Commodity futures price behaviour following large one-day price changes

Abstract

This study examines individual commodity futures price reactions to large one-day price changes, or "shocks". The mean-adjusted abnormal return model suggests that investors in 6 of the 18 commodity futures examined in this study either underreact or overreact to positive surprises. It also detects underreaction patterns in 8 commodity future prices following negative surprises. However, after making appropriate systematic risk and conditional heteroskedasticity adjustments, we show that almost all commodity futures react efficiently to shocks.

JEL classification: C13, C22, G14

Keywords: Commodity price behaviour; market efficiency; underreaction; overreaction.

1. Introduction

This study investigates the commodity futures price reaction to large one-day price changes or “shocks”. Its main objective is to examine whether investment strategies based on price shocks can generate subsequent risk-adjusted abnormal returns. While investigating the predictability of asset prices following shocks is not entirely new to the literature, existing studies tend to focus on the post-shock price patterns associated with individual stocks, stock indices and stock index futures, and their evidence is largely mixed. For example, Bremer and Sweeney (1991) and Bowman and Iverson (1998) report positive and statistically significant abnormal returns following stock price changes in excess of -10%. They argue that their evidence is consistent with the view that stock market investors overreact to the arrival of negative news. Grant et al. (2005) find that US stock index futures overreact to large intraday price changes. Similar evidence is reported by Fung and Lam (2004) and Rentzler et al. (2006) in the case of the Hang Seng Index futures and Japanese stock index futures, respectively. Lasfer et al. (2003) show that large positive (negative) price changes in stock index prices are followed by significantly positive (negative) abnormal returns. They argue that their observed price patterns imply that stock market investors underreact to news announcements.

The observed overreaction and underreaction patterns in stock returns are commonly viewed as the most important challenges to the efficient market hypothesis. However, several studies argue that these patterns may not be exploitable after accounting for transaction costs, illiquidity and other risk. Cox and Peterson (1994) and Atkins and Dyl (1990), for example, show that the statistical significance of the post-shock cumulative abnormal returns associated with US stocks disappears completely after controlling for the bid-ask spread bounces. Similarly, Lasfer et al. (2003) report a significant association between the magnitude of the post-shock abnormal returns and stock market liquidity, with higher after-shock momentum being observed in less liquid markets. In a more recent work, Mazouz et al. (2012) find that the price continuation patterns in the FTSE 100 stocks are related to the systematic liquidity risk, with low systematic liquidity risk stocks reacting efficiently and high systematic liquidity risk stocks underreacting to shocks.

The purpose of this study is to test whether investors react efficiently or irrationally to price shocks in the commodity futures markets. We believe that commodity futures markets may offer a better environment in which to study the price reaction to shocks than stock markets for at least two important reasons. First, it has commonly been suggested that the abnormal stock returns following shocks may be driven by transaction costs (e.g., Cox and

Peterson, 1994; Atkins and Dyl, 1990) or illiquidity (e.g., Lasfer et al., 2003; Mazouz et al., 2012). Cornell (1985) and Locke and Venkatesh (1997) show that futures markets offer a relatively lower transaction costs environment than stock markets. Locke and Venkatesh (1997) show that the transaction costs in the futures markets range between 0.0004% and 0.033%. These figures are much smaller than the stock market transaction costs of 0.5% and 2.3% reported by Jegadeesh and Titman (1993) and Lesmond et al. (2004), respectively. Second, futures contracts tend to be highly liquid close to maturity, and not subject to the short-selling constraints that are often imposed in stock markets (Miffre and Rallis, 2007). Thus, the abnormal returns associated with commodity futures following large one-day changes are unlikely to be eroded by transaction costs or a lack of liquidity.

This study makes a number of important contributions to the literature. Firstly, it investigates investors' reactions to shocks in an environment in which price patterns are unlikely to be eroded by transaction costs or a lack of liquidity. Secondly, it provides an alternative test of short-term efficiency. Existing studies on the informational efficiency of commodity futures markets can be split into two broad categories. The first group of studies focus on the long-term and medium-term efficiency of the commodity futures markets. Erb and Harvey (2006), for example, show that abnormal profits can be generated from a momentum strategy with a 12-month ranking period and a 1-month holding period. Miffre and Rallis (2007) study the performance of medium-term (up to 12 months) momentum strategies and long-term (2 to 5 years) contrarian strategies in commodity futures markets. They show that contrarian strategies are not profitable, whilst momentum strategies generate a positive return of 9.38% per annum. The second group of studies investigate the short-term efficiency in commodity futures markets, focusing mainly on the relationship between futures and spot prices. McKenzie and Holt (2002), for example, use cointegration and error correction models with a Generalised-Quadratic Autoregressive Conditional Heteroskedasticity (GQARCH)-in-mean process to test the market efficiency and unbiasedness of four commodity futures traded in the Chicago Board of Trade. Their results indicate that commodity futures markets are unbiased in the long run, but most commodity futures are inefficient in the short run. Similarly, Wang and Ke (2005) use Johansen's cointegration to test the efficiency of the Chinese commodity futures markets. Their findings also suggest a long-term equilibrium relationship between futures and spot prices and weak short-term efficiency, in the soybean futures market. Unlike previous studies, we examine the short-term price efficiency of commodity futures by analysing the speed at which price shocks are incorporated into prices. Finally, we argue that while some of the existing studies detect short-term anomalies in commodity futures, they do not test whether profitable trading strategies can be formulated to exploit these anomalies. By investigating the persistence in the price movements, this study allows us to verify the possibility of generating abnormal returns following unprecedented price movements.

