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Abstract

This paper contributes to the debate on commodity financialization by extending tests of herd behavior to the commodity futures markets. Utilizing a regime-switching model, we test the presence of herd behavior in a number of commodity sectors including energy, metals, grains and livestock during the low and high market volatility states. We find significant evidence of herd behavior in grains only during the high volatility state. We also find that large price movements in the energy and metals sectors significantly contribute to herd behavior in the market for grains. Finally, we find no significant effect of the stock market on herd behavior in the commodity futures market. Our findings in general do not support the much debated commodity financialization hypothesis.

JEL Classification Code: G14, G15

Keywords: Herd behavior, Commodity financialization, Return dispersion, Markov switching

1. Introduction

Speculation in commodity markets has been the source of heated discussions among policy makers as well as in the media. Particularly, the 2008 bubble in the prices of a wide range of commodities has focused policy makers' attention to the role of financial investors' activities in commodity markets. Echoing George Soros' statements in a testimony before the U.S. Senate Commerce Committee Oversight Hearing on FTC Advanced Rulemaking on Oil Market Manipulation[1], Gilbert (2009) suggests that a new class of investors that has emerged in financial markets regard commodities as an asset class, comparable to stocks, bonds, real estate, and emerging market assets, and take positions on commodities as a group in order to capture profits that are not possible to obtain from traditional assets. Amazingly, at the peak of the price bubble in 2008, commodity fund investors, including hedge funds like Soros Fund Management, controlled a record 4.51 billion bushels of corn, wheat and soybeans through the futures markets of Chicago Board of Trade, equal to half the amount held in U.S. silos on March 1, 2008.[2] In a testimony before the U.S. Senate Committee of Homeland Security and Government Affairs, Michael W. Masters, a portfolio manager and partner at the ***Masters*** Capital Management, LLC stated:[3]

> "… You have asked the question "Are institutional investors contributing to food and energy price inflation?" And my unequivocal answer is YES."

In his testimony before the U.S. Senate Commerce Committee, George Soros also stated that commodity investment, as a new venue for institutional investors, had become "the elephant in the room" and as a result, investment in these assets might exaggerate price rises. To this end, a number of studies on financial markets have suggested that herd formation among large

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[1] Soros, G. (2008), Testimony before the U.S. Senate Commerce Committee Oversight Hearing on FTC Advanced Rulemaking on Oil Market Manipulation, Washington D.C., 4 June 2008.

[2] Wilson, J. (2008), "Wall Street Grain Hoarding Brings Farmers, Consumers Near Ruin," Bloomberg, (April 28, 2008)

[3] Masters, M.W. (2008), Testimony before the U.S. Senate Committee of Homeland Security and Government Affairs, Washington, DC, 20 May 2008.

institutional investors may destabilize market prices and create excess volatility (Dennis and Strickland, 2002; Luo, 2003; Gabaix et al., 2006). Therefore, one may argue that herd behavior in the commodity market, possibly driven by financial investors moving funds in and out of commodities, is a contributing factor behind the booms and busts observed in a wide range of commodities.

On the other hand, studies including Krugman (2008), Hamilton (2009), and Kilian (2009) reject the so-called commodity financialization hypothesis and suggest that commodity price cycles are mainly driven by supply and demand balances in global markets, largely due to growth trends in emerging economies. Adding support to this view, Buyuksahin and Harris (2011) examine the trading positions of various types of traders in the crude oil market and find little evidence that financial investors' position changes cause price changes in the oil market. Given the conflicting views in both directions, investor behavior in the commodity market and how it relates to the excessive price movements is yet to be explored.

The main goal of this paper is to contribute to the discussion on the financialization of commodities from a different angle by extending tests of herd behavior to commodity futures markets. Utilizing a methodology applied to a number of financial markets, we examine price data from energy, grains, livestock, and metals futures and test whether herd behavior is present during the low and high market volatility states. Our findings suggest the presence of herd behavior in the market for grains only with no evidence of herding in other commodity sectors. Herd behavior in grains is observed during the high market volatility state only. Furthermore, the results do not suggest a significant effect of stock market movements on herding in commodity markets, thus providing evidence against the commodity financialization hypothesis. On the other hand, a significant cross-market herding effect on grains is observed from the energy and metals markets, suggesting that large price movements in energy and metals tend to contribute to herding among investors in grains futures. Our findings are robust during the post-2004 period when the commodity market experienced a large influx of financial investors driving a dramatic rise in open interest and trading volume in commodities (Figure 1), further supporting evidence against the commodity financialization hypothesis.

An outline of the remainder of the paper is as follows. Section 2 summarizes the literature on herd behavior. Section 3 provides the details of the testing methodology and data description. Section 4 presents empirical results. Finally, Section 5 concludes the paper.

2. Previous Studies

A number of studies in the literature have examined herd behavior in different markets and using alternative methodologies. Christie and Huang (1995) describe herd behavior as a tendency for individuals to suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions. Bikhchandani and Sharma (2001) define herding as an obvious intent by investors to copy the behavior of other investors and buy and sell an asset as a group. Studies including Shleifer and Summers (1990), Avery and Zemsky, (1998), and Chari and Kehoe (2004) propose an information based theory for herding where individual investors follow the signals from the trades of more informed agents with better access to information compared to individual investors. Devenow and Welch (1996) suggest that managers in an imperfectly informed market may prefer either to 'hide in the herd' not to be evaluable, or to 'ride the herd' in order to prove quality. Other studies including Scharfstein and Stein (1990), Rajan (1994), Graham (1999), and Swank and Visser (2008) suggest that fund managers imitate others as a result of the incentives provided by the compensation scheme or in order to maintain their reputation. Nevertheless, whatever the rationale behind such behavior may be, studies including Dennis and Strickland (2002), Luo (2003), and Gabaix et al. (2006) suggest that herd behavior may lead to excess volatility by leading asset prices deviate from fundamental values.

The literature offers an extensive list of studies on herd behavior applied to a number of different markets. A commonly used testing methodology that is based on asset return dispersions is utilized in Christie and Huang (1995) on U.S. equities, Chang et al. (2000) on international equities, Gleason et al. (2003) on commodity futures traded on European exchanges, Gleason at al. (2004) on exchange traded funds, Demirer and Kutan (2006) and Tan et al. (2008) on Chinese stocks, Demirer et al. (2010) on Taiwanese stocks, Chiang and Zheng (2010) on global stock markets, and more recently Philippas et al. (2013) on REITs and Balcilar et al. (2013) on Gulf Arab stock markets. However, these tests have not yet been extended to U.S. commodity futures. Regarding studies on commodity markets, starting with Pindyck and Rotemberg (1990), several studies have suggested that herding among traders may lead to excess comovements among commodity prices. Wiener (2006) examines speculative behavior in the international oil market in the mid-1990s and finds that some subgroups of investors tend to act in parallel in their trades. Similarly, Gilbert (2009) distinguishes between speculators and commodity funds and finds some evidence of short-run explosive behavior in non-ferrous metals markets due to speculative activities.

