Speculation in bearish commodity markets : The role of liquidity

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Abstract

This paper analyses the possibility of speculative traders behaviour in commodity futures markets in the presence of liquidity constraints. We use a series of multinomial logistic models to discern the influence of speculators on the probability of explosive price episodes. Speculators taking short positions tend to increase the likelihood of negative bubbles in most commodities, while those with long positions often reduce the chance of positive bubbles. We also find that probability of negative bubbles are more sensitive to the net short positions held by money managers when both market and funding liquidity are constrained.

Keywords: Speculation, Commodity Markets, Financialization

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1 Introduction

Over the years commodities have become an investable asset class thanks to its low correlation with traditional financial assets (stocks and bonds), being good inflation hedges and offering higher returns during early recession and late expansion periods (Gorton & Rouwenhorst 2006). Commodity prices experienced several boom and bust episodes over the last two decades. Although standard economic theory tells us price determinants are supply and demand, such extreme movements paved the way for examining the role of speculation on prices.

Micheal W. Masters (Masters 2008) made a public statement in 2008 attributing the price increase in commodities, crude oil in particular, to index traders who are considered to be speculators in commodity futures markets. This is widely known as Masters hypothesis. A Trader with a speculative mindset could realise positive returns by taking long futures positions in a bullish market and closing-out at higher prices before the expiry of the contract. Such traders could create an upward pressure on the prices by reinvesting these profits again and again. According to Masters (2008) such investment cycles deviate the market price of commodities from its fundamental value. Many academics including Büyükşahin & Harris (2011) and Alquist & Gervais (2013) in relation to crude oil and Irwin et al. (2011) in relation to agricultural commodities, examine the validity of Masters hypothesis. However, they do not find any evidence to support Masters's claim. Although, Masters hypothesis is studied in relation to crude oil, natural gas and agricultural commodities, there is very little evidence to either accept or rule out the price impact of speculative activities in other less popular commodity markets. Evidence shows that speculators provide liquidity to the commodity market and help price efficiency Kim (2015). This might imply that speculation is stronger and more vital for illiquid markets. We further argue the opposite of Masters hypothesis that traders could also profit from taking short futures positions under bear market conditions and closing-out their positions at lower prices prior to expiry. Repeating this cycle by a large number of traders could create a sudden downward pressure on the price, deviating it from its value determined by physical demand and supply.

In an examination for evidence on speculation in agricultural commodities, Etienne et al. (2015) argue that if there is any truth to Masters hypothesis, then the speculative positions in the respective commodity market should be able to explain the explosiveness of the futures price. Therefore, it is of utmost importance to understand such explosive price episodes (herein forth called as a "bubble") and their driving factors. It is crucial to determine whether a bubble is of a positive or negative nature, as this can aid market participants or policymakers in responding promptly to the emergence of bubbles. In essence, a positive bubble occurs when prices surge rapidly and subsequently undergo a significant drop, while a negative bubble, also referred to as a deflationary or downward bubble, manifests when prices rapidly decline (Fang et al. 2023).

In this paper, we first determine bubble episodes for 20 commodities for the period between 2006 and 2023. We use a testing procedure known as Supremum Augmented Dickey-Fuller Test (SADF) proposed by Phillips et al. (2015) to identify bubble episodes. We find that all commodities exhibit positive as well as negative bubble episodes on more than one occasion during the 2006-2023 period. Our multinomial logistic regression analysis shows that long positions taken by money managers, who are considered as pure speculators in commodity futures literature (Basu & Miffre 2013), either decrease or do not affect the probability of positive price bubbles. This is consistent with literature that explores evidence of speculation during the commodity price boom prior to the Global Financial Crisis. Interestingly, we find that short positions taken money managers increase the probability of negative price bubbles in a majority of commodities in our sample.

Kang et al. (2020) show that there are two independent premiums that explain commodity futures return. They are; 1) insurance premium which hedgers pay speculators in return for protection against future price risks and 2) liquidity premium that speculators pay hedgers in return for market liquidity. This implies that speculators incur a higher cost to compensate for the supply of liquidity. Moreover, Cho et al. (2019) find that this liquidity premium is even larger for relatively illiquid commodities during market downturns. Brunnermeier & Pedersen (2009) show that in addition to market liquidity, speculators are affected by funding liquidity. Moreover, initial losses to speculators may impose funding constraints to speculators which would raise the cost of funding. They could either closeout their positions and exist or go further short in expectation of higher returns to compensate for the increase in funding cost. One could therefore argue that speculators could drive commodity prices even further from its fundamental values, when they take short positions in when either the commodity-specific liquidity or funding liquidity is low and decreasing in price.

We therefore examine how liquidity conditions affect speculative behavior. Our findings reveal that low market liquidity, especially combined with short positions, raised the chances of negative bubbles in several commodities. Although we do not find any evidence of price speculation under normal circumstances, our results suggest that net short positions taken by money managers in crude oil futures contracts increase the probability of negative price explosiveness. We also show the impact of funding liquidity constraints on speculators' behavior, noting that some commodities experienced price increases during periods of low funding liquidity. To the best of our knowledge, we are the first to study the contribution of both commodity-market-specific illiquidity and funding illiquidity towards speculation. The remainder of the paper is organised as follows; section 2 contains a brief literature review while section 3 explains the data and methodology in applied. We explain our results in section 4 along side a number of robustness tests in section 5. Section 6 concludes.

2 Literature Review

The existing literature on the irrational exuberance of commodity prices shows that while both direct and indirect methods are used, indirect tests, especially those developed by Phillips et al. (2011, 2015), are more commonly employed. Following the literature, we use the same methodology to identify bubbles by checking for deviations from a random walk using the GSADF method. Additionally, most studies find the presence of bubbles across commodities, except for a few that use other techniques (e.g. (**?**Brooks et al. 2015, Lucey & O'Connor 2013, Zhang & Yao 2016).