To account for the volatility of returns, which is expected to vary from one commodity futures to another, we use Lasfer et al.'s (2003) approach to detect shocks in stock indices. Specifically, we define a positive (negative) price shock as one where the return on a given day is above (below) two standard deviations the average market daily returns over the [-60, -11] day window relative to the day of the shock. Whilst the choice of the benchmark window is arbitrary, the days immediately before shocks are excluded in order to mitigate the influence of abnormal price movements that may be caused by investors' attempts to capitalise on the anticipated large price changes[1]. After the shocks have been identified, we use a dummy variable approach, similar to that of Karafiath (1988) and Mazouz et al. (2009), to estimate the abnormal returns following the shocks.

Our initial results indicate that the persistence of price movements following shocks varies substantially across markets. We show that 12 out the 18 commodity futures included in our sample react efficiently to positive surprises. However, investors in cocoa, live cattle, feeder cattle and pork bellies futures underreact to positive shocks. We also report significant overreaction patterns following positive shocks in the case of both sugar and copper. Our results also suggest that 8 of the 18 commodity futures underreact to negative shocks, whilst the remaining 10 absorb negative shocks immediately. The underreaction evidence is in line with the findings for equity market indices (Lasfer et al., 2003; Mazouz et al., 2009).

Although our definition of shocks accounts for the discrepancies in the volatility of returns across different commodity futures, the abnormal returns following shocks need to undergo more stringent tests before we can draw any conclusions. Miffre and Rallis (2007) show that individual commodity futures prices are significantly affected by the price movements in equity, bond and commodity indices. Brown et al. (1988) also argue that large unprecedented price changes increase uncertainty and cause a temporary increase in the asset's systematic risk. To account for the potential effect of systematic risk on our results, we repeat our analysis on the commodity futures with significant post-shock abnormal returns using a multifactor model similar to that of Miffre and Rallis (2007). After conducting appropriate systematic risk adjustments, we show that cocoa, copper, feeder cattle and pork

[1] Note that the identification of shocks is not very sensitive to the estimation window. The use of [-50, -10] or of [-45, -5] has little influence on the number or magnitude of identified shocks.

bellies (sugar and pork bellies) are the only commodity futures with statistically significant first-day abnormal returns following positive (negative) shocks. A conditional heteroskedasticity adjustment reduces the number of overreaction and underreaction cases even further. Specifically, with the exception of a one- to two-day delay in the price adjustments of cocoa and feeder cattle (sugar) futures to positive (negative) surprises, all other commodity futures react efficiently to both positive and negative shocks.

The remainder of this paper is structured as follows. Section 2 describes our dataset. Section 3 outlines the methodology and discusses the empirical test results. Section 4 concludes.

2. Data

We analyse a wide range of commodity futures from the agricultural, energy and metal commodity futures markets. These commodity futures are as follows: soybeans, soybean meal, soybean oil, corn, oats, wheat, cocoa, coffee, sugar, cotton, heating oil, gold, silver, copper, live cattle, feeder cattle, hogs and pork bellies. The daily futures contract settlement prices are obtained from DataStream. For all the commodity futures except silver and copper, the datasets span a 30-year period from 01/03/1981 to 28/02/2011. Table 1 provides further details on the sample data. The futures prices are obtained from the nearest contract that is rolled over to the next contract on the first business day of the contract month. As the nearby futures contract is highly liquid and most actively traded, it is considered appropriate for forming the daily futures price series (Yang et al., 2001). Other data, such as the government bond index, the S&P composite index, the Goldman Sachs Commodity Index (GSCI) and the 3-month Treasury bill, are also downloaded from DataStream.

Insert Table 1 about here

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3. Tests and results

3.1. Identifying shocks

Previous studies tend to use quantitative trigger values to identify "large" price changes. Howe (1986) defines price shocks as weekly price changes exceeding 50%. Atkins and Dyl (1990) focus on the largest one-day price change in a 300-day window. Bremer and Sweeney (1991) examine stock price behaviour following daily price changes of ≤ -10%. Lasfer et al. (2003) argue that using a single value to identify the day of a significant price change may not be appropriate as it does not take into account factors such as the volatility of returns, which varies across different markets. They, therefore, propose a new approach to account for the potential volatility effects.

In this study, we adopt Lasfer et al.'s approach to identify price shocks in the commodity futures series. Specifically, we define a positive (negative) price shock, i.e. the event day 0, as one where the return on a particular day is above (below) the average daily market return plus (minus) two standard deviations of the daily return. The average market return and the standard deviation of the return are calculated over [-60, -11] days relative to the day of the price shock. As argued earlier, the period immediately before a large price change is excluded from the analysis to reduce the potential effect of forward-looking commodity futures traders who may attempt to capitalise on large price movements. In unreported results, we find that the number and magnitude of shocks are not highly sensitive to the use of alternative estimation windows such as [-50, -10] and [-45, -5]. To avoid any confounding effects, shocks occurring within 10 days of a given event day are ignored. This process is necessary to ascertain that abnormal returns following a given shock are due to the market reaction to that particular rather than to the arrival of other price-sensitive news.

Table 2 reports the summary statistics of the commodity futures price shocks. The distribution of positive and negative shocks across our sample is almost symmetric. Specifically, the total number of positive (negative) shocks associated with all the commodity futures over the entire study period is 2800 (2805). Soybean oil and feeder cattle futures contain the highest number of positive and negative shocks, respectively, while the lowest number of positive and negative shocks is found in the daily return series of pork bellies and copper futures, respectively.

