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# Are commodity futures markets short-term efficient? An empirical investigation

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## Abstract

This study examines individual commodity futures price reaction 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 conducting appropriate systematic risk and conditional heteroskedasticity adjustments, we show that almost all commodity futures react efficiently to shocks.

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

**JEL code** C13, C22, G14

## 1. Introduction

Several studies report price anomalies following large one-day asset price changes or "shocks". Most of these studies focus on the post-shock abnormal returns of individual stocks, stock indexes and stock index futures[1]. Consistent with the prediction of the overreaction hypothesis, Bremer and Sweeney (1991) and Bowman and Iversion (1998) report significantly positive abnormal returns after stock daily price changes of -10% or less. Although Cox and Peterson (1994) and Atkins and Dyl (1990) find overreaction disappear after controlling for the bid-ask spread bounces, Lehmann (1990) and Bremer et al. (1997) show that the overreaction patterns persist even after accounting for the bid-ask spread bounces or transaction costs. Lasfer et al. (2003) show that stock index prices exhibit momentum patterns post-shocks. Grant et al. (2004) find that US stock index futures overreact to large intraday price changes. Fung and Lam (2004) provide a strong overreaction evidence of intraday trading and market closing on Hang Seng Index futures. Similar results are also reported by Rentzler et al. (2006) in the Japanese stock futures market.

This study is the first to examine the commodity price reaction to large one day price changes. There are several advantages to studying the short-term price reaction to shocks in the commodity futures markets rather stock markets. It has been argued 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 relatively low transactions cost environment than stock markets[2]. Furthermore, futures contracts tend to be highly liquid nearby maturities 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 lack of liquidity.

Several studies examine the long-term and medium-term efficiency of the commodity futures markets. Erb and Harvey (2006) show that abnormal profits can be generated from a momentum strategy with a 12-month ranking period and 1-month holding period. Miffre and Rallis (2007) study the performance of medium-term (up to 12 months) momentum and long-

[1] Bremer and Sweeney (1991), Bowman and Iversion (1998), Cox and Peterson (1994) and Atkins and Dyl (1997) examine stock price reaction shocks. Lasfer et al. (2003) and Mazouz et al. (2009), among others, focus on the stock index price patterns following large daily changes. Studies on the index futures price reaction to daily shocks include Grant et al. (2004), Fung and Lam (2004) and Rentzler et al. (2006).

[2] Locke and Vekatesh (1997) show that the transaction costs in the futures markets range between 0.0004% and 0.033%. These figures are much smaller than the transaction costs of 0.5% and 2.3% reported by Jegadeesh and Titman (1993) and Lesmond et al. (2004), respectively, in the stock market.

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.

Studies on the short-term efficiency in commodity futures markets focus mainly on the relationship between futures and spot prices. McKenzie and Holt (2002), for example, use cointegration and error correction models with GQARCH-in-mean process to test the market efficiency and unbiasedness of four commodity futures traded in 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 Soybean futures market. Although some of the existing studies detect short-term anomalies in the commodity futures, they do not test whether profitable trading strategies can formulated to exploit these anomalies. By investigating the persistence in the price movements, this study does not only offer an alternative test for the short-term efficiency in the commodity futures markets, but it also allow 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. 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] window relative to the day of the shock. Then, we use a dummy variable approach, similar to that of Karafiath (1988) and Mazouz et al. (2009), to estimate the abnormal returns following shocks.

Our initial results indicate that the persistence of price movements following shocks varies substantially across markets. Although 12 out the 18 commodity futures, included in our sample, react efficiently to positive surprises, investors in Cocoa, Live Cattle, Feeder Cattle and Pork Bellies (Sugar and Copper) futures underreact (overreact) to positive shocks. We also find that 8 of the 18 commodity futures underreact to negative shocks and remaining 10 absorb negative shocks immediately. The underreaction evidence is in line with the findings in equity market indexes (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 drawing any conclusions. Miffre and Rallis (2007) show individual commodity future 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 uncertainly 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 the 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, Feeder Cattle and Pork Bellies (Sugar and Pork Bellies) are the only commodity futures with statistically significant first day abnormal return following positive (negative) shocks. Conditional heteroskedasticy adjustment reduced the number of overreaction and underreaction cases even further. Specifically, with the exception of a one- to two-day delay in the price adjustment of Cocoa and Feeder Cattle (Sugar) futures to positive (negative) surprises, all other commodity futures react efficiently to both positive and negative shocks.

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

## 2. Data

We analyse a wide range of commodity futures from agricultural, energy and metal commodity futures markets. These commodity futures are: 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. The dataset for all the commodity futures, except Silver and Copper, spans over 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 to be appropriate to form the daily futures price series (Yang et al. 2001). Other data, such as government bond index, the S&P composite index, Goldman Sachs Commodity (GSCI) and the 3-month Treasury bill, is also downloaded from DataStream.

**[Insert Table 1 about here]**

## 3. Test 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 behavior following daily price change of ≤ -10%. Lasfer et al. (2003) argue that using a single value to identify the day of 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 positive (negative) shocks in the commodity futures series. Specifically, the day of a positive (negative) price shock, i.e. the event day 0, is defined as one where the return on a particular day is above (below) the average market daily returns plus (minus) two standard deviations of daily returns. The average market return and the standard deviation of returns are calculated over [-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.

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 the maximum values of the price shock contained in the price series of our commodity futures. The average value of the positive (negative) shocks 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 positive (negative) shocks, we employ the following dummy variable approach to estimate both the event and post-event abnormal returns[3]

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

where $R_{i,t}$ is the daily log return. $\alpha_i$ 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 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], …, [+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 by testing for the null hypothesis of the coefficient $\theta_{i,n} = 0$, if the null hypothesis is rejected, it would indicate the weak-from efficiency hypothesis is violated and therefore the opportunities of earning abnormal profits may 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 a commodity futures $i$ over a window of $n$ days following price shocks. $\varepsilon_{i,t}$ is normally distributed error term with a zero mean and a constant variance.