Since commodities have diverse characteristics, previous studies either individually assess bubble tests for commodities within subgroups such as grains or energy (i.e. Etienne et al. 2014, Ozgur et al. 2021) or they focus on individual commodities (i.e. Alexakis et al. 2017, Białkowski et al. 2015). Studies which perform bubble tests for all commodities is scarce and limited by a few studies such as Brooks et al. (2015), Potrykus (2023).

Although all papers presented aim to detect bubble episodes in selected commodities, few also attempt to uncover underlying reasons for bubble formations. Especially following the financialization of commodity markets, investigating the role of index traders and speculators in bubble formations become a more prominent research question. Because, the presence of a speculative bubble does not necessarily mean that index traders are the culprit.

Moreover, papers which explicitly investigate how commodity index trader or speculative positions affect bubble formations is scarce. What is missing in the current literature is the examination of the role of speculators on the formation of negative bubbles during bearish episodes. Brunnermeier (2009) indicate that the simultaneous unwinding of similar positions of institutional investors lead to blowout of bubbles. Moreover liquidity is an indispensable factor for markets to operate. In low liquidity times, where concurrently similar positions are unwind, markets experience the shock. Keynes' famous analogy between bubbles and musical chairs tell us the one thing we need to know: "When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing." (Nakamoto & Wighton 2007). Hence, it is of sheer importance to understand how the market players reacts to low-liquidity times and whether speculators move the market to a negative price explosiveness easier since the liquidity is shallow.

3 Data & Methodology

We use a sample of 20 commodities covering a number of sectors such as, agriculture, softs, energy, metals and livestock. These commodities include, Corn, Oats, Rough rice, Soybean, Soybean meal, Soybean oil, Wheat, Cocoa, Coffee, Cotton, Sugar, Copper, Gold, Platinum, Silver, Feeder cattle, Live cattle, Crude oil, Heating oil and Natural gas. We obtain daily prices, open interest and trade volume of first and second futures contracts for all commodities, and the 3-month TED spread from Bloomberg over the 2006/03-2023/06 time period. We use weekly positions taken by money managers and the open interest published in Disaggregate Commitment of Traders (DCOT) reports by Commodities and Futures Trading Commission (CFTC). We use the real economic activity index introduced by Kilian (2009) and the daily nominal advanced foreign economies US Dollar index ($EXRate$) are obtained from the Federal Reserve of St. Louise (FRED) database.

3.1 Commodity market liquidity

The Amihud measure (Amihud 2002) has been widely used in literature to represent market liquidity. However, Cho et al. (2019) find that the turnover based Amihud measure introduced by Brennan et al. (2013)[1] is more suitable in order to capture liquidity in commodity markets. We first construct our measure of commodity market liquidity. The turnover based Amihud measure (herein forth known as the Amihud measure) is constructed as follows;

[1]Brennan et al. (2013) originally proposed this decomposition for stocks. See Cho et al. (2019) for the derivation of the turnover based Amihud measure for commodity markets.

$$\text{Amihud}^T = \frac{|r|}{contracts\, traded} \times open\, interest$$

where, r is the daily return of the commodity. Based on this measure we define a dummy variable (D_{com}) to capture the liquidity condition of each commodity. We assign $D_{com} = 1$ if the current Amihud value is in the fourth quartile of Amihud values over the past 150 days, or zero otherwise.

3.2 Funding liquidity

The TED spread, which is the difference between 3-month Eurodollar deposits yield (LIBOR) and 3-month U.S. treasury bills has been widely used in literature as a proxy for funding liquidity (Brunnermeier 2009, Boudt et al. 2017). In fact, Boudt et al. (2017) show that there is a strong positive relationship between the TED spread and funding liquidity, primarily through the credit risk and flight-to-quality. Therefore, we define a dummy variable based on TED spread to capture changes to funding liquidity. We assign $D_{fun} = 1$ if the current TED spread is greater than its average over the past 150 days, or zero otherwise.

3.3 Testing for explosiveness (bubbles)

Phillips et al. (2015) generalizes the single-bubble testing procedure known as Sup Augmented Dickey-Fuller Test (SADF) proposed by Phillips et al. (2011). The main difference between the two tests is that instead of fixing the starting point of the recursive ADF test window, Phillips et al. (2015) change the end point as well as the starting point of the recursive ADF test window. This approach allows them to capture multiple price bubbles and to time-stamp the bubble origin and termination dates. In fact this method is previously used by Sharma & Escobari (2018) to access the explosiveness of energy commodity prices.

The estimation process starts with the following equation,

$$\Delta F_{i,t} = \alpha_{r_1,r_2} + \beta_{r_1,r_2} F_{i,t-1} + \sum_{n=1}^{k} \lambda^{j}_{r_1,r_2} \Delta F_{i,t-j} + \epsilon_t \tag{1}$$

where F_i is the daily prices of each nearby futures contract of a commodity i and k lagged difference terms are included to control for serial correlation. The subscripts r_1 and r_2 are fractions of the total sample size that represent the starting and ending points of a subsample period. The error term ϵ_t is assumed to be a standard normal distribution. The ADF test statistic therefore;

$$ADF^{r2}_{r1} = \frac{\hat{\beta}_{r_1,r_2}}{S.E.(\hat{\beta}_{r_1,r_2})} \tag{2}$$

We conduct this recursive right-tailed unit root test repeatedly on a sequance of price windows. The sup value of test statistic, also known as the backward SADF statistic is defined as;

$$BSADF_{r_2}(r_0) = sup_{r1 \in [0, r_2 - r_0]} ADF^{r2}_{r1} \tag{3}$$

We set the minimum bubble length to 3-days following Etienne et al. (2015) who study the explosiveness of daily agricultural commodity prices.