Insert Table 2 about here

Table 2 also reports the average and maximum price shocks in our commodity futures price series. The average positive (negative) shock across all the commodity futures is 4.30% (-4.26%). The highest positive and negative daily price changes of almost 133% and -75% are found in sugar and cotton futures, respectively. The lowest maximum price shocks, of -5.43% and 5.88%, are contained in the daily return series of feeder cattle futures.

3.2. Mean-adjusted abnormal returns

After identifying the positive (negative) shocks, we employ the following dummy variable approach to estimate both the event and post-event abnormal returns[2]

$$R_{i,t} = \alpha_i + \theta_{i,n} D_{t,n} + \varepsilon_{i,t} \quad (1)$$

where $R_{i,t}$ is the log return of commodity futures i on day t. α_i is a constant. $D_{t,n}$ is a dummy variable with a value of unity during event period n and 0 otherwise. The subscript $n \in [0, +N]$ refers to the number of days following a price shock. For instance, $D_{t,0}$ is a dummy that equals 1 when t is the event day (day 0) and 0 otherwise. $D_{t,1}$ is a dummy that equals 1 when t is the first day after the event day and 0 otherwise. $D_{t,2}$, $D_{t,3}$, ..., $D_{t,N}$ are dummy variables that equal 1 when $t \in$ [+1,+2], [+1,+3], …, [+1,+N], respectively, and 0 otherwise. $\theta_{i,n}$ is the coefficient for the average abnormal return of the event day or post-event days. The regression analysis is conducted to test the null hypothesis that the coefficient $\theta_{i,n} = 0$. If the null hypothesis is rejected, it indicates that the weak-form efficiency hypothesis is violated and therefore opportunities to earn abnormal profits exist. The coefficient $\theta_{i,n}$ in Eq.(1) is also used to compute the post-event average cumulative abnormal returns (ACAR) over a post-event window of n days. Specifically, we define $ACAR_{i,n} = \theta_{i,n} \times n$ as the average cumulative abnormal return associated with commodity futures i over a window of n days following price shocks. $\varepsilon_{i,t}$ is a normally distributed error term with zero mean and constant variance. The statistical significance of $ACAR_{i,n}$ is based on the t-statistic associated with parameter $\theta_{i,n}$ in Eq.(1).

Table 3 presents the ACARs over a window of 10 days after a positive shock for each commodity futures. Although all the abnormal returns on the event day (day 0) are significant, the statistical significance of post-shock ACARs varies substantially across the series. Consistent with the predictions of the efficient market hypothesis, the ACARs over the [+1, +10] window associated with 12 out of 18 commodity futures are not significantly different from zero. However, the ACARs associated with the cocoa, live cattle, feeder cattle and pork bellies futures are positive and statistically significant for up to ten days following positive shocks. This price pattern indicates that investors in these commodities underreact to positive news. Our results also indicate that investors in sugar and copper futures overreact to positive news. The ACARs of the sugar futures are negative for up to ten days following

[2] Although the two-stage residual method is commonly used in prior literature, the dummy variable approach is regarded as a more efficient abnormal return estimator (Karafiath, 1988; Mazouz et al., 2009).

positive shocks, but only ACAR1 and ACAR2 (i.e. the ACARs one and two days after a positive shock) are shown to be statistically significant. The overreaction to positive shocks is much stronger in the copper futures, as all the ACARs in the [+1, +10] window after positive shocks are negative and statistically significant.

Insert Table 3 about here

Table 3 also reports the post-event ACARs after negative shocks over a window of 10 days. Our results indicate that 10 out of the 18 commodities included in our sample react efficiently to negative shocks. However, the negative ACARs associated with soybeans, soybean oil, corn, sugar, live cattle, feeder cattle, hogs and pork bellies following negative shocks indicate that investors in these commodities underreact to the arrival of negative news. The speed at which negative shocks are incorporated into the commodity futures prices varies considerably across markets. Specifically, the negative ACARs associated with soybeans, feeder cattle and live cattle remain significant for up to 7, 6 and 5 days following negative shocks, respectively. However, the negative ACARs associated with soybean oil, sugar, hogs and pork bellies are only significant on the first day after negative shocks.

3.3. Systematic risk adjustments

So far, we have not taken into consideration the impact of systematic risk on the abnormal return estimates. Miffre and Rallis (2007) show that individual commodity prices are affected by the price movements in equity, bond and commodity markets. Brown et al. (1988) also find that, in the aftermath of news, both the risk and the expected returns of the affected firms increase systematically. Several studies, including Chordia and Shivakumar (2002) and Miffre and Rallis (2007), also suggest that systematic risk adjustments affect both the magnitude and the statistical significance of the abnormal returns associated with momentum strategies.

To account for the potential impact of systematic risk on our results, we use a multifactor model similar to that of Miffre and Rallis (2007). Our model is specified as follows[3]:

[3] There is no clear consensus in the literature as to which factors are likely to influence commodity prices. Clare et al. (2014) use the traditional Fama-French-Carhart four-factor model and the eight hedge fund factors of Fung and Hsieh (2001). Miffre and Rallis (2007) use the prices of equity, bond and commodity indices to predict the commodity futures returns. Since finding the determinants of commodity price returns is not the main objective of this study, and due to the absence of a clear consensus in the literature on the exact factors that would influence commodity futures prices, we have chosen to adopt the approach proposed by Miffre and Rallis (2007), who also examine the pricing efficiency of commodity futures, for our analysis.