On the other hand, Chunrong et al. (2006) reject speculation and herding as the source of commodity price comovements, providing evidence against herding in commodity markets. Adrangi and Chatrath (2008) acknowledge some degree of relation among the positions of commodity traders, however their results show the relatedness falls short of herding. Similarly, Boyd et al. (2009) examine trading data and find that herding among hedge funds does not destabilize the crude oil market. More recently, Steen and Gjolberg (2013) examine the correlation patterns and principal components describing commodity returns in order to make inferences on herd behavior and find no significant support. In short, the literature provides conflicting evidence on herd behavior in commodity markets. Interestingly, the return dispersion based methodology that is used extensively in the literature to test the presence of herd behavior has not yet been extended to U.S. commodity futures markets. The only exception is Gleason et al. (2003) who examine commodity futures traded on European exchanges and find that traders in European futures markets do not have herding tendencies. To the best of our knowledge, this study is the first to extend return dispersion based herding tests to U.S. commodity futures.

3. Data and Methodology

3.1 Data

The dataset consists of twenty futures contracts: five energy (crude oil, heating oil, natural gas, gasoline and ethanol), four livestock (feeder cattle, live cattle, lean hogs, and pork bellies), six grains and oil seeds (wheat, corn, soybeans, oats, rapeseed and rough rice), and five metals (gold, silver, platinum, palladium and copper). Daily nearby futures prices covering the period between Jan. 17, 1995 and Nov. 30, 2012 are obtained from Commodity Systems Inc. The returns for the nearby month futures contracts are utilized in the tests. Nearby futures prices are constructed with contract rollover occurring about one week before the maturity in most cases. The trading volume is used as a criterion in deciding the actual rollover date.

3.2 Methodology

We follow a commonly utilized methodology to detect herding behavior in financial markets. Originally suggested by Chang et al. (2000), the testing methodology focuses on the relation between the dispersion of asset returns within a portfolio of assets with similar characteristics and market movements. Dispersion of returns within a portfolio is measured by the cross-sectional absolute deviation of returns (CSAD) expressed as

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} | R_{i,t} - R_{m,t} | \qquad \textbf{(1)}$$

where N is the number of assets in the portfolio, $R_{i,t}$ is the return on asset i for day t and $R_{m,t}$ is the daily return on a measure of the overall sector. Bikhchandani and Sharma (2001) suggest that herding behavior would be more likely to occur at the level of investments in similar assets where investors face similar decision problems and can observe the trades of others in the group. For this purpose, we organize each futures contract into four commodity sectors, i.e. energy livestock, grains and metals. Each commodity sector is represented by the corresponding S&P GSCI index.

The return dispersion measure in Equation 1 can be regarded as a proxy to individual asset return dispersion around the market return. From an efficient market perspective, one would expect return dispersion to increase with the absolute value of market return since each asset in the portfolio differs in its sensitivity to market shocks. However, Chang et al. (2000) argue that the presence of herding behavior would lead asset returns not to deviate far from the overall market return. In other words, the correlated actions of traders as they suppress their own beliefs and make investment decisions based solely on the collective actions of the market, would lead asset returns to display greater directional similarity, thus leading to lower return dispersion within the commodity portfolio. Since such an investment behavior would be more likely to occur during periods of market stress characterized by large price movements, Chang et al. (2000) propose a testing methodology based on a general quadratic relationship between return dispersion and market return in order to detect herd behavior. In this study, we estimate a generalized version of the model by Chang et al. (2000) which accounts for the GARCH effects in the time series and estimate for commodity sector *k*

$$
\begin{aligned}
CSAD_{k,t} &= \alpha_0 + \alpha_1 \left| R_{k.t} \right| + \alpha_2 R_{k.t}^2 + e_t \\
e_t &= \sqrt{h_t}\,\varepsilon_t, \quad \varepsilon_{t|t-1} \sim N(0,1) \\
h_t &= \beta_0 + \beta_1 h_{t-1} + \beta_2 e_{t-1}^2
\end{aligned}
\qquad \textbf{(2)}
$$

where $CSAD_{k,t}$ is the cross-sectional absolute deviation of futures contract returns in commodity sector *k* and $R_{k,t}$ is the return on commodity sector *k* on day *t*. In this specification, h_t stands for the conditional variance assumed to follow a standard GARCH(1,1) process. According to the testing methodology, herding would be evidenced by a lower or less than proportional increase in the cross-sectional absolute deviation (CSAD) during periods of large price movements. As a result, observing a negative and statistically significant α_2 would be consistent with the presence of herd behavior.

A significant weakness of the model in Equation (2) is that it is static in nature, i.e. the parameters are assumed to be constant over time, ignoring possible structural breaks. Therefore, the model fails to differentiate market states during which herding behavior may or may not be present. For this purpose, we extend the static model in Equation (2) to a regime-switching framework and differentiate between low and high market volatility states. If investors are more likely to herd during periods of high market volatility, then a regime-based model should be able to identify herding and non-herding market states. In the literature, Balcilar et al. (2013) is the first study to extend herding tests to a regime-switching framework and their results show that herding tests based on the static model can fail to identify such behavior when herding is present during a particular market state only. For this purpose, we estimate a two-state Markov-Switching (MS) model in the form

$$\begin{aligned} CSAD_{k,t} &= \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t}R_{k,t}^2 + e_{t,S_t} \\ e_t &= \sqrt{h_{t,S_t}}\,\varepsilon_t\,, \quad \varepsilon_{t|t-1} \sim N(0,1), \\ h_{t,S_t} &= \beta_{0,S_t} + \beta_{1,S_t}h_{t-1,S_t} + \beta_{2,S_t}e_{t-1,S_t}^2 \end{aligned} \qquad \textbf{(3)}$$

where $S_t \in \{1,2\}$ follows a first-order two-state MS process. Similarly, h_{t,S_t} stands for the state-dependent conditional variance and is assumed to follow an independent switching GARCH(1,1) process in order to avoid problems of recombining and analytical intractability (Haas et. al., 2004). In this specification, β_{2,S_t} measures the impact of unexpected random shocks on volatility in state S_t, whereas β_{1,S_t} and β_{2,S_t} together measures the degree of state-dependent volatility persistence. If herd behavior is indeed present during the high volatility state only, $S_t = 2$, then one would expect $\alpha_{2,2}$ to be negative and significant and $\alpha_{2,1}$ to be insignificant.