Since the distribution of $BSADF_{r_2}(r_0)$ test statistics are non-standard, we generate critical values at 95% levels from Monte Carlo simulation with 2000 replications[2]. We recognise a price bubble whenever the backward SADF statistic is greater than the critical value.

4 Results

4.1 Bubble test

We estimate the backward SADF (BSADF hereinforth) test statistics for each commodity along with its critical value. A bubble is recognised whenever BSADF statistic remains above the critical value. Figure 1 represents the nearby futures price of all commodities (in Blue). Red markers on each plot represents a the presence of a bubble. We observe that all commodities in our sample show signs of price explosiveness. All commodities except Feeder cattle exhibit a bubble during the commodity market boom during 2006-2008 period. Further, all commodities except Rough rice and platinum show signs of price explosiveness following the Russian

[2]see Phillips et al. (2015) for further information on the generation of critical values

invasion of Ukraine. Results in figure 1 exhibit instances of explosiveness in bearish markets. We observe such instances in Oats, Soybean oil, Copper, Platinum, Live cattle, Crude oil and Heating oil markets following the market downturn during the Global Financial Crisis. This shows that commodity prices can be explosive during both bullish and bearish market episodes.

Once these bubbles are identified, we categorise each bubble in to negative or positive depending on the underlying market condition. We denote a negative (positive) bubble if the futures price is in a decreasing (increasing) trend over the past 5 days while the bubble is being formed. Table 1 reports the number days on which prices exhibit positive or negative explosive behavior along with the average daily price change. In a sample of 4164 days, prices are non-explosive more than 85% of the time. The number of days of negative bubbles are significantly less than positive bubbles in most commodities. Positive bubbles are as regular as negative bubbles in the case of commodities such as Platinum, Live cattle, Crude oil, Heating oil, Natural gas, Cocoa and Oats.

4.2 Speculative behavior and price bubbles

Once the bubble episodes are identified, we estimate a series of Multinomial Logit (ML) models to analyse the relationship between bubble occurrence and, speculative and fundamental factors.

The dependent variable of all these models takes the value 1 when a negative bubble occurs, 2 when a positive bubble occurs and zero otherwise. In order to establish a baseline, we first estimate a ML model to examine the link between bubble occurrence and speculator behavior. We use changes in net long positions of money managers (MM) who are defined as pure speculators(Basu & Miffre 2013) to represent the speculator behavior. The CFTC releases long and short positions of traders at a weekly frequency. Therefore, we convert these weekly time series to daily frequency to match the daily date-sampling of bubbles, assuming constant values throughout a given week. We further employ three control variables in our regression model. Specifically, we utilise the real economic index (REA) as introduced by Kilian (2009). This choice aligns with the findings of Nguyen & Okimoto (2019), who observed a positive effect of real economic activity on natural gas prices in the US [3]. Additionally, we incorporate the USD exchange rate ($EX\ Rate$). A weaker USD is likely to increase commodity exports from the US, potentially influencing prices increases due to additional export demand. In this regard,

[3] Kilian (2009) and Peersman & Robays (2012) among others explain similar findings in relation to of crude oil market

Gilbert (2010) find that changes to USD Granger cause changes to commodity prices. REA is available in monthly frequency and therefore converted to daily frequency under the assumption of constant values throughout a given month. The accumulation and release of inventories should be associated with the price. In fact, Kilian & Murphy (2014) attributes the increasing real price to the movement of inventories. Therefore, we use the daily $Spread$ to represent the incentive to hold inventories, in addition to control variables mentioned in Etienne et al. (2015). Results of this ML model (4) are reported in table 2.

$$logit(Bubble_t) = \beta_1.MM_{t-1} + controls + c \tag{4}$$

Literature suggest that money managers move with the market sentiment, i.e. they take long (short) positions when futures prices are rising (declining)[4]. Therefore, it is crucial to consider the opposite signs and coefficients of net short positions taken by money managers when interpreting results related to negative bubbles. Results show that the probability of a negative bubble increases when money managers increase short positions in all commodities except Cocoa, Copper, Platinum, Crude oil and Heating oil. Interestingly, increase in net short positions taken by money managers in Crude oil and Heating oil futures contracts reduce the probability of negative bubbles. These findings support our hypothesis that speculators influence commodity prices under bearish market conditions.

Further, all statistically significant coefficients of net long positions in relation to positive bubbles imply that the probability of positive bubbles decrease with the increase in long positions taken by money managers, with the exception of Live cattle. Our findings confirm that long positions taken by money managers in all but one commodity during bullish market episodes do not necessarily cause prices to rapidly increase and therefore consistent with literature that opposes Masters hypothesis (Alquist & Gervais 2013, Etienne et al. 2015, Büyükşahin & Harris 2011).

4.3 Speculation and market liquidity

Kang et al. (2020) show that there are two independent premiums that explain commodity futures return. They are; 1) insurance premium which hedgers pay speculators in return for pro-

[4] Kang et al. (2020) show that futures market hedgers (producers, manufactures and consumers) trade against the market sentiment while speculators (money managers) trade with the market sentiment.

tection against future price risks and 2) liquidity premium that speculators pay hedgers in return for market liquidity. This implies that speculators incur a higher cost to compensate for the supply of liquidity. Moreover, Cho et al. (2019) find that this liquidity premium is even larger for relatively illiquid commodities during market downturns. Our results above already show that the change in net short positions held by money managers increase the probability of further price declines on average. One could therefore argue that speculators could drive commodity prices even further from its fundamental values, when they take short positions in a commodity that is illiquid and decreasing in price, which falls in line with the construction of Amihud's illiquidity measure (Amihud 2002) (also the turnover based Amihud measure (Brennan et al. 2013)).