$$R_{i,t} = \alpha_i + \gamma_{i,n}D_{t,n} + \beta_{Bond0}(R_{Bond,t} - R_{f,t}) + \beta_{Bond1}(R_{Bond,t} - R_{f,t})D_{t,n} + \beta_{S\&P0}(R_{S\&P,t} - R_{f,t}) + \beta_{S\&P1}(R_{S\&P,t} - R_{f,t})D_{t,n} + \beta_{GSCI0}(R_{GSCI,t} - R_{f,t}) + \beta_{GSCI}(R_{GSCI,t} - R_{f,t})D_{t,n} + \varepsilon_{i,t} \quad (2)$$

where $R_{Bond,t}$, $R_{S\&P,t}$ and $R_{GSCI,t}$ are the returns on the DataStream government bond index, the S&P 500 composite index and GSCI, respectively; $R_{f,t}$ is the risk-free rate; $\gamma_{i,n}$ is the coefficient of the abnormal return on the event day or a given window after the shock. The coefficient $\gamma_{i,n}$ in Eq.(2) informs us of whether the post-shock abnormal returns remain significant after accounting for the event-induced systematic risk. In line with the above model, $ACAR_{i,n} = \gamma_{i,n} \times n$. $\varepsilon_{i,t}$ is a normally distributed random disturbance with zero mean and constant variance.

In this section, we focus our analysis on the commodity futures with statistically significant post-shock ACARs in Table 2. Specifically, we verify whether the significant post-shock ACARs obtained from Eq.(1) survive systematic risk adjustments. The systematic risk-adjusted ACARs are reported in Table 4. In unreported results, we show that the parameters β_{Bond0}, $\beta_{S\&P0}$ and β_{GSCI0} are significantly different from zero for all the commodity futures, suggesting that the prices of individual commodity futures are indeed affected by the price movements in the bond market, the equity market and the commodity market. The coefficients β_{Bond1}, $\beta_{S\&P1}$ and β_{GSCI} are also shown to be significant on various occasions, indicating that price shocks have a significant effect on the systematic risk of commodity futures[4].

Insert Table 4 about here

Table 4 reports the risk-adjusted ACARs following both positive and negative shocks. Panel A of Table 4 presents the post-positive-shock ACARs. It shows that the abnormal returns associated with sugar are negative. However, with the exception of ACAR2, which is significant at the 10% level, all the remaining ACARs are not significantly different from zero. This finding suggests that the post-positive-shock reversal patterns observed in the case of sugar in Table 3 cannot be exploited after accounting for the systematic risk. Similarly, the statistical significance of the post-positive-shock abnormal returns associated with the live cattle futures disappears completely after adjusting for risk. This finding also implies that live cattle futures prices react efficiently to positive news. The abnormal returns of copper are negative in periods following large positive price changes. However, the extent of the copper

[4] More details on these results are available upon request.

price reversal weakens after the systematic risk is controlled for. Unlike Panel A of Table 3, where all of the post-shock ACARs are negative and significant, Panel A of Table 4 shows that the reversal pattern of copper prices breaks between day +3 and +5 after the positive shock. Panel A of Table 4 also indicates the presence of some weak evidence of underreaction in the case of cocoa, feeder cattle and pork bellies futures. However, the statistical significance of the positive ACARs associated with these commodities is relatively weak and limited to the first one or two days after the positive shocks.

Panel B of Table 4 reports the risk-adjusted post-negative-shock ACARs. The results suggest that the number of commodity futures with statistically significant post-negative-shock first-day ACARs reduces substantially after the systematic risk is controlled for. Specifically, the risk-adjusted ACARs of soybean oil and corn are not significant, indicating that these commodities adjust quickly and accurately to negative events. The soybean futures risk-adjusted ACARs are only significant at 10% for days +3 through +7 after negative shocks. The hypothesis that live cattle and feeder cattle futures react efficiently to negative events cannot be rejected as their first-day post-shock risk-adjusted ACARs are not significantly different from zero. The results in Panel B of Table 4 suggest that sugar and, to a lesser extent, pork bellies futures are the only commodity futures that underreact to negative events after the systematic risk is controlled for.

3.4. Conditional heteroskedasticity adjustments

One weakness of Eq.(2) stems from the explicit assumption that the variance of the residual term, $\varepsilon_{i,t}$, is constant over time. Several studies, including Black (1976) and Christie (1982), show that the variance of stock returns varies systematically over time. Corhay and Rad (1996) and Hahn and Reyes (2004) show that controlling for the ARCH effect in the residuals improves the efficiency of the estimators and affects both the magnitude and the statistical significance of the abnormal returns associated with a given event. Savickas (2003) also finds that controlling for the conditional heteroskedasticity in the residuals increases the probability of rejecting the null hypothesis.

We use the Lagrange multiplier (LM) test to assess the significance of the ARCH effect (Engle, 1982) in the price series of the cocoa, copper, feeder cattle, pork bellies and sugar futures. The results in Table 5 suggest the presence of first-order ARCH (ARCH(1)) in copper and feeder cattle futures, ARCH(4) in both cocoa and sugar, and no ARCH effect in pork bellies. However, other unreported tests, including Breusch-Pagan-Godfrey (BPG), Glejser, and White, reject the hypothesis that the price series of pork bellies futures is homoskedastic[5]. To test whether the post-shock ACARs associated with the cocoa, copper, feeder cattle, pork bellies and sugar futures remain significant after accounting for the ARCH effect, we employ the following GJR-GARCH model proposed by Glosten et al. (1993) to estimate the variance of the residual term in Eq.(2):

$$h_{i,t}^2 = \delta_i + \pi_{0,i}\varepsilon_{t-1}^2 + \pi_{1,i}h_{i,t-1}^2 + \pi_{2,i}I_{i,t-1}\varepsilon_{t-1}^2 \qquad (3)$$

where $h_{i,t}^2$ is the conditional variance of the residual error, $\varepsilon_{i,t}$; δ_i is the permanent component of the conditional variance; $\pi_{0,i}$ and $\pi_{1,i}$ capture the impact of recent news and prior period volatility, respectively; $I_{i,t-1}$is a dummy variable with a value of unity if $\varepsilon_{i,t-1}$ is negative and zero otherwise and $\pi_{2,i}$ captures the asymmetric impact of positive and negative news on the conditional variance[6]. Eq.(3) is estimated under the assumption that the residuals are normally distributed[7].

