.08%**	**0.28**	**131**	**0.22%**	**0.78**	**75**
CME Cattle Feeder(Average) FC	*0.26%*	*4.29*	*250*	*-0.14%*	*-1.53*	*229*
CBOT Wheat No. 2 Soft Red W-	**0.27%**	**2.12**	**351**	**0.11%**	**0.95**	**234**
WCE Canola No. 1 WC	**0.25%**	**2.26**	**257**	**-0.17%**	**-1.46**	**175**
CBOT Soybean Meal 48% Protein SM	**0.39%**	**2.88**	**395**	**0.00%**	**0.01**	**208**
CME Hogs, Lean Average IowaS Minn LH	*0.41%*	*2.85*	*156*	*-0.23%*	*-1.18*	*111*
ICE Coffee C Columbia KC	**0.32%**	**1.24**	**242**	**0.33%**	**1.27**	**156**
KCBT Wheat No. 2 Hard Winter KW	**0.46%**	**3.55**	**327**	**0.22%**	**1.46**	**161**
CME Cattle Live Choice Average LC	*0.28%*	*3.71*	*258*	*-0.06%*	*-0.59*	*230*
CBOT Soybeans No. 1 Yellow S-	**0.26%**	**2.59**	**435**	**-0.05%**	**-0.31**	**238**
TYCOM Rubber #3 YR	**0.13%**	**0.58**	**121**	**-0.42%**	**-1.07**	**83**
ICE Cotton 1-1 16 CT	0.13%	0.93	242	0.03%	0.26	258
LIFFE Sugar #5, White LW	0.07%	0.42	128	0.29%	1.41	99
LIFFE Cocoa #7 LO	0.33%	1.99	151	-0.21%	-0.11	96
Metals						
Comex Copper High Grade HG	0.00%	0.01	421	0.14%	0.84	228
Comex Gold GC	-0.04%	-0.26	231	0.09%	0.74	181
COMEX Silver SI	0.16%	0.92	325	-0.36%	-1.46	202
Energy						
NYMEX Crude Oil WTI CL	-0.42%	-1.39	156	0.13%	0.49	147
NyMEX Heating Oil HO	-0.28%	-1.01	186	0.18%	0.77	123
NYMEX Crude Oil Brent NB	0.11%	0.47	142	0.068	0.29	114
TYCOM Kerosene IO	0.64%	4.21	85	-0.35%	-1.25	61
ICE Gas-Oil-Petroleum LF	0.07%	0.26	162	0.12%	0.49	120
NYMEX Gasoline, Blendstock RB	-0.23%	-0.71	46	0.35%	0.68	44
Tocom Gasoline IN	0.19%	0.99	67	-0.34%	-1.16	61
NYMEX Natural Gas, Henry Hub NG	0.24%	0.45	129	-0.34%	-0.76	94

Table 5

Table 6 displays the result for Scenario 3. In the food and agricultural group, certain contracts such as CME Lean Hog, Liffe Sugar and Liffe Cocoa are starting to show signs of overreaction, while the proportion of the rest of contracts that are still showing sufficient evidence of under-reaction is smaller compared to that in scenario 1. Results in metals and energy remain mostly random. In general, results from Scenario 3 show insufficient evidence for either overreaction or under-reaction, due to scattered results and small sample size.

Results in this Scenario 3, although derived from a smaller sample size, remain in line with our prior hypothesis that market is inclined to show stronger over-reaction and weaker under-reaction in the next day when the initial price change on the previous day is larger. This matches with the findings of Larson and Mardura(2003) in the equity market. As more has been incorporated into market prices in the extreme movement in the prior day, the amount of private information that could cause under-reaction in the following day is less; hence under-reaction becomes less evident in Scenario 3.