Figure 2 exhibits the evolution of market liquidity for each commodity. This graph implies that market liquidity of commodities such as Cotton, Sugar and Feeder cattle has depleted over time. However, there is no significant change in the level of market liquidity for commodities that are in agricultural and precious metal categories. We assess the current level of market liquidity for a particular commodity with respect to its own market liquidity in the recent past. Therefore we introduce an additional interactive dummy variable, D_{com} to measure the incremental effects of a position change on the probability of negative/positive bubbles when the liquidity of the given commodity is lower in comparison to the past 150 days. The new ML model will be as follows,

$$logit(Bubble_t) = \beta_1.MM_{t-1} + \beta_2.D_{com}.MM_{t-1} + controls + c \quad (5)$$

We report estimates for β_1 and β_2 Coefficients are reported in table 3. Results show that the inclusion of the interactive dummy variable has not triggered any significant changed in the β_1 coefficient except in the case of Live cattle and Natural gas. Moreover, the coefficients of interactive dummy variable associated with negative bubbles, is negative and statistically significant in the case of Corn, Soybean, Coffee, Gold, Live cattle, Crude oil and Natural gas. This implies that the probability of negative bubbles further increases when speculators take short positions in these commodities during times of low market liquidity. Interestingly, we observe that long positions taken by speculators in Live cattle increase the probability of positive explosiveness when liquidity is low. This implies that money managers are still willing to take long positions in this commodity despite the lack of liquidity. Thus causing large price increases.

4.4 Speculation and funding liquidity

Brunnermeier & Pedersen (2009) show that in addition to market liquidity, speculators are affected by funding liquidity. Moreover, initial losses to speculators may impose funding constraints to speculators which would raise the cost of funding. They could either closeout their positions and exist or go further short in expectation of higher returns to compensate for the increase in funding cost. As a result, speculators in particular could drive commodity futures prices down during bearish market conditions in comparison to bullish markets. Therefore, we examine whether speculators drive the probability of bubble occurrence in times of low funding liquidity. Phases of low funding liquidity (widened TED spread) is captured by the interactive dummy variable, D_{fun} and we change our ML model as follows,

$$logit(Bubble_t) = \beta_1.MM_{t-1} + \beta_2.D_{fun}.MM_{t-1} + controls + c \tag{6}$$

Coefficient estimates of the above ML model are reported in table 4. Results show that β_2 coefficient leading to negative bubbles, is negative and statistically significant in the case of Soybean, Soybean oil, Wheat, Cotton, Copper, Platinum, Silver, Feeder cattle, Live cattle and Crude oil. This suggests that money mangers increase their short positions in these commodities when there are funding constraints which subsequently drive prices further down. Our findings are consistent with the argument of Koch (2014) that the likelihood of extreme price drops in commodity market in the presence of funding constraints.In contrast, money mangers may reduce their short positions in Cocoa and Natural gas, reducing the probability of negative explosiveness when funding liquidity is low. β_1 coefficient of Oats, Rough rice and Platinum offsets the effect of β_2 in relation to positive bubbles. Therefore,we do not find evidence of speculators increasing the likelihood of positive bubbles when funding liquidity is low.

Figure 3 depicts the time varying equally weighted 60-day moving average of commodity market liquidity and 3-month TED spread which is the proxy for funding liquidity. We observe several spikes in average commodity market illiquidity around the Global Financial Crisis (2008-2010), 2013-2016 and during the Covid-19 pandemic in 2020. Funding liquidity remains low during the Global Financial Crisis and the Covid-19 pandemic. However, we observe a consistent level of high liquidity from 2012 to 2017. This supports findings of Brunnermeier & Pedersen (2009) that funding liquidity could decrease as a result of financiers expectation of a higher return to compensate for the increase in market liquidity risk. Figure 3 also implies that there could be phases where funding liquidity remain high despite the low market liquidity. This is due to financiers belief that the current low market liquidity condition is temporary and as a result, they choose not to improve funding constraints on traders(Brunnermeier & Pedersen 2009).

Table 5 reports average net long positions held by money managers when, both market and funding liquidity are high, market liquidity is low, funding liquidity is low and when both market and funding liquidity are low. net long positions held by money managers decrease when liquidity conditions worsen on average under bearish market conditions. This implies that traders either closeout their positions or take additional short positions in expectation of further price decreases. Surprisingly, we observe that traders increase their long positions in most commodities under bullish market conditions, as liquidity depletes. One would have expected long positions to reduce as money managers experience higher transaction and borrowing costs. This implies that liquidity shortages do not necessarily drive traders away from the market when prices are increasing. We therefore examine whether speculators drive the probability of bubble occurrence in times of low market and funding liquidity. Phases of low market and funding liquidity is captured by the interactive dummy variable, $D_{fun}.D_{com}$ and we change our ML model as follows,

$$logit(Bubble_t) = \beta_1.MM_{t-1} + \beta_2.D_{fun}.D_{com}.MM_{t-1} + controls + c \tag{7}$$

Results reported in table 6 show that the probability of negative bubbles increase when money managers trading Corn, Soybean, Coffee, Gold, Feeder cattle, Live cattle and Crude oil increase their short positions when both market liquidity and funding liquidity are low. Moreover, the β_2 coefficient of these commodities are much higher in comparison to the corresponding β_2 coefficients of model (5) and (6). This implies that probability of negative bubbles are more sensitive to the net short positions held by money managers in these commodities as both market and funding liquidity worsen. This is consistent with Brunnermeier & Pedersen (2009).