On the other hand, if commodity financialization is indeed a factor driving volatility in commodity prices, then one might argue that shocks in the stock market can also be a contributing factor for herd behavior in the commodity market. That is, financial investors' correlated trading activities moving funds across stock and commodity markets may lead to a possible link between large price movements in the stock market and herd behavior in the commodity market. Therefore, in order to test possible stock market effects on herd behavior in the commodity market, we modify Equation (3) and estimate

$$
\begin{aligned}
&CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t} R_{k,t}^2 + \alpha_{3,S_t} R_{SP,t}^2 + e_{t,S_t} \\
&e_{t,S_t} = \sqrt{h_{t,S_t}}\,\varepsilon_t\,, \quad \varepsilon_{t|t-1} \sim N(0,1) \\
&h_{t,S_t} = \beta_{0,S_t} + \beta_{1,S_t} h_{t-1,S_t} + \beta_{2,S_t} e_{t-1,S_t}^2 \qquad \textbf{(4)}
\end{aligned}
$$

where $R_{SP,t}$ is the return on the S&P 500 index on day t. A similar model is utilized by Chiang and Zheng (2010) in order to examine the effect of the U.S. market on herd behavior in a number of global stock markets. In this model, observing a negative and statistically significant estimate for $\alpha_{3,s}$ suggests that large price movements in the stock market contributes to herd behavior in commodity sector k during state s.

Following Kyle and Xiong (2001), one can argue that portfolio rebalancing of commodity index funds can lead to correlated trades in related markets and thus create spillover effects across different commodities. Furthermore, a number of studies in the literature including Tyner (2010), Alghalith (2010), Du et al. (2011), and Sari et al. (2012) document causality and spillover effects across commodity sectors, in particular between energy and agricultural sectors. To this end, one might argue that the presence of herd behavior in a particular commodity sector can be associated with similar investor behavior in another sector of the commodity market. Therefore, herding comovements across different commodity sectors can be observed either as a result of common risk factors driving commodity returns or through spillover effects. Furthermore, following the commodity financialization hypothesis, one can also argue that financial investors' trading activity, particularly during periods of market stress, may lead to correlated trades across the different commodity sectors and thus lead to an association of herd behavior across different market sectors. For this purpose, we examine possible cross-herding effects and estimate an augmented model of the form

$$\begin{aligned} &CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t} R_{k,t}^2 + \alpha_{3,S_t} CSAD_{j,t} + \alpha_{4,S_t} R_{j,t}^2 + e_{t,S_t} \\ &e_{t,S_t} = \sqrt{h_{t,S_t}}\,\varepsilon_t\,, \quad \varepsilon_{t|t-1} \sim N(0,1) \\ &h_{t,S_t} = \beta_{0,S_t} + \beta_{1,S_t} h_{t-1,S_t} + \beta_{2,S_t} e_{t-1,S_t}^2 \end{aligned} \qquad \textbf{(5)}$$

where $CSAD_{j,t}$ and $R_{j,t}$ are the cross-sectional absolute deviation and the return for the commodity sector j on day t, respectively. In this model, observing a negative and statistically significant estimate for $\alpha_{4,s}$ suggests that commodity sector k tends to herd with commodity sector j during state s. Similarly, observing a positive and statistically significant estimate for $\alpha_{3,s}$ suggests the presence of co-varying risk associated with commodity sectors so that a shock in sector j tends to be correlated with a shock in commodity sector k.

4. Empirical results

4.1 Descriptive statistics

Panels A and B in Table 1 present the descriptive statistics for the average daily index returns and the cross-sectional absolute standard deviations of returns (CSAD) for each commodity sector, respectively. All commodity sectors experienced positive average returns during the sample period with the average return ranging between a high of 0.038% for energy and low of 0.010% for livestock. On the other hand, energy is the most volatile sector followed by grains. Examining the higher moments, all commodity returns with the exception of grains are negatively skewed. Livestock sector has the smallest kurtosis and volatility.

The highest level of return dispersion (Panel B) is observed in the energy sector, suggesting higher market variations across energy futures returns, compared to other commodity sectors. The high level of return dispersion observed may be due to unexpected shocks observed in the energy sector, possibly driven by the uncertainty surrounding the energy market due to a number of geopolitical issues and wars during much of the 2000s. Livestock futures, on the other hand, exhibit the lowest level of return dispersion suggesting that futures contracts in this sector display greater directional similarity, thus leading to smaller return dispersion across futures returns in this commodity sector. The low dispersion observed across livestock futures returns could be utilized in cross-hedging strategies in this commodity sector as low dispersion suggests greater directional similarity across the different livestock contracts and thus greater cross-correlations within this commodity sector.

4.2 Herding during low and high volatility states

Table 2 presents our findings for Equations 2 and 3 for the whole sample period. The estimations are done using the common sample for the period between Jan. 17, 1995 and Nov. 30, 2012 with 4,477 daily observations for each commodity sector. Consistent with standard asset pricing models, the models yield positive estimates for $\alpha_{1,s}$ (s=1,2) for all commodity sectors, as the cross-sectional variation in asset sensitivities leads to greater return dispersion as each commodity responds differently to the market return. In the case of herding tests, the static model of Equation 2 rejects herding for all commodity sectors. However, the regime-based specification yields support for herd behavior in grains during the high volatility state only (state 2) indicated by a negative and significant estimate for $\alpha_{2,2}$. As explained earlier, a non-linear and negative relation between return dispersion and market return suggests that asset returns display greater directional similarity during periods of large price movements and, according to this methodology, is consistent with herd behavior. The finding of herd behavior during the high volatility state only is also consistent with the basic rationale behind the testing methodology that investors would be more likely to exhibit herding tendencies during periods of market stress. On the other hand, the findings reject herding for the other commodity sectors. In fact, the finding of no herding for energy and metals is consistent with Pierdzioch et al. (2010) and Pierdzioch et al. (2013) who document evidence of anti-herding among oil and metal price forecasters, respectively. Pierdzioch et al. (2013) suggest that anti-herding behavior reflects a strategy among forecasters driven by incentives to scatter forecasts around a consensus forecast.

In the volatility equation, β_{2,S_t} measures the state-dependent impact of unexpected random shocks on volatility. We consistently find that the unexpected random shocks have a larger impact on volatility in the high volatility state (state 2). Similarly, we observe that volatility clustering is more pronounced in the high volatility state indicated by greater values for ($\beta_{1,S_t} + \beta_{2,S_t}$). In the case of grains for instance, $\beta_1 + \beta_2$ is estimated to be 0.217 and 0.665 for the low and high volatility states, respectively. Examining the estimates across the commodity sectors, we find that grains have the lowest volatility clustering in the high volatility state with a value of 0.665. Coupled with the earlier finding of herd behavior in grains during the high volatility state only, the relatively low degree of volatility clustering in this commodity sector is consistent with prior studies suggesting that herd behavior is a short-lived phenomenon.