Scenario 3						
	Next day Return of Bullish Events	t value	obs	Next day Return of Bearish Events	t value	obs
Food and Agriculture						
CBOT Soybean Oil Crude BO	*0.25%*	*2.09*	*436*	*0.09%*	*0.61*	*289*
LIFFE Coffee, Robusta (10 Tonne) LQ	0.43%	1.62	154	-0.08%	-0.38	136
CME Cattle Feeder(Average) FC	0.27%	3.6	162	-0.15%	-1.48	171
CBOT Wheat No. 2 Soft Red W-	*0.12%*	*0.88*	*314*	*0.00%*	*0.02*	*265*
WCE Canola No. 1 WC	0.11%	0.9	271	-0.37%	-3.04	226
CBOT Soybean Meal 48% Protein SM	*0.25%*	*1.82*	*419*	*0.07%*	*0.41*	*290*
CME Hogs, Lean Average IowaS Minn LH	**-0.84%**	**-2.11**	**46**	**1.24%**	**1.58**	**52**
ICE Coffee C Columbia KC	0.34%	1.19	273	-0.06%	-0.3	249
KCBT Wheat No. 2 Hard Winter KW	*0.33%*	*2.27*	*304*	*0.10%*	*0.67*	*235*
CME Cattle Live Choice Average LC	0.25%	2.53	124	-0.16%	-1.32	138
CBOT Soybeans No. 1 Yellow S-	0.23%	2.24	429	-0.09%	-0.8	383
TYCOM Rubber #3 YR	0.22%	0.7	96	-0.78%	-2.56	128
ICE Cotton 1-1 16 CT	-0.13%	-1.07	269	-0.03%	-0.26	271
LIFFE Sugar #5, White LW	**-0.26%**	**-1.66**	**128**	**0.41%**	**1.72**	**108**
LIFFE Cocoa #7 LO	**-0.29%**	**-1.47**	**168**	**0.18%**	**0.98**	**148**
Metals						
Comex Copper High Grade HG	-0.04%	-0.29	383	0.16%	1.27	328
Comex Gold GC	0.04%	0.27	266	0.09%	0.9	259
COMEX Silver SI	0.18%	1.07	372	-0.31%	-1.89	364
Energy						
NYMEX Crude Oil WTI CL	-0.11%	-0.48	180	-0.21%	-0.88	171
NyMEX Heating Oil HO	-0.11%	-0.42	203	-0.05%	-0.21	186
NYMEX Crude Oil Brent NB	-0.24%	-1.08	156	0.08%	0.33	131
TYCOM Kerosene IO	0.58%	2.8	63	-0.28%	-0.86	51
ICE Gas-Oil-Petroleum LF	0.06%	0.24	165	-0.33%	-1.56	144
NYMEX Gasoline, Blendstock RB	0.03%	0.06	47	0.06%	0.12	52
Tocom Gasoline IN	0.02%	0.07	36	-0.23%	-0.78	51
NYMEX Natural Gas, Henry Hub NG	-0.03%	-0.05	120	-0.29%	-0.83	109

Table 6

Our result so far displays evidence for under-reaction in food and agricultural commodity futures in general, while the energy and metal sector shows insignificant sign of either overreaction or under-reaction. Future contracts that are less active are also more inclined to under-react compared to future contracts that are fully developed and actively used by hedgers and investors. In the meantime, results from Scenario 2 and 3 have echoed with the hypothesis by Hong and Stein (1999) that under-reaction is caused by the gradual incorporation of information among investors.

To test the robustness of our results, we used the AR II model to measure the predictability of the next of event-day return relative to the return on the event day. We did this for all contracts studied that had showed signs of under-reaction in Scenario 1. The result of the regression is shown in table 7 below. While the R-Square is generally a bit small, The R Square statistics show stronger predictability in meat commodities compared to agricultural contracts, in line with the results indicated by t-stats.

Scenario 1							
	Next day return of bullish events	t value	obs	Next day return of bearish events	t value	obs	R2
CBOT Soybean Oil Crude BO	0.21%	4.5	1683	-0.06%	-1.35	1548	0.51%
LIFFE Coffee Robusta (10 Tonne) LQ	0.39%	3.43	518	-0.27%	-2.36	478	2.35%
CME Cattle Feeder (Average) FC	**0.18%**	**6.36**	**1168**	**-0.12%**	**-3.38**	**1037**	**2.97%**
CBOT Wheat No. 2 Soft Red W-	0.09%	1.88	1522	-0.08%	-2	1525	0.50%
WCE Canola No. 1 WC	0.09%	1.94	1065	-0.23%	-5.09	1018	0.99%
CBOT Soybean Meal 48% Protein SM	0.24%	4.19	1547	-0.09%	-1.24	1308	0.26%
CME Hogs, Lean Average LH	**0.18%**	**3.22**	**903**	**-0.08%**	**-1**	**792**	**1.71%**
ICE Coffee C Columbia KC	0.13%	1.35	1043	-0.04%	-0.51	1023	0.41%
KCBT Wheat No. 2 Hard Winter KW	0.20%	3.72	1273	-0.10%	-2.02	1138	0.34%
CME Cattle Live Choice Average LC	**0.21%**	**7.16**	**1291**	**-0.11%**	**-3.14**	**1168**	**2.49%**
CBOT Soybeans No. 1 Yellow S-	0.15%	3.14	1592	-0.12%	-2.36	1438	1.53%
TYCOM Rubber #3 YR	0.27%	2.61	504	-0.32%	-2.53	470	2.10%
LIFFE Cocoa #7 LO	0.04%	0.59	710	-0.03%	-0.35	694	0.62%
TYCOM Kerosene IO	0.34%	3.85	344	-0.16%	-1.32	267	2.15%
ICE Gas Oil Petroleum LF	0.15%	1.74	755	-0.12%	-1.27	673	0.98%
Tocom Gasoline IN	0.14%	1.33	292	-0.08%	-0.75	284	0.62%