5 Robustness checks

5.1 Speculation and relative liquidity

In addition to the commodity market and funding liquidity, we explore if the relative liquidity of commodities influence the speculative behavior of money mangers. We measure relative liquidity in two different ways. First, we define a variable (rel_liq) to capture relative liquidity of each commodity in comparison to the most liquid commodity at any given time. Therefore,

$$rel\_liq_{i,t} = \frac{Amihud^T_{i,t}}{min(Amihud^T_{1-20,t})}$$

where, $rel\_liq_{i,t}$ is the relative liquidity of commodity i at time t, $Amihud^T_{i,t}$ is the Amihud liquidity of commodity i at time t and $min(Amihud^T_{1-20,t})$ is the minimum $Amihud^T$ value across all commodities, i.e. the $Amihud^T$ value of the most liquid commodity at time t. Based on this measure we define a dummy variable, $D_{rel} = 1$ if $rel\_liq_{i,t}$ of a given commodity i is the fourth quartile among relative liquidity of other commodities at time t, or zero otherwise. D_{rel} therefore captures if a commodity is significantly low in liquidity in comparison to the most liquid commodity at the time.

In our second measure, we assess liquidity of each commodity relative to the liquidity of Crude oil (rel_liq_oil) . Therefore,

$$rel\_liq\_oil_{i,t} = \frac{Amihud^T_{i,t}}{Amihud^T_{Crude\ oil,t}}$$

where, $rel\_liq\_oil_{i,t}$ is the relative liquidity of commodity i at time t with respect to the liquidity of crude oil ($Amihud^T_{Crude\ oil,t}$) at time t. In order to identify the most illiquid commodities relative to Crude oil, we assign the dummy variable $D_{rel\_oil} = 1$ if $rel\_liq\_oil_{i,t}$ of a given commodity i is the fourth quartile among other commodities at time t, or zero otherwise.

In this section we examine whether money managers cause bubbles to form when the liquidity of a given commodity is measured relative to another commodity. We use dummy variables, D_{rel} and $D_{rel-oil}$ to capture the most illiquid commodities with respect to, 1) the most liquid commodity at the time and 2) the liquidity of crude oil given that it is the most liquid futures contract among all commodities(Geman & Kharoubi 2008).

$$logit(Bubble_t) = \beta_1.MM_{t-1} + \beta_2.D_{rel}.MM_{t-1} + controls + c \tag{8}$$

We replace the dummy variable, D_{com} in (5) by D_{rel} and re-estimate the ML model. Results reported in table 7 show that money managers trading in Corn, Wheat and Crude oil increase their short positions when markets are bear and therefore, increasing the probability of negative bubbles. On the other hand money managers who trade Cotton either increase their long positions or closeout their short positions when Cotton is relatively illiquid compared to the most liquid commodities at the time. This decreases the probability of negative explosiveness of Cotton.

$$logit(Bubble_t) = \beta_1.MM_{t-1} + \beta_2.D_{rel\_oil}.MM_{t-1} + controls + c \tag{9}$$

We then assess the contribution of speculators towards explosive prices when liquidity of commodities are measured against the liquidity of Crude oil as a benchmark for market liquidity. We subsequently estimate the ML model (9) and report results in table 8. Money managers trading commodities such as Corn, Soybean, Soybean meal, Gold and Natural gas increase their short positions in bear markets, when the liquidity of Crude oil market is significantly higher that those commodity markets. This increases the likelihood of negative bubbles, thus confirming the speculator influence on commodity prices under bearish market conditions.

6 Conclusion

We delve into the dynamic world of commodity prices in this paper, which have experienced significant fluctuations over the past two decades. Commodity prices are critical to follow up, since they are the major input for economic growth and volatility in prices could have significant detrimental impact on economic fundamentals. While conventional economic theory emphasizes supply and demand as the primary price determinants, extreme price movements have prompted a closer look at the impact of speculation. Therefore, we mainly aim to uncover the underlying factors that contribute to negative price bubbles, with a particular focus on the role of speculators. More importantly, we discuss the impact of market and funding liquidity conditions on the speculative role of traders in commodity markets. To the best of our knowledge, this is the first time that speculation in commodity futures markets is studied in relation to market and funding liquidity conditions.

To address these objectives, we first employ the Backward Sup Augmented Dickey-Fuller Test (SADF) to identify bubble episodes (price explosiveness) across 20 different commodities spanning from 2006 to 2023. Once the bubbles are identified, we categorise those in to positive and negative bubbles according to the price trend over the past trading week. We subsequently analyse the impact of the change in positions taken by money managers who are considered as pure speculators in commodity markets, on the probability of positive and negative bubbles using a series of multinomial logit models.

The findings reveal that most commodities exhibit signs of price explosiveness, with the presence of these bubbles varying depending on market conditions. Speculators taking short positions tend to increase the likelihood of negative bubbles in most commodities, while those with long positions often reduce the chance of positive bubbles. Moreover, market liquidity conditions and funding liquidity constraints also play a significant role in shaping speculative behavior and bubble formation.

We believe our study makes a valuable contribution to the literature in three-folds. Firstly, we find evidence to support existing literature that opposes Masters hypothesis. We find that long positions taken by speculators in commodity markets do not increase the probability of explosive price (positive bubbles) under bullish market conditions. Secondly, we find that short positions taken by speculators in most commodities increase the probability of negative bubbles. This implies that although speculators are unable to influence commodity market prices by taking long positions in bullish markets, they could drive prices down by taking short positions under bearish market conditions.

Finally, we show that shortage of market liquidity and funding liquidity could further enhance the influence of speculators on commodity market price decrease. One should understand that not all commodities are influenced by the positions taken by speculators and therefore the impact of speculator positions on prices is not to be generalised across all commodities.