Insert Tables 5 and 6 about here

The conditional heteroskedasticity-adjusted ACARs associated with cocoa, copper, feeder cattle and pork bellies futures following positive shocks, and sugar and pork bellies futures following negative shocks, are reported in Table 6. Consistent with the existing literature (Corhay and Rad, 1996; Savickas, 2003; Mazouz et al., 2009), we show that conditional heteroskedasticity adjustment generates different parameters from those of the standard OLS model. The statistical significance of the first-day post-shock ACARs of pork bellies futures disappears completely after allowing the variance of $\varepsilon_{i,t}$ to vary systematically over time. However, the first-day post-negative-shock ACAR associated with the sugar futures remains significant at 5%, and positive shocks are incorporated into the cocoa (feeder cattle) futures prices with a one-day (two-day) delay.

[5] The LM test detects the ARCH effect in almost all of the other commodity futures included in our earlier analysis. Details of these results are available upon request.

[6] Most financial economists agree on the presence of asymmetries in asset returns due to the impact of volatility clustering (e.g., Engle et al., 1990) and volatility feedback (e.g., Pindyck, 1984; French et al., 1987). Similarly to the case of GJR-GARCH, EGARCH has been widely used to control the asymmetric impact of positive and negative news on the conditional variance. Using daily returns of Japanese stocks, Engle and Ng (1993) show that GJR-GARCH is the best parametric model for modelling asymmetry. They also show that, although EGARCH can also capture most of the asymmetry, it expresses the variability of the conditional variance at a higher than normal level. For robustness purposes, we also use the EGARCH model to verify the validity of our results to alternative conditional variance specifications. The details of the EGARCH results are not reported, as they are quantitatively similar to those of the GJR-GARCH, but they are available upon request.

[7] The results obtained from assuming a generalised error distribution and a t-distribution are quantitatively similar to those obtained from the normal distribution assumption. Details are available upon request.

5. Conclusion

This study examines, for the first time, individual commodity futures price reactions to shocks. It shows that the post-shock price patterns are highly sensitive to the way in which abnormal returns are estimated. The mean-adjusted abnormal return model suggests that investors in cocoa, live cattle, feeder cattle and pork bellies (sugar and copper) futures underreact (overreact) to positive shocks. It also suggests that 8 of the 18 commodity futures included in our analysis underreact to negative shocks. However, the efficient market hypothesis is rejected less frequently after conducting appropriate systematic risk and heteroskedasticity adjustments. Our final results indicate that underreaction to price shocks is only observed in feeder cattle and cocoa and sugar futures, as these are the only commodities with a statistically significant first-day post-shock ACAR. This finding indicates that commodity futures tend to absorb price shocks quickly and accurately. Thus, fund managers are unlikely to benefit from formulating portfolio strategies to exploit a possible reaction to unprecedented commodity futures price movements. In other words, any return associated with the trading strategies following large commodity price changes is likely to be a compensation for risk. This evidence is inconsistent with McKenzie and Holt (2002) and Wang and Ke (2005), who show that the prices of their selected commodity futures are inefficient in the short term.

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Table 1:Data description and sources

Futures price series	Futures exchange	Start date	Contract months
Soybeans	CBT	01/03/1981	1, 3, 5, 7, 8, 9, 11
Soybean meal	CBT	01/03/1981	1, 3, 5, 7, 8, 9, 10, 12
Soybean oil	CBT	01/03/1981	1, 3, 5, 7, 8, 9, 10, 12
Corn	CBT	01/03/1981	3, 5, 7, 9, 12
Oats	CBT	01/03/1981	3, 5, 7, 9, 12
Wheat	CBT	01/03/1981	3, 5, 7, 9, 12
Cocoa	CSCE	01/03/1981	3, 5, 7, 9, 12
Coffee	CSCE	01/03/1981	3, 5, 7, 9, 12
Sugar	CSCE	01/03/1981	3, 5, 6, 9, 12
Cotton	CSCE	01/03/1981	3, 5, 7, 10, 12
Heating oil	NYMEX	01/03/1981	Every month
Gold	CMX	01/03/1981	Every month
Silver	CMX	10/06/1988	Every month
Copper	CMX	01/09/1989	Every month
Live cattle	CME	01/03/1981	2,4,6,8,10,12
Feeder cattle	CME	01/03/1981	1,3,4,5,8,9,10,11
Hogs	CME	01/03/1981	2,4,5,6,7,8,10,12
Pork bellies	CME	01/03/1981	2,3,5,7,8

Table 2: Summary statistics of positive and negative shocks in commodity futures markets

The day of a positive (negative) price shock, i.e. the event day 0, is defined as one where the return on that day is above (below) the average daily market return plus (minus) two standard deviations of the daily return. The average market return and the standard deviation of the return are calculated over the [-60, -11] days relative to the day of the price shock. To avoid any confounding effects, shocks occurring within 10 days of a given event day are ignored. N is the number of shocks in the daily return series of a given commodity future. Mean (%) and Max (%) are the average value and the maximum value of the shock (as a percentage) observed in each of the commodity futures return series.