Table 7 Regression results for contracts that show signs of under-reaction

To fully understand the economic significance of our findings, we built a momentum strategy trading on food and agricultural commodities to measure the arithmetic average return for the strategy. Details of the strategy are as follows: the trader will monitor the standard deviation for the past 200 trading days actively; so when the market moved up or moved down more than the standard deviation of the past 200 days in a certain trading day, or we could call such days event day, the trader will buy or sell the corresponding futures contract at the closing price of that day. The position will be established in the same direction of the market movement on the event day, and will be held until the next day and closed off at the closing price. We assume that the trader uses 100% leverage in its trading, which means 50% of the contract value will be pledged with the exchange as margin, rather than he 5%-10% typically required by the exchange. This level of low leverage ensures that the trader does not get into over-loss when extreme market conditions cause market to move against his position. Simulations of trades will be carried out respectively for all food and agricultural commodities examined in this study, and the Cumulative average return will be calculated to derive a yearly return for each product. The return data using 100% leverage is listed in table 8 below.

	Cumulative Return	Yearly Return
CBOT Soybean Oil Crude BO	9.179	17.93%
LIFFE Coffee, Robusta (10 Tonne) LQ	6.623	33.96%
CME Cattle Feeder(Average) FC	6.781	17.49%
CBOT Wheat No. 2 Soft Red W-	5.273	10.30%
WCE Canola No. 1 WC	6.652	18.48%
CBOT Soybean Meal 48% Protein SM	9.765	19.08%
CME Hogs, Lean Average IowaS Minn LH	4.449	9.99%
ICE Coffee C Columbia KC	3.609	9.48%
KCBT Wheat No. 2 Hard Winter KW	7.382	18.15%
CME Cattle Live Choice Average LC	8.04	17.57%
CBOT Soybeans No. 1 Yellow S-	8.099	15.82%
TYCOM Rubber #3 YR	5.741	32.46%
ICE Cotton 1-1 16 CT	1.524	2.98%
LIFFE Sugar #5, White LW	0.185	0.91%
LIFFE Cocoa #7 LO	0.984	4.06%

Table 8 Arithmetic cumulative and average return for each contract

From the results above, we are able to find significant yearly return for most food and agriculture commodity futures. Among the 15 contracts categories studied, we were able to attain yearly return of more than 15% for 9 of them, and yearly return of more than 9% for 12 contract categories. The results suggest strong economic significance of the under-reaction phenomena in the food and agricultural commodities sector.

Summary of Conclusions

Previous studies testing overreaction and under-reaction in he commodity futures market have yield mixed results. Some studies have found evidence of overreaction in commodity futures, some found evidence of under-reaction, and other found no evidence supporting either of these two phenomena.

In this study, we seek to shed light on the existence of under-reaction and overreaction in commodity futures using a series of data spanning across meat, agricultural, metal and energy commodities. By examining the return data for three different scenarios, we have been able to find strong evidence of under-reaction in the food and agricultural commodity market. The result appears to be both statistical and economical significant, and is more evident in less active commodity contracts. Evidence in our findings appear to support the hypothesis by Hong and Stein (1999) that under-reaction is caused by the gradual incorporation of information; it also echoes with findings by Larson and Mardura 2003 and 2001, which shows that market is more inclined to overreact after an extreme initial price change in the previous day.

Based on our findings in Scenario 1, we were able to form a momentum strategy in the food and agricultural commodities sector. By conducting basic in-sample tests on this momentum strategy, we were able to obtain economically significant return on most contracts; this has further boosted the implication of our findings.

Despite these, due to insufficient time and resources, we were unable to dig further in certain aspect of our findings. Further research on the reason that under-reaction was only found in food and agricultural contracts but not meals and energy contracts could be studied, and the application of momentum strategy to profit from the under-reaction in food and agricultural commodities could be examined in more detail.

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