Table 3 presents the estimates for Equation 4. The findings show that large price movements in the stock market are generally associated with greater return dispersions across commodity returns indicated by positive estimates for $\alpha_{3,S}$ (s=1,2) in general. This suggests that stock market movements have no significant herding effect on commodities since herding would be evidenced by significantly lower dispersion across commodity returns during large market movements. This is indeed consistent with the standard asset pricing models suggesting that assets would behave differently during periods of large movements as each asset would be different in its sensitivity to the market return shock. On the other hand, significant α_3 estimates observed, particularly in the case of metals, suggest that correlations among metal futures returns are significantly affected by large price movements in the stock market as return dispersion and correlation are closely related.[4] The lack of a significant herding effect of the stock market is consistent with Adrangi and Chatrath (2008), Buyuksahin and Harris (2011) and Steen and Gjolberg (2013) and provides support against the financialization of commodities from a different angle.

Table 4 presents the findings for cross-market herding effects described in Equation 5. In each panel, we focus on a target commodity sector and examine, in separate columns in the panel, the cross-herding effects of the remaining three commodity sectors described as the originating sector where the cross-herding effect is assumed to originate from. The findings suggest that energy and grains in general exhibit the greatest cross-market sensitivities. For example, in Panel A where the target sector is energy, all other commodity sectors are found to have significant cross-market effects with negative and significant $\alpha_{4,2}$ estimates, during the high volatility state only. Similarly, in the case of grains reported in Panel C, all commodity sectors are found to have negative effects although livestock is found to be insignificant. This suggests that grains tend to herd during the high volatility state around the energy and metals sectors, suggesting an association between herd behavior in grains and large price movements in energy and metals sectors. The finding of cross-commodity market herding effects between grains and energy futures is consistent with a number of prior studies documenting dynamic interrelationships between energy and agricultural markets including Tyner (2010), Du et al. (2011), Sari et al. (2012), and Nazlioglu et al. (2013). Our findings also show that a cross-market herding effect is present from energy to grains. The findings also suggest that positions in energy and grains futures will not provide significant diversification benefits in a portfolio as large price movements in each commodity sector would be associated with greater directional similarity across futures returns. The cross-market dispersion effect estimates $\alpha_{3,S}$ (s=1,2) in Equation 5 do not suggest a consistent pattern regarding the association of return dispersions across commodity sectors. Overall, the empirical results for the whole sample period suggest that herd behavior is present in grains

[4] See Demirer (2013) for a more detailed analysis of the relation between return dispersion and correlation.

during high volatility state with significant cross-market herding effects across energy and grains.

4.3 The effect of the post-2004 period

A number of studies including Irwin and Sanders (2012), Tang and Xiong (2012), Steen and Gjolberg (2013), among others, note the dramatic increase in the open interest and trading volume in the commodity market after 2003 due to the influx of financial investors. Malkowski (2011) notes a CFTC staff report stating that the total value of various commodity index related instruments purchased by institutional investors increased from an estimated \$15b in 2003 to at least \$200b in mid-2008. The open interest for selected commodities in Figure 1 clearly demonstrates the dramatic increase, particularly after 2004. Steen and Gjolberg (2013) document evidence of increased co-movements across commodities after 2004, however they conclude that this result is mainly driven by extreme price movements during 2008, suggesting no significant support for financialization or contamination from financial investor's activities. In order to check the robustness of our findings regarding the role of financialization on herd behavior in commodity markets, we modify Equation 3 and estimate

$$
\begin{aligned}
&CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t} R_{k,t}^2 + \delta_{1,S_t} D_{k,t} R_{k,t}^2 + e_{t,S_t} \\
&e_{t,S_t} = \sqrt{h_{t,S_t}}\,\varepsilon_t\,, \quad \varepsilon_{t|t-1} \sim N(0,1) \\
&h_{t,S_t} = \beta_{0,S_t} + \beta_{1,S_t} h_{t-1,S_t} + \beta_{2,S_t} e_{t-1,S_t}^2
\end{aligned}
\qquad \textbf{(6)}
$$

where $D_{k,t}$ is a dummy variable that takes on the value one starting with January 1, 2004. In this specification, observing a significant and negative estimate for ($\alpha_{2,S}+\delta_{1,s}$) suggests the presence of herd behavior during the post-2004 period only. Similarly, Equation 4 is modified as

$$
\begin{aligned}
&CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t} R_{k,t}^2 + \delta_{1,S_t} D_{k,t} R_{k,t}^2 + \alpha_{3,S_t} R_{SP,t}^2 + \delta_{2,S_t} D_{k,t} R_{SP,t}^2 + e_{t,S_t} \\
&e_{t,S_t} = \sqrt{h_{t,S_t}}\,\varepsilon_t\,, \quad \varepsilon_{t|t-1} \sim N(0,1) \\
&h_{t,S_t} = \beta_{0,S_t} + \beta_{1,S_t} h_{t-1,S_t} + \beta_{2,S_t} e_{t-1,S_t}^2
\end{aligned}
\qquad \textbf{(7)}
$$

in which the term $\delta_{2,s}$ is used to test the possible herding effect of the stock market during the post-2004 period.

Table 5 presents the findings for Equation 6. In general, the post-2004 period is found to have a negative effect on return dispersions overall indicated by negative and highly significant δ_1 estimates. This suggests a significant structural break in the relationship between the dispersion of commodity returns and market return shocks after 2004 and is consistent with the finding by Steen and Gjolberg (2013) of increased co-movements across commodities during this period. However, examining the estimates for ($\alpha_{2,S}+\delta_{1,s}$), we conclude that herd behavior was not present during this period, further supporting our findings for the whole sample period. The findings for Equation 7 presented in Table 6 lead to similar conclusions regarding the role of the stock market during the post-2004 period, suggesting no significant herding effect of the stock market during this period. Overall, our findings for the whole sample period as well as the post-2004 period do not yield support for the commodity financialization hypothesis.

5. Conclusions

The main goal of this paper is to contribute to the debate on commodity financialization by extending tests of herd behavior to commodity futures markets. Utilizing data from four commodity sectors including energy, grains, livestock and metals, we employ a return dispersion based testing methodology extensively used in the literature to detect herd behavior. Our findings yield significant evidence of herd behavior in the market for grains during the high volatility state only indicated by significantly lower return dispersions across grains futures returns during periods of large price movements. The finding of significantly lower return dispersions across grains futures suggests that cross-hedging strategies using grains futures may be utilized, particularly during periods of high volatility, as returns in this commodity sector would display greater directional similarity leading to lower dispersion. We also find that large price movements in energy and metals futures significantly contribute to herding in grains, providing support for the dynamic relationship between energy and agricultural commodity returns from a different angle. It is possible that volatility transmission across the energy and agricultural markets acts as a contributing factor for herd behavior among investors in the market for grains. This finding also suggests that combining assets from the energy, metals and agricultural commodity sectors in a portfolio will not provide significant diversification benefits as large price movements in each commodity sector would be associated with greater directional similarity across futures returns in the other commodity sectors, thus eroding benefits from diversification.