Commodity futures	Positive shocks			Negative shocks		
	N	Mean (%)	Max (%)	N	Mean (%)	Max (%)
Soybeans	171	3.27	7.44	170	-3.52	-13.61
Soybean meal	165	3.66	9.02	163	-4.05	-24.84
Soybean oil	188	3.52	8.9	153	-3.6	-9.09
Corn	178	4.03	9.83	152	-3.54	-21.78
Oats	168	5.3	13.4	148	-5.07	-19.67
Wheat	159	4.34	13.19	139	-4.1	-15.93
Cocoa	174	4.85	12.94	171	-4.69	-12.22
Coffee	167	5.21	12.84	177	-5.47	-18.92
Sugar	156	7.67	132.82	171	-6.52	-23.48
Cotton	166	3.75	16.58	164	-4.25	-75.14
Heating oil	168	4.73	13.21	178	-5.61	-38.64
Gold	169	2.31	8.8	174	-2.55	-7.91
Silver	110	3.69	11.9	146	-4.22	-15.2
Copper	127	3.71	12.46	112	-4.06	-11.67
Live cattle	145	2.74	9.06	158	-2.79	-9.9
Feeder cattle	154	2.01	5.88	180	-2.11	-5.43
Hogs	130	6.78	29.55	120	-5.68	-26.25
Pork bellies	105	5.82	45.61	129	-4.84	-34.61
Total	2800	4.3		2805	-4.26	

Table 3: Commodity price reaction to shocks: Mean-adjusted ACARs

The mean-adjusted average cumulative abnormal returns (ACARs) are estimated using the following equation:

$$R_{i,t} = \alpha_i + \theta_{i,n} D_{t,n} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the daily log return, $D_{t,n}$ is a dummy variable with a value of unity during event period n and 0 otherwise and $\varepsilon_{i,t}$ is a normally distributed error term with zero mean and constant variance. The subscript $n \in [0, +N]$ refers to the number of days following a price shock. For instance, $D_{t,0}$ is a dummy that equals 1 when t is the event day (day 0) and 0 otherwise. $D_{t,1}$ is a dummy that equal 1 when t is the first day after the event day and 0 otherwise. $D_{t,2}$, $D_{t,3}$, ..., $D_{t,N}$ are dummy variables that equal 1 when $t \in [+1,+2], [+1,+3], \ldots, [+1,+N]$, respectively, and 0 otherwise. $\theta_{i,n}$ is the coefficient of the average abnormal return on the event day or post-event days. The coefficient $\theta_{i,n}$ is also used to compute the post-event ACARs over a post-event window of n days. We define $ACAR_{i,n} = \theta_{i,n} \times n$ as the ACAR associated with commodity future i over the window of n days following the price shocks. The statistical significance of the $ACAR_{i,n}$ is based on the t-statistic associated with parameter $\theta_{i,n}$. Specifically, ACAR0 and ACAR1 are the abnormal returns on the day of the shock and the day after the shock, respectively. ACAR2, ACAR3, ..., ACAR10 are the ACARs over the [1, 2], [1, 3], ..., [1, 10] day windows after the shock. The asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Panel A: ACARs following positive shocks

Commodity	ACAR0	ACAR1	ACAR2	ACAR3	ACAR4	ACAR5	ACAR6	ACAR7	ACAR8	ACAR9	ACAR10
Soybeans	3.347***	0.038	0.025	0.03	0.016	-0.063	-0.065	-0.033	-0.042	0.001	-0.007
Soybean meal	3.735***	-0.016	0.076	0.128	0.103	0.021	0.049	0.047	0.075	0.094	0.062
Soybean oil	3.539***	-0.139	-0.19	-0.076	-0.056	-0.077	-0.073	-0.029	-0.011	0.001	-0.007
Corn	4.100***	-0.021	0.086	0.104	0.091	0.046	0.048	0.062	0.039	0.057	0.047
Oats	5.376***	0.124	0.069	0.071	0.088	0.075	0.063	0.037	0.024	0.053	0.044
Wheat	4.380***	0.111	0.113	0.153	0.086	0.023	0	-0.004	0.01	0.046	0.048
Cocoa	4.903***	0.264*	0.11	0.043	0.031	0.017	0.013	-0.007	0.038	-0.012	-0.009
Coffee	5.268***	-0.06	0.05	0.127	0.121	0.094	0.007	-0.037	-0.003	-0.014	0.003
Sugar	7.718***	-0.510**	-0.541***	-0.211	-0.097	-0.089	-0.044	-0.025	-0.068	-0.088	-0.079
Cotton	3.807***	0.095	0.057	0.101	0.116	0.096	0.054	0.066	0.05	0.081	0.067
Heating oil	4.810***	-0.194	-0.124	-0.013	0.045	-0.014	-0.063	0.003	-0.014	-0.05	-0.041
Gold	2.339***	0.08	0.046	0.065	0.03	0.004	0.004	0.025	0.019	0.025	0.029
Silver	3.739***	0.224	0.243	0.228	0.154	0.127	0.107	0.069	0.048	0.057	0.047
Copper	3.746***	-0.521***	-0.287***	-0.189***	-0.197***	-0.168***	-0.172***	-0.153***	-0.150***	-0.136***	-0.107**
Live cattle	2.758***	0.196***	0.134***	0.138***	0.119***	0.078*	0.065*	0.066*	0.049	0.043	0.034
Feeder cattle	2.011***	0.155***	0.114***	0.068	0.039	0.037	0.019	0.016	0.016	0.001	-0.006
Hogs	6.821***	-0.163	-0.146	-0.102	-0.176	-0.146	-0.174	-0.174	-0.163	-0.158	-0.148
Pork bellies	5.685***	0.534***	0.361***	0.298***	0.267***	0.275***	0.413***	0.345***	0.344***	0.336***	0.353***