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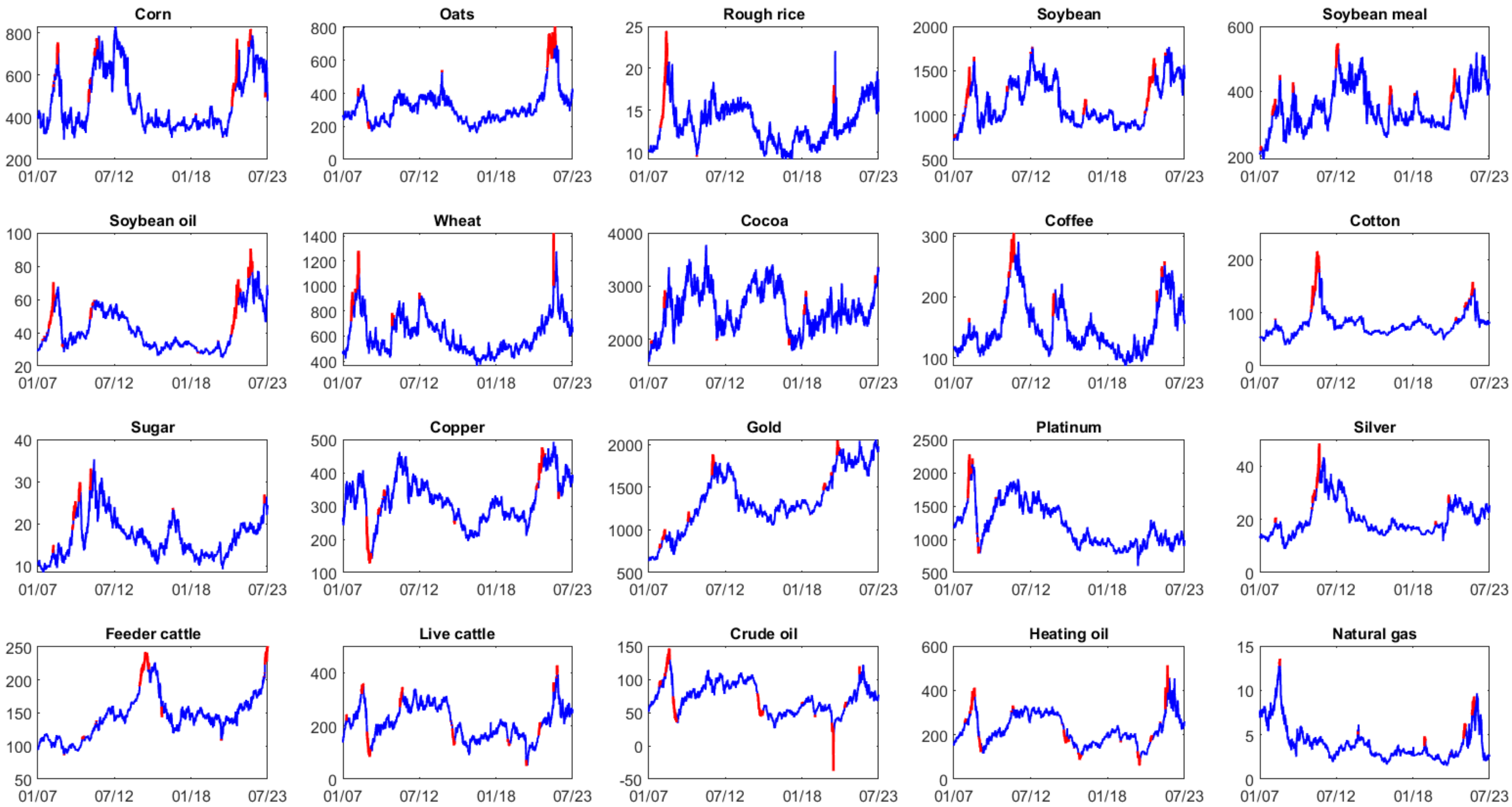

Figure 1: This graph reports the daily movement of commodity market futures prices (in Blue colour) and bubble episodes identified (in Red colour) using the SADF testing procedure introduced by Phillips et al. (2015). All prices are given in U.S. dollars per unit of each commodity.

Table 1: Mild-explosiveness of commodity prices

	Non-explosive		Negative bubbles		Positive bubbles	
	Days	Average price change (%)	Days	Average price change (%)	Days	Average price change (%)
Corn	3857	-0.012	87	-0.019	220	0.047
Oats	3971	0.026	75	-0.018	118	0.032
Rough rice	3970	0.011	61	-0.009	133	0.027
Soybean	3731	-0.009	109	-0.010	324	0.050
Soybean meal	3873	0.006	80	-0.009	211	0.038
Soybean oil	3686	-0.008	142	-0.023	336	0.064
Wheat	3970	-0.005	59	-0.010	135	0.047
Cocoa	4063	0.030	43	-0.008	58	0.032
Coffee	3915	-0.011	67	-0.019	182	0.048
Cotton	3883	-0.006	83	-0.014	198	0.052
Sugar	4004	0.012	34	-0.004	126	0.034
Copper	3783	0.019	161	-0.036	220	0.040
Gold	3917	0.013	60	-0.006	187	0.026
Platinum	3956	0.010	104	-0.020	104	0.019
Silver	3966	0.002	40	-0.006	158	0.040
Feeder cattle	3725	0.022	166	-0.019	273	0.027
Live cattle	3825	0.065	182	-0.065	157	0.069
Crude oil	3669	0.067	263	-0.105	232	0.075
Heating oil	3583	0.044	282	-0.078	299	0.073
Natural gas	4025	0.002	47	-0.015	92	0.044

Note: the table reports the number of days with explosive and non-explosive price behavior along with the average daily return for each commodity. Price explosiveness is identified following Phillips et al. (2015) and the explosive days are further divided in to positive and negative. It is called a positive (negative) bubble if the price trend of each commodity over the past 5-days is positive (negative).