Consistent with Adrangi and Chatrath (2008), Buyuksahin and Harris (2011) and Steen and Gjolberg (2013), our findings for the whole sample period do not suggest that herd behavior is present in other commodity sectors. The robustness checks for the post-2004 period during which the commodity market experienced a significant influx of financial investors lead to similar results suggesting that herd behavior is not present in the other commodity sectors. Similarly, our tests do not yield a significant stock market effect on herd behavior in the commodity market both during the whole sample period and the post-2004 period. The findings are consistent with previous literature documenting anti-herding among energy and metal market forecasters. Overall, our findings do not provide any support for the commodity financialization hypothesis much debated in the media as well as among policy makers.

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Figure 1. Monthly open interest for selected commodities.

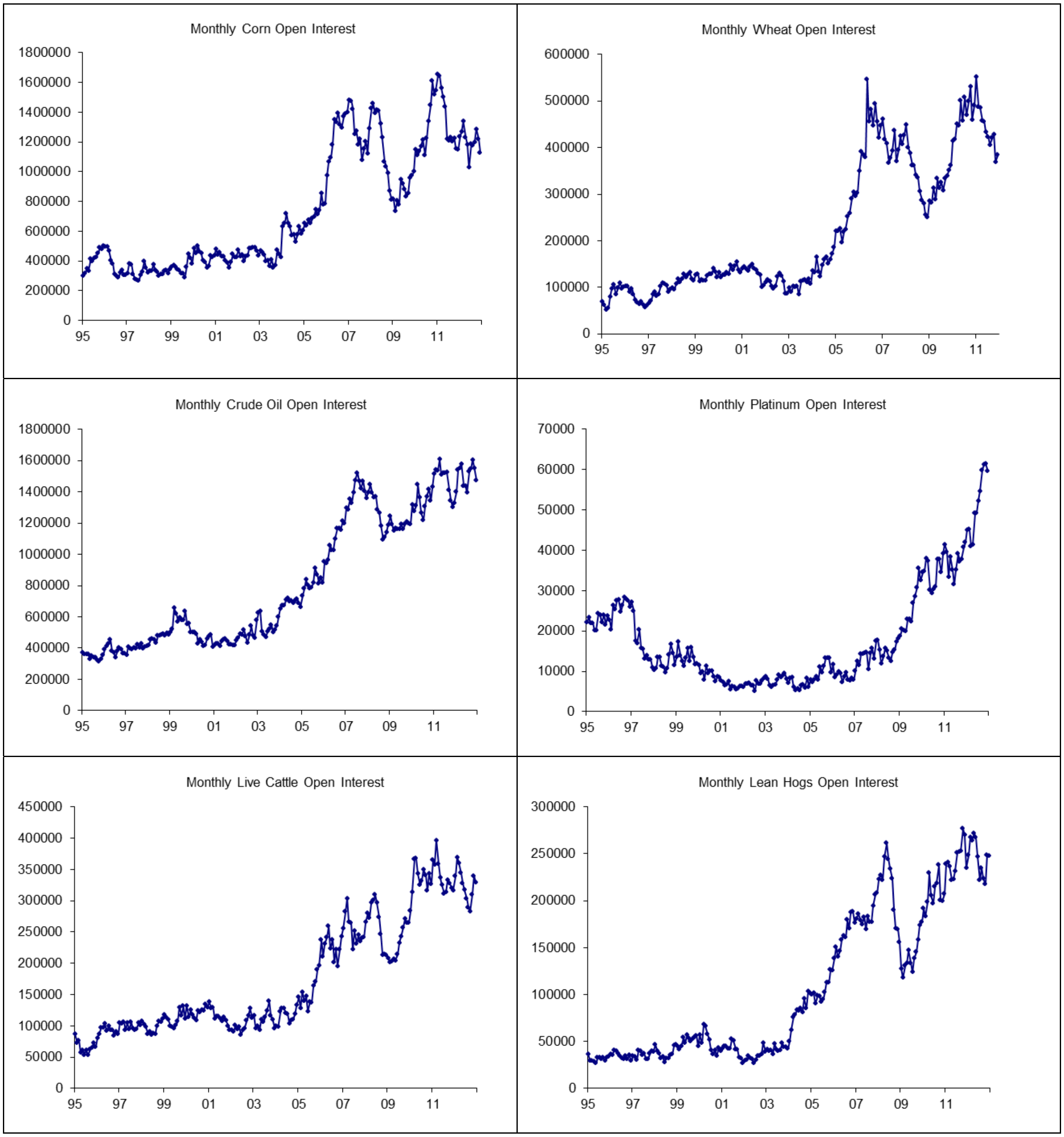

Table 1. Descriptive statistics for daily return dispersion and index returns.

	All commodities	Energy	Livestock	Grains	Metals
Panel A: Index return					
Mean (%)	0.028	0.038	0.010	0.021	0.017
Std. dev. (%)	1.453	1.998	0.912	1.507	1.180
Min. (%)	-9.145	-14.399	-4.250	-8.582	-7.171
Max (%)	7.215	9.809	4.631	7.687	6.684
Skewness	-0.242	-0.212	-0.068	0.008	-0.288
Kurtosis	5.717	5.298	3.781	5.036	6.418
Panel B: Return dispersion (CSAD)					
Mean (%)	1.360	1.076	0.793	0.853	1.039
Std. dev. (%)	0.603	0.680	0.461	0.495	0.617
Min. (%)	0.374	0.087	0.035	0.017	0.091
Max (%)	7.323	5.763	4.697	4.760	5.507
Skewness	1.947	1.935	1.433	1.667	1.923
Kurtosis	10.288	9.187	6.901	8.143	9.147

Note: The common sample covers the period Jan. 17, 1995 – Nov. 30, 2012 with 4,477 observations. CSAD is the daily return dispersion within each commodity sector as defined in Equation (1) and the sector index is the S&P GSCI index for the corresponding commodity sector.

Table 2. Herding behavior in the commodity market.