Table 3 (Continued)

Panel B: ACARs following negative shocks											
Commodity	ACAR0	ACAR1	ACAR2	ACAR3	ACAR4	ACAR5	ACAR6	ACAR7	ACAR8	ACAR9	ACAR10
Soybeans	-3.534***	-0.216*	-0.161**	-0.186***	-0.153***	-0.112***	-0.099***	-0.082*	-0.069	-0.062	-0.047
Soybean meal	-4.092***	-0.135	-0.122	-0.068	-0.055	-0.033	0.022	0.006	0.022	-0.013	-0.017
Soybean oil	-3.634***	-0.226*	-0.102	-0.063	-0.115	-0.043	0.004	0.025	0.006	0.005	0.014
Corn	-3.576***	-0.415***	-0.141	-0.073	-0.051	-0.047	0	0.006	0.006	-0.002	0.006
Oats	-5.110***	-0.182	-0.117	-0.033	0.007	0.076	0.111	0.116	0.109	0.065	0.034
Wheat	-4.128***	-0.189	-0.019	0.108	0.096	0.053	0.016	0	-0.023	-0.038	0
Cocoa	-4.777***	-0.023	0.057	-0.017	-0.038	-0.023	-0.01	-0.045	-0.04	-0.035	-0.033
Coffee	-5.545***	-0.244	0.035	-0.039	-0.056	-0.005	-0.023	-0.069	-0.07	-0.06	-0.065
Sugar	-6.643***	-0.664***	-0.282	-0.229	-0.193	0.071	0.132	0.078	0.105	0.121	0.11
Cotton	-4.281***	0.04	0.021	0.025	-0.084	-0.095	-0.031	-0.016	-0.039	-0.028	-0.006
Heating oil	-5.707***	0.061	0.104	0.171	0.095	0.12	0.096	0.126	0.138	0.12	0.111
Gold	-2.580***	-0.021	0.061	0.017	-0.026	0.018	0.019	0.014	0.021	0.01	-0.006
Silver	-4.258***	-0.216	-0.053	-0.045	-0.043	-0.041	-0.026	-0.021	0.02	0.001	0.004
Copper	-4.073***	-0.212	-0.125	-0.11	-0.02	-0.03	-0.088	-0.065	-0.054	-0.051	-0.017
Live cattle	-2.818***	-0.223***	-0.116*	-0.108***	-0.105***	-0.067*	-0.022	-0.033	-0.027	-0.026	-0.025
Feeder cattle	-2.149***	-0.114*	-0.094*	-0.097***	-0.060*	-0.054*	-0.049*	-0.037	-0.011	0.011	0.019
Hogs	-5.798***	-0.394***	-0.155	-0.161	-0.118	-0.167	-0.116	-0.1	-0.068	-0.09	-0.115
Pork bellies	-4.958***	-0.534***	-0.061	-0.043	-0.094	-0.133	-0.144	-0.201	-0.187	-0.155	-0.176

Table 4: Commodity futures price reaction to shocks: Risk-adjusted ACARs

The risk-adjusted abnormal return estimates are obtained as follows:

$$R_{i,t} = \alpha_i + \gamma_{i,n}D_{t,n} + \beta_{Bond0}(R_{Bond,t} - R_{f,t}) + \beta_{Bond1}(R_{Bond,t} - R_{f,t})D_{t,n} + \beta_{S\&P0}(R_{S\&P,t} - R_{f,t}) + \beta_{S\&P1}(R_{S\&P,t} - R_{f,t})D_{t,n} + \beta_{GSCI0}(R_{GSCI,t} - R_{f,t}) + \beta_{GSCI}(R_{GSCI,t} - R_{f,t})D_{t,n} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the log return of commodity i on day t; $R_{Bond,t}$, $R_{S\&P,t}$ and $R_{GSCI,t}$ are the returns on the DataStream government bond index, the S&P 500 composite index and GSCI (Goldman Sachs Commodity Index), respectively; $R_{f,t}$ is the risk-free rate; $\varepsilon_{i,t}$ is the residual term with zero mean and constant variance. The coefficient $\gamma_{i,n}$ captures the abnormal return on the event day of the shock or post-event day, after accounting for the event-induced systematic risk. The cumulative abnormal return over a window of n days is specified as $ACAR_{i,n} = \gamma_{i,n}$ x n. Specifically, ACAR0 and ACAR1 are the abnormal returns on the day of the shock and the day after the shock, respectively. ACAR2, ACAR3,..., ACAR10 are the average cumulative abnormal returns over the [1, 2], [1, 3], ..., [1, 10] day windows after the shock. The asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Panel A: Risk-adjusted ACARs following positive shocks											
Commodity	ACAR0	ACAR1	ACAR2	ACAR3	ACAR4	ACAR5	ACAR6	ACAR7	ACAR8	ACAR9	ACAR10
Cocoa	4.625***	0.573**	0.321*	0.25	0.069	0.007	-0.032	-0.05	-0.01	-0.118	-0.102
Sugar	6.855***	-0.481	-0.581*	-0.247	-0.016	-0.144	-0.162	-0.152	-0.201	-0.141	-0.117
Copper	3.769***	-0.897***	-0.327**	-0.201	-0.115	-0.193	-0.221**	-0.191**	-0.231**	-0.186*	-0.165*
Live cattle	3.082***	-0.05	0.138	0.158	0.036	-0.009	-0.033	-0.019	-0.05	-0.056	-0.055
Feeder cattle	1.840***	0.283**	0.202**	0.102	0.067	0.138**	0.065	-0.022	-0.037	-0.056	-0.022
Pork bellies	3.385***	0.787*	0.367	0.28	0.261	0.233	0.317	0.274	0.169	0.162	0.187
Panel B: Risk-adjusted ACARs following negative shocks											
Commodity	ACAR0	ACAR1	ACAR2	ACAR3	ACAR4	ACAR5	ACAR6	ACAR7	ACAR8	ACAR9	ACAR10
Soybeans	-4.267***	0.121	-0.005	-0.205*	-0.173*	-0.171*	-0.148*	-0.134*	-0.123	-0.097	-0.088
Soybean oil	-3.634***	0.033	-0.208	-0.175	-0.158	-0.135	-0.098	-0.107	-0.101	-0.087	-0.098
Corn	-4.162***	-0.142	0.028	-0.036	0.062	-0.071	-0.008	0.004	-0.022	-0.028	-0.009
Sugar	-6.364***	-1.632***	-0.852***	-0.632**	-0.646***	0.052	0.096	0.073	0.043	0.067	0.087
Live cattle	-2.703***	-0.144	-0.225**	-0.226**	-0.144*	-0.106	-0.075	-0.118	-0.088	-0.082	-0.086*
Feeder cattle	-2.177***	-0.161	-0.294***	-0.257***	-0.170**	-0.153**	-0.117**	-0.084	-0.038	-0.041	-0.054
Hogs	-6.148***	-0.502	-0.581**	-0.386	-0.407**	-0.284	-0.119	-0.218	-0.126	-0.162	-0.158
Pork bellies	-4.580***	-0.760***	-0.117	-0.023	-0.145	-0.203	-0.135	-0.208	-0.172	-0.137	-0.107