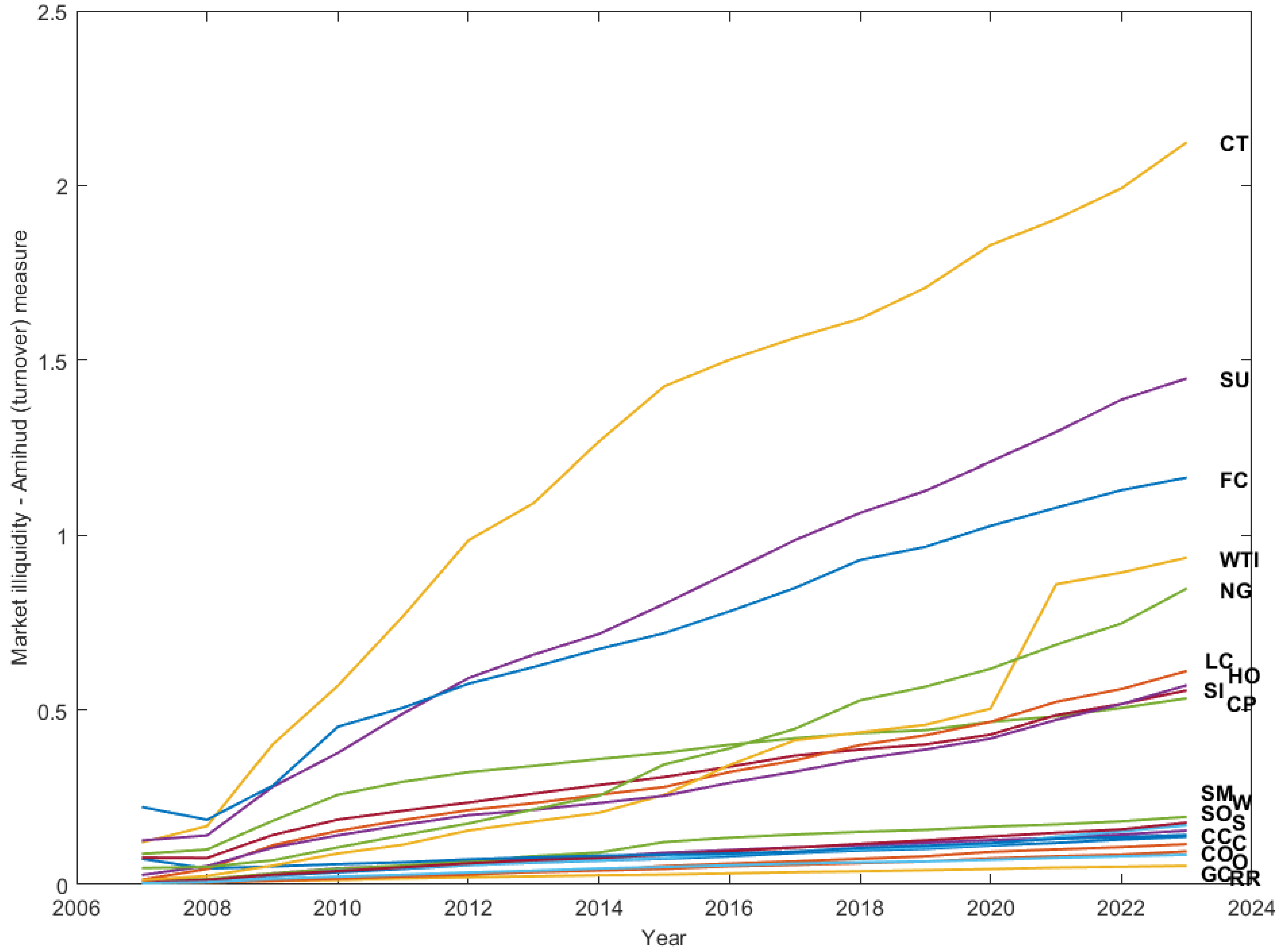

Figure 2: This graph reports annual average of daily liquidity measured by the turnover based Amihud measure ($Amihud^T$) for the sample of 20 commodities. These are; C-Corn, O-Oats, RR- Rough rice, S-Soybean, SM-Soybean meal, SO- Soybean oil, W-Wheat, CC-Cocoa, CO-Coffee, CT-Cotton, SU-Sugar, CP-Copper, GC-Gold, PL-Platinum, SI-Silver, FC-Feeder cattle, LC-Liver cattle, WTI-Crude oil, HO- Heating oil, NG- Natural gas. $Amihud^T = \frac{|r|}{contracts\ traded} \times open\ interest$ where, r is the daily return of the commodity.