	All Commodities		*Energy*		*Livestock*		*Grains*		*Metals*	
	Static	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*
	Mean Equation		*Mean Equation*		*Mean Equation*		*Mean Equation*		*Mean Equation*	
$\alpha_{0,1}$	0.935	0.848	0.879	0.752	0.667	0.505	0.651	0.574	0.803	0.678
	(0.011)***	(0.014)***	(0.017)***	(0.023)***	(0.012)***	(0.014)***	(0.013)***	(0.014)***	(0.014)***	(0.014)***
$\alpha_{0,2}$		1.065		1.305		0.955		0.992		1.154
		(0.022)***		(0.050)***		(0.022)***		(0.032)***		(0.039)***
$\alpha_{1,1}$	0.315	0.266	0.035	0.04	0.051	0.117	0.125	0.055	0.14	0.117
	(0.015)***	(0.017)***	(0.017)***	(0.019)**	(0.026)**	(0.047)***	(0.016)**	(0.023)**	(0.022)***	(0.021)***
$\alpha_{1,2}$		0.383		0.093		0.011		0.190		0.237
		(0.023)***		(0.038)***		(0.021)		(0.033)***		(0.048)***
$\alpha_{2,1}$	0.037	0.011	0.017	0.007	0.062	-0.009	0.003	0.015	0.04	0.015
	(0.004)***	(0.004)***	(0.003)***	(0.003)**	(0.011)***	(0.021)	(0.004)	(0.008)**	(0.006)***	(0.006)**
$\alpha_{2,2}$		0.038		0.016		0.106		-0.022		0.031
		(0.005)***		(0.006)***		(0.012)***		(0.006)***		(0.012)***
	Volatility Equation		*Volatility Equation*		*Volatility Equation*		*Volatility Equation*		*Volatility Equation*	
$\beta_{0,1}$	0.005	0.063	0.013	0.127	0.002	0.059	0.011	0.055	0.010	0.085
	(0.001)***	(0.005)***	(0.002)***	(0.008)***	(0.001)***	(0.004)***	(0.003)***	(0.076)	(0.002)***	(0.005)***
$\beta_{0,2}$		0.003		0.012		0.000		0.110		0.008
		(0.001)***		(0.014)		(0.002)		(0.046)***		(0.004)**
$\beta_{1,1}$	0.929	0.000	0.892	0.000	0.960	0.008	0.875	0.217	0.902	0.000
	(0.014)***	(0.043)	(0.013)***	(0.070)	(0.007)***	(0.057)	(0.019)***	(1.094)	(0.014)***	(0.029)
$\beta_{1,2}$		0.958		0.912		0.972		0.542		0.927
		(0.012)***		(0.046)***		(0.015)***		(0.158)***		(0.019)***
$\beta_{2,1}$	0.039	0.000	0.075	0.000	0.031	0.000	0.078	0.000	0.065	0.000
	(0.007)***	(0.014)	(0.008)***	(0.050)	(0.005)***	(0.053)	(0.010)***	(0.024)	(0.009)***	(0.008)
$\beta_{2,2}$		0.019		0.069		0.025		0.123		0.051
		(0.007)***		(0.026)***		(0.007)***		(0.035)***		(0.011)***
LL	-2259.56	-1931.04	-3965.9	-3520.61	-2518.3	-2116.93	-2820.71	-2314.41	-3439.71	-2967.84

Note: Figures in parentheses are standard errors and *, ** and *** indicate significance at 10%, 5% and 1%, respectively. *LL* stands for the likelihood value.

Table 3. The role of the stock market on commodity market herding.

	All Commodities		*Energy*		*Livestock*		*Grains*		*Metals*	
	Static	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*
	Mean Equation		*Mean Equation*		*Mean Equation*		*Mean Equation*		*Mean Equation*	
$\alpha_{0,1}$	0.930	0.894	0.871	0.747	0.667	0.504	0.646	0.574	0.784	1.138
	(0.012)***	(0.027)***	(0.016)***	(0.018)***	(0.013)***	(0.014)***	(0.014)***	(0.014)***	(0.014)***	(0.039)***
$\alpha_{0,2}$		1.164		1.306		0.954		0.985		0.665
		(0.034)***		(0.049)***		(0.026)***		(0.033)***		(0.014)***
$\alpha_{1,1}$	0.317	0.059	0.039	0.043	0.051	0.118	0.128	0.059	0.139	0.212
	(0.015)***	(0.062)	(0.015)***	(0.016)***	(0.026)**	(0.029)***	(0.017)***	(0.023)***	(0.022)***	(0.047)***
$\alpha_{1,2}$		0.250		0.100		0.011		0.192		0.117
		(0.059)***		(0.038)***		(0.032)		(0.035)***		(0.020)***
$\alpha_{2,1}$	0.035	0.158	0.015	0.006	0.062	-0.009	0.002	0.014	0.039	0.034
	(0.004)***	(0.014)***	(0.003)***	(0.003)**	(0.011)***	(0.013)	(0.004)	(0.007)**	(0.006)***	(0.011)**
$\alpha_{2,2}$		0.026		0.016		0.106		-0.023		0.013
		(0.009)***		(0.005)***		(0.015)***		(0.007)***		(0.006)**
$\alpha_{3,1}$	0.004	0.016	0.007	0.005	0.000	0.000	0.003	-0.002	0.017	0.019
	(0.002)**	(0.007)***	(0.002)***	(0.002)***	(0.001)	(0.001)	(0.002)**	(0.002)	(0.002)***	(0.003)***
$\alpha_{3,2}$		0.000		0.000		0.000		0.006		0.009
		(0.003)		(0.005)		(0.003)		(0.003)**		(0.002)***
	Volatility Equation		*Volatility Equation*		*Volatility Equation*		*Volatility Equation*		*Volatility Equation*	
$\beta_{0,1}$	0.005	0.062	0.013	0.008	0.002	0.035	0.011	0.056	0.010	0.013
	(0.002)***	(0.098)	(0.002)***	(0.003)***	(0.001)***	(0.023)*	(0.003)***	(0.044)	(0.002)***	(0.007)**
$\beta_{0,2}$		0.005		0.007		0.000		0.103		0.083
		(0.002)***		(0.013)		(0.002)		(0.040)***		(0.005)***
$\beta_{1,1}$	0.927	0.136	0.890	0.930	0.960	0.410	0.874	0.205	0.900	0.907
	(0.015)***	(1.378)	(0.013)***	(0.023)***	(0.007)***	(0.385)	(0.021)***	(0.630)	(0.015)***	(0.026)***
$\beta_{1,2}$		0.953		0.926		0.972		0.563		0.000
		(0.014)***		(0.048)***		(0.015)***		(0.137)***		(0.017)
$\beta_{2,1}$	0.040	0.012	0.077	0.004	0.031	0.000	0.079	0.000	0.064	0.057
	(0.007)***	(0.014)	(0.009)***	(0.002)***	(0.005)***	(0.006)	(0.011)***	(0.010)	(0.009)***	(0.013)***
$\beta_{2,2}$		0.027		0.064		0.025		0.121		0.000
		(0.008)***		(0.030)**		(0.007)***		(0.030)**		(0.010)
LL	-2257.11	-2010.32	-3960.52	-3513.26	-2518.3	-2116.78	-2818.43	-2311.16	-3415.09	-2945.86

Note: Figures in parentheses are standard errors and *, ** and *** indicate significance at 10%, 5% and 1%, respectively. *LL* stands for the likelihood value.