Table 3 presents the ACARs over a window of 10 days after a positive shock for each commodity futures. Although all the abnormal returns in 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 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 Sugar futures are negative for up to ten days following positive shocks, but only ACAR1 and ACAR2 are significantly different from zero. The overreaction

[3] 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)

to positive shocks is much stronger in 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 significantly 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 take 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 return of the affected firms increase systematically. Several studies, including Cahordia 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 the 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

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

where $R_{Bond,t}$ , $R_{S\&P,t}$ and $R_{GSCI,t}$ are the returns on 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; $\gamma_{i,n}$ is the coefficient for the abnormal return of the event day or window after the shock. The coefficient $\gamma_{i,n}$ in Eq.(2) informs us 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 a 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 the parameters$\beta_{Bond0}$, $\beta_{S\&P0}$ and $\beta_{GSCI0}$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, equity market and commodity market. The coefficients $\beta_{Bond1}$ , $\beta_{S\&P1}$ and $\beta_{GSCI}$ are also shown to be significant in various occasions, indicating that price shocks cause significant effect on the systematic risk of the commodity futures[4].

[**Insert Table 4 about here**]

Table 4 shows that the post-positive-shock underreaction patterns observed in Sugar and Live Cattle futures disappears completely following appropriate risk adjustments. In other words, after adjusting the systematic risk, significant first day ACARs exist only in Cocoa, Feeder Cattle and Pork Bellies commodity futures following positive shocks. Similarly, the number of commodity futures with statistically significant post-negative-shock first day ACARs has reduced substantially after controlling for the systematic risk. The results from Eq.(2) indicate that Sugar and Pork Bellies are the only commodities with significant ACARs following negative shocks.

[**Insert Table 4 about here**]

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

*3.4. Conditional heteroskedasticity adjustments*

One weakness of Eq.(2) is the 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 affect 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 leads to substantially higher rejection rate than the traditional OLS methods.

The results from the LM test indicates the presence of the first order ARCH (ARCH(1)) in the residual series of all the commodity futures included in our analysis[5]. To test whether the post-shock ACARs associated with Cocoa, Feeder Cattle, Pork Bellies and Sugar futures remain significant after accounting for the ARCH effect, we use the following GJR-GARCH (1,1) process to model the variance of 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, $\varepsilon_{i,t}$; $\delta_i$ 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.

[**Insert Table 5 about here**]

The conditional heteroskedasticity-adjusted ACARs associated with Cocoa, Feeder Cattle and Pork Bellies futures following positive shocks and Sugar and Pork Bellies futures following negative shocks are reported in Table 5. 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.

[5] Details on the LM test are available upon request.

However, the first day post-negative-shock ACAR associated with Sugar futures remains significant at 5% and positive surprises are incorporated into Feeder Cattle (Cocoa) futures prices with a one day (two days) delay.

## 5. Conclusion

This study examines, for the first time, individual commodity futures price reaction to shocks. It shows that the post-shock price patterns are highly sensitive to the abnormal returns are estimated. The mean-adjusted abnormal return model suggest 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 positive shocks is only observed in Feeder Cattle and Cocoa and Sugar is the only commodity with a statistically significant first day post-negative-shock ACAR. This finding indicates that the efficient market hypothesis should not be rejected unless the post-shock price patterns pass highly stringent tests.

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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 a particular day is above (below) the average market daily returns plus (minus) two standard deviations of daily returns. The average market return and the standard deviation of returns are calculated over [-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 (in 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 Eq.(1) in Section 3.2. ACAR0 and ACAR 1 are the abnormal returns on the day of the shock and one after the shock, respectively. ACAR2, ACAR3, ..., ACAR10 are the average cumulative abnormal returns over the [1, 2], [1, 3], ..., [1, 10] 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)**

**Commodity price reaction to shocks: Mean-adjusted ACARs**

The mean adjusted abnormal return estimates are obtained from Eq.(1) in Section 3.2. ACAR0 and ACAR 1 are the abnormal returns on the day of the shock and one after the shock, respectively. ACAR2, ACAR3, ..., ACAR10 are the average cumulative abnormal returns over the [1, 2], [1, 3], ..., [1, 10] windows after the shock. The asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

| Panel B: ACARs following negative shocks | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Commodity | Mean AR | CAR1 | CAR2 | CAR3 | CAR4 | CAR5 | CAR6 | CAR7 | CAR8 | CAR9 | CAR10 |
| 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 returns estimates are obtained from Eq.(2) in Section 3.3. ACAR0 and ACAR 1 are the abnormal returns on the day of the shock and one after the shock, respectively. ACAR2, ACAR3, ..., ACAR10 are the average cumulative abnormal returns over the [1, 2], [1, 3], ..., [1, 10] windows after the shock. The asterisks $^{***}$, $^{**}$ and $^{*}$ indicate significance at 1%, 5% and 10%, respectively.

Panel A: Risk-adjusted ACARs following positive shocks

| Commodity | Mean AR | 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 | Mean AR | 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**

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

The risk- and conditional heteroskedasticity-adjusted abnormal returns estimates are obtained from Eq.(3) in Section 3.4. ACAR0 and ACAR 1 are the abnormal returns on the day of the shock and one after the shock, respectively. ACAR2, ACAR3, ..., ACAR10 are the average cumulative abnormal returns over the [1, 2], [1, 3], ..., [1, 10] windows after the shock. The asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

| Panel A: ACARs following positive shocks | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Commodity | Mean AR | 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 | Mean AR | 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 |