Table 5: LM test for the ARCH effect

This table reports the results of the Lagrange multiplier (Engle's ARCH) test used to assess the presence of first-order ARCH in the commodity futures price series.

Commodity futures	F-statistics	Probability
Cocoa (lag4)	33.656	0.000
Sugar (lag4)	33.656	0.000
Copper	232.044	0.000
Feeder cattle	165.72	0.000
Pork bellies	0.002	0.966

Table 6: Commodity price reaction to shocks: Risk-adjusted and conditional heteroskedasticity-adjusted ACARs

The risk-adjusted and conditional heteroskedasticity-adjusted abnormal return estimates are obtained as follows:

$$R_{i,t} = \alpha_i + \gamma_{i,n} D_{t,n} + \beta_{Bond0}(R_{Bond,t} - R_{f,t}) + \beta_{Bond1}(R_{Bond,t} - R_{f,t})D_{t,n} + \beta_{S\&P0}(R_{S\&P,t} - R_{f,t}) + \beta_{S\&P1}(R_{S\&P,t} - R_{f,t})D_{t,n} + \beta_{GSCI0}(R_{GSCI,t} - R_{f,t}) + \beta_{GSCI}(R_{GSCI,t} - R_{f,t})D_{t,n} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the log return of commodity i on day t; $R_{Bond,t}$, $R_{S\&P,t}$ and $R_{GSCI,t}$ are the returns on the DataStream government bond index, the S&P 500 composite index and GSCI (Goldman Sachs Commodity Index), respectively; $R_{f,t}$ is the risk-free rate; $\varepsilon_{i,t}$ is the residual term, assumed to have constant mean and time-varying variance $h_{i,t}^2 = \delta_i + \pi_{0,i}\varepsilon_{t-1}^2 + \pi_{1,i}h_{i,t-1}^2 + \pi_{2,i}I_{i,t-1}\varepsilon_{t-1}^2$.

The coefficient $\gamma_{i,n}$ captures the abnormal return on the event day of the shock or post-shock, after accounting for the event-induced systematic risk and conditional heteroskedasticity in the residuals. The average cumulative abnormal return over a window of n days is specified as $ACAR_{i,n} = \gamma_{i,n}$ x n. More specifically, ACAR0 and ACAR1 are the abnormal returns on the day of the shock and the day after the shock, respectively. ACAR2, ACAR3,..., ACAR10 are the average cumulative abnormal returns over the [1, 2], [1, 3],..., [1, 10] day windows after the shock. The asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Panel A: ACARs following positive shocks											
Commodity	ACAR0	ACAR1	ACAR2	ACAR3	ACAR4	ACAR5	ACAR6	ACAR7	ACAR8	ACAR9	ACAR10
Cocoa	4.472***	0.537*	0.281	0.216	0.026	-0.03	-0.05	-0.078	-0.059	-0.133	-0.108
Copper	3.248***	-0.344	-0.094	0.081	0.047	-0.026	-0.038	-0.039	-0.092	-0.083	-0.081
Feeder cattle	1.684***	0.250**	0.184**	0.088	0.045	0.12	0.054	-0.022	-0.024	-0.04	-0.011
Pork bellies	2.918***	0.441	0.37	0.196	0.377***	0.274**	0.372***	0.368***	0.271***	0.208**	0.211**
Panel B: ACARs following negative shocks											
Commodity	ACAR0	ACAR1	ACAR2	ACAR3	ACAR4	ACAR5	ACAR6	ACAR7	ACAR8	ACAR9	ACAR10
Sugar	-6.375***	-0.691**	-0.32	-0.333	-0.306*	-0.343**	-0.253*	-0.13	-0.094	-0.107	-0.024
Pork bellies	-4.341***	-0.1	0.286	0.389**	0.213	0.115	0.123	-0.052	-0.021	-0.054	-0.032