Table 4. Herding effects across commodity sectors.

	Panel A: Energy (Target market)						**Panel B: Livestock (Target market)**					
	Originating Market						*Originating Market*					
	Livestock		**Grains**		**Metals**		**Energy**		**Grains**		**Metals**	
	Static	Regime	Static	Regime	Static	Regime	Static	Regime	Static	Regime	Static	Regime
$\alpha_{0,1}$	0.859	0.769	0.872	0.742	0.859	0.754	0.650	0.927	0.645	0.938	0.624	0.475
	(0.022)***	(0.020)***	(0.020) ***	(0.032)***	(0.021)***	(0.018)***	(0.016)***	(0.036)***	(0.016)***	(0.025)***	(0.016)***	(0.041)***
$\alpha_{0,2}$		1.186		1.32		1.304		0.497		0.494		0.914
		(0.060)***		(0.061)***		(0.132)***		(0.019)***		(0.017)***		(0.046)***
$\alpha_{1,1}$	0.034	0.04	0.034	0.038	0.035	0.04	0.052	0.015	0.049	0.005	0.053	0.119
	(0.017)**	(0.014)***	(0.017)**	(0.016)***	(0.016)**	(0.015)***	(0.026)**	(0.041)	(0.027)**	(0.019)	(0.027)**	(0.120)
$\alpha_{1,2}$		0.081		0.101		0.103		0.118		0.122		0.015
		(0.034)***		(0.046)**		(0.037)***		(0.035)***		(0.032)***		(0.112)*
$\alpha_{2,1}$	0.017	0.007	0.017	0.007	0.017	0.007	0.062	0.105	0.062	0.108	0.060	-0.011
	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.003)**	(0.011)***	(0.018)***	(0.012)***	(0.011)***	(0.012)***	(0.059)
$\alpha_{2,2}$		0.018		0.016		0.016		-0.009		-0.013		0.104
		(0.005)***		(0.006)***		(0.005)***		(0.017)		(0.015)		(0.041)***
$\alpha_{3,1}$	0.027	-0.035	0.014	0.011	0.021	-0.005	0.016	0.023	0.018	0.000	0.049	0.034
	(0.017)*	(0.016)**	(0.014)	(0.030)	(0.016)*	(0.006)	(0.009)*	(0.021)	(0.014)*	(0.025)	(0.011)***	(0.018)**
$\alpha_{3,2}$		0.155		0.005		0.014		0.006		0.003		0.045
		(0.044)***		(0.029)		(0.080)		(0.009)		(0.015)		(0.030)*
$\alpha_{4,1}$	0.001	0.006	-0.002	0.000	0.001	0.005	(0.000)	0.000	0.004	0.007	-0.005	-0.002
	(0.007)	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)*	(0.001)	(0.001)	(0.001)***	(0.003)***	(0.002)***	(0.002)
$\alpha_{4,2}$		-0.008		-0.011		-0.008		0.000		0.003		-0.005
		(0.002)***		(0.005)***		(0.006)*		(0.001)		(0.001)**		(0.004)*
LL	-3964.76	-3512.05	-3965.29	-3515.43	-3964.67	-3516.18	-2516.83	-2115.55	-2512.46	-2110.97	-2507.51	-2109.05

Table 4 continued

	Panel C: Grains (Target market)						Panel D: Metals (Target market)					
	Originating Market						*Originating Market*					
	Energy		**Livestock**		**Metals**		**Energy**		**Livestock**		**Grains**	
	Static	Regime-switching	Static	Regime-switching	Static	Regime-switching	Static	Regime-switching	Static	Regime-switching	Static	Regime-switching
$\alpha_{0,1}$	0.644	0.572	0.654	0.588	0.638	0.576	0.786	0.663	0.728	0.624	0.808	0.681
	(0.017)***	(0.016)***	(0.015)***	(0.016)***	(0.017)***	(0.016)***	(0.018)***	(0.017)***	(0.019)***	(0.018)***	(0.017)***	(0.018)**
$\alpha_{0,2}$		0.992		0.954		1.030		1.166		1.078		1.177
		(0.044)***		(0.042)***		(0.043)***		(0.045)***		(0.049)***		(0.060)***
$\alpha_{1,1}$	0.125	0.057	0.126	0.055	0.126	0.057	0.140	0.115	0.145	0.118	0.140	0.114
	(0.016)***	(0.021)***	(0.017)***	(0.020)***	(0.016)***	(0.022)***	(0.022)***	(0.020)***	(0.022)***	(0.020)***	(0.022)***	(0.020)***
$\alpha_{1,2}$		0.189		0.191		0.185		0.234		0.220		0.217
		(0.032)***		(0.033)***		(0.032)***		(0.050)**		(0.049)***		(0.050)***
$\alpha_{2,1}$	0.003	0.014	0.003	0.015	0.002	0.013	0.039	0.017	0.039	0.017	0.040	0.018
	(0.004)	(0.007)***	(0.004)	(0.007)**	(0.004)	(0.007)**	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.006)***
$\alpha_{2,2}$		-0.021		-0.023		-0.019		0.034		0.038		0.036
		(0.006)***		(0.006)***		(0.006)***		(0.012)***		(0.012)***		(0.012)***
$\alpha_{3,1}$	0.006	-0.002	-0.008	-0.019	0.009	-0.011	0.008	0.012	0.072	0.057	-0.009	0.002
	(0.009)	(0.012)	(0.010)	(0.014)*	(0.011)	(0.013)	(0.012)	(0.009)*	(0.016)***	(0.014)***	(0.010)	(0.015)
$\alpha_{3,2}$		0.016		0.055		-0.025		-0.013		0.086		-0.031
		(0.031)		(0.034)*		(0.029)		(0.022)		(0.043)**		(0.049)
$\alpha_{4,1}$	0.000	0.001	0.003	0.001	0.003	0.008	0.002	0.001	0.017	0.008	0.001	-0.002
	(0.001)	(0.001)*	(0.005)	(0.005)	(0.002)	(0.003)***	(0.001)**	(0.001)	(0.006)***	(0.005)*	(0.002)	(0.002)***
$\alpha_{4,2}$		-0.004		-0.004		-0.008		0.004		0.029		0.014
		(0.002)**		(0.009)		(0.004)**		(0.003)*		(0.013)**		(0.004)***
LL	-2820.48	-2311.53	-2820.44	-2312.20	-2819.18	-2305.92	-3436.79	-2964.27	-3420.58	-2949.47	-3439.44	-2960.33

Note: The table reports the estimates for $CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t} R_{k,t}^2 + \alpha_{3,S_t} CSAD_{j,t} + \alpha_{4,S_t} R_{j,t}^2 + e_t$. Figures in parentheses are standard errors and *, ** and *** indicate significance at 10%, 5% and 1%, respectively. *LL* stands for the likelihood value. The volatility equation estimates are not included for brevity and are available upon request.

Table 5. The effect of the post-2004 period.

	All Commodities		*Energy*		*Livestock*		*Grains*		*Metals*	
	Static	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*
	Mean Equation		*Mean Equation*		*Mean Equation*		*Mean Equation*		*Mean Equation*	
$\alpha_{0,1}$	0.940	0.840	0.887	0.755	0.653	0.920	0.643	0.573	0.809	0.688
	(0.011)***	(0.012)***	(0.017) ***	(0.019)***	(0.013)***	(0.028)***	(0.014)***	(0.013)***	(0.014)***	(0.014)***
$\alpha_{0,2}$		1.144		1.249		0.492		0.998		1.221
		(0.025)***		(0.047)***		(0.013)***		(0.032)***		(0.048)***
$\alpha_{1,1}$	0.291	0.260	0.022	0.023	0.091	0.115	0.144	0.061	0.076	0.056
	(0.014)***	(0.014)***	(0.016)*	(0.017)*	(0.027)***	(0.049)***	(0.018)***	(0.021)***	(0.023)***	(0.022)***
$\alpha_{1,2}$		0.308		0.128		0.118		0.182		0.159
		(0.027)***		(0.036)***		(0.023)***		(0.032)***		(0.114)*
$\alpha_{2,1}$	0.079	0.06	0.027	0.014	0.088	0.098	-0.012	0.005	0.152	0.157
	(0.004)***	(0.003)***	(0.003)***	(0.004)***	(0.012)***	(0.018)***	(0.006)**	(0.007)	(0.013)***	(0.032)***
$\alpha_{2,2}$		0.088		0.024		0.010		-0.017		0.065
		(0.007)***		(0.005)***		(0.010)		(0.010)**		(0.148)
$\delta_{1,1}$	-0.056	-0.051	-0.011	-0.006	-0.081	-0.083	0.013	0.015	-0.102	-0.126
	(0.003)***	(0.003)***	(0.002)***	(0.002)**	(0.008)***	(0.016)***	(0.004)***	(0.004)***	(0.010)***	(0.027)***
$\delta_{1,2}$		-0.051		-0.019		-0.037		-0.006		-0.023
		(0.003)***		(0.004)***		(0.008)***		(0.008)		(0.128)
LL	-2089.38	-1812.76	-3955.62	-3507.72	-2469.49	-2097.01	-2815.24	-2307.52	-3390.15	-2927.48

Note: The table reports the estimates for $CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t}R_{k,t}^2 + \delta_{1,S_t}D_{k,t}R_{k,t}^2 + e_{t,S_t}$. Figures in parentheses are standard errors and *, ** and *** indicate significance at 10%, 5% and 1%, respectively. *LL* stands for the likelihood value. The volatility equation estimates are not included for brevity and are available upon request.

Table 6. The role of the stock market during the post-2004 period.

	All Commodities		*Energy*		*Livestock*		*Grains*		*Metals*	
	Static	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*	*Static*	*Regime-based*
	Mean Equation		*Mean Equation*		*Mean Equation*		*Mean Equation*		*Mean Equation*	
$\alpha_{0,1}$	0.931	0.832	0.878	0.745	0.649	0.919	0.643	0.576	0.797	0.666
	(0.011)***	(0.012)***	(0.016)***	(0.020)***	(0.013)***	(0.031)***	(0.014)***	(0.037)***	(0.014)***	(0.013)***
$\alpha_{0,2}$		1.140		1.238		0.490		0.990		1.189
		(0.026)***		(0.046)***		(0.018)***		(0.087)***		(0.039)***
$\alpha_{1,1}$	0.296	0.267	0.023	0.028	0.090	0.117	0.144	0.061	0.069	0.078
	(0.014)***	(0.014)***	(0.015)*	(0.017)*	(0.027)***	(0.056)***	(0.017)***	(0.064)	(0.022)***	(0.020)***
$\alpha_{1,2}$		0.310		0.117		0.116		0.184		0.085
		(0.029)***		(0.034)***		(0.042)***		(0.104)**		(0.049)**
$\alpha_{2,1}$	0.075	0.057	0.026	0.013	0.087	0.095	-0.011	0.005	0.154	0.103
	(0.004)***	(0.003)***	(0.003)***	(0.005)***	(0.012)***	(0.019)***	(0.005)**	(0.027)	(0.013)***	(0.010)***
$\alpha_{2,2}$		0.088		0.023		0.009		-0.017		0.169
		(0.008)***		(0.004)***		(0.023)		(0.023)		(0.029)***
$\alpha_{3,1}$	0.009	0.012	0.011	-0.006	0.008	0.013	-0.003	-0.003	0.010	0.008
	(0.002)***	(0.003)***	(0.004)***	(0.004)*	(0.003)***	(0.010)*	(0.002)*	(0.004)	(0.003)***	(0.003)***
$\alpha_{3,2}$		0.005		0.020		0.006		0.006		0.005
		(0.005)		(0.008)***		(0.003)**		(0.041)		(0.008)
$\delta_{1,1}$	-0.055	-0.050	-0.012	-0.008	-0.078	-0.078	0.011	0.015	-0.105	-0.080
	(0.003)***	(0.003)***	(0.002)***	(0.003)***	(0.008)***	(0.033)***	(0.004)***	(0.011)*	(0.010)***	(0.008)***
$\delta_{1,2}$		-0.054		-0.016		-0.035		-0.006		-0.112
		(0.005)***		(0.004)***		(0.009)***		(0.008)		(0.023)***
$\delta_{2,1}$	-0.005	-0.009	-0.004	0.013	-0.008	-0.013	0.009	0.002	0.014	0.002
	(0.003)*	(0.004)**	(0.004)	(0.005)***	(0.003)**	(0.012)	(0.003)***	(0.008)	(0.004)***	(0.004)
$\delta_{2,2}$		0.002		-0.021		-0.006		-0.001		0.021
		(0.007)		(0.009)**		(0.003)**		(0.043)		(0.009)***
LL	-2082.13	-1799.77	-3947.33	-3495.77	-2466.10	-2092.88	-2808.90	-2303.80	-3363.61	-2905.45

Note: The table reports the estimates for $CSAD_{k,t} = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{k,t}\right| + \alpha_{2,S_t} R_{k,t}^2 + \delta_{1,S_t} D_{k,t} R_{k,t}^2 + \alpha_{3,S_t} R_{SP,t}^2 + \delta_{2,S_t} D_{k,t} R_{SP,t}^2 + e_t$. Figures in parentheses are standard errors and *, ** and *** indicate significance at 10%, 5% and 1%, respectively. *LL* stands for the likelihood value. The volatility equation estimates are not included for brevity and are available upon request.