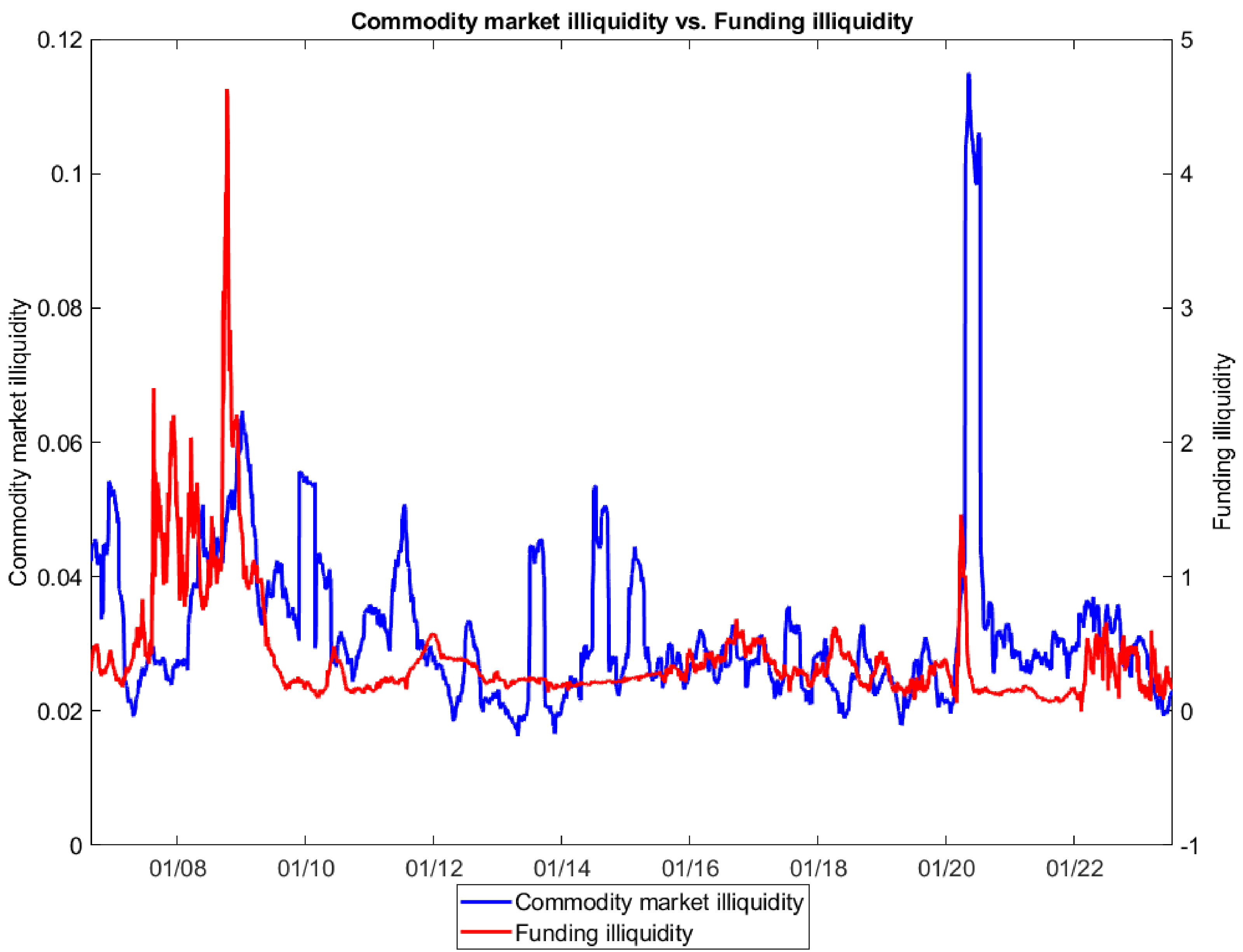

Figure 3: This graph reports, 1) the daily movement of average commodity market illiquidity (in blue colour), represented by the equally weighted, 60-day moving average of daily Amihud (turnover) measure and 2) the daily funding illiquidity position represented by daily 3-month TED spread (in red colour)

Table 2: Multinomial Logit model: Mild explosiveness (bubbles) and speculation

Commodity	Bubble	β_1	Commodity	Bubble	β_1
Corn	Negative	-11.861^{***}	Sugar	Negative	-12.816^{***}
		(0.921)			(1.661)
	Positive	-8.270^{***}		Positive	-9.328
		(2.276)			(9.048)
Oats	Negative	-1.535^{***}	Copper	Negative	-0.046
		(0.577)			(0.374)
	Positive	-9.480^{**}		Positive	-3.529^{***}
		(4.948)			(0.672)
Rough Rice	Negative	-3.520^{***}	Gold	Negative	-7.200^{***}
		(0.791)			(0.853)
	Positive	-5.809		Positive	-11.885^{***}
		(3.225)			(2.836)
Soybean	Negative	-11.277^{***}	Platinum	Negative	-0.242
		(0.823)			(0.474)
	Positive	-11.183^{***}		Positive	-8.348^{***}
		(4.130)			(2.613)
Soybean meal	Negative	-7.572^{***}	Silver	Negative	-8.861^{***}
		(0.704)			(1.039)
	Positive	-9.523^{***}		Positive	-14.644^{***}
		(3.278)			(4.257)
Soybean oil	Negative	-9.388^{***}	Feeder cattle	Negative	-8.179^{***}
		(0.747)			(0.535)
	Positive	-12.024^{***}		Positive	-1.628
		(1.918)			(1.642)
Wheat	Negative	-28.211^{***}	Live cattle	Negative	-0.956^{*}
		(2.795)			(0.557)
	Positive	-20.125^{***}		Positive	2.040^{*}
		(4.826)			(1.222)
Cocoa	Negative	1.267	Crude oil	Negative	7.240^{***}
		(0.826)			(1.715)
	Positive	-27.060^{***}		Positive	-7.265^{**}
		(8.742)			(3.109)
Coffee	Negative	-14.908^{***}	Heating oil	Negative	18.823^{***}
		(1.078)			(1.030)
	Positive	-6.277^{***}		Positive	-19.409^{***}
		(2.456)			(2.693)
Cotton	Negative	-7.631^{***}	Natural Gas	Negative	-6.776^{**}
		(0.807)			(3.967)
	Positive	-0.245		Positive	-83.981^{***}
		(4.941)			(26.256)

Note: the table reports multinomial logistic regression (Equation 4) results between the dependent variable that indicates a positive/negative bubble (indicator variable takes 1 for a negative bubble, 2 for a positive bubble and zero otherwise), and net long positions held by money managers (β_1). A negative (positive) bubble is when the nearby futures price is in a decreasing (increasing) trend over the 1-week period prior to the detected bubble. Standard errors are given in parenthesis while, ***,**,* represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 3: Multinomial Logit model: Commodity market liquidity and speculation

Commodity	Bubble	β_1	β_2	Commodity	Bubble	β_1	β_2
Corn	Negative	−11.441***	−1.844***	Sugar	Negative	−12.750***	−0.276
		(0.945)	(0.784)			(1.682)	(1.094)
	Positive	−7.545***	−2.792		Positive	−9.928	−2.275
		(2.367)	(1.792)			(9.122)	(3.013)
Oats	Negative	−1.316**	−1.133	Copper	Negative	−0.344	1.232
		(0.616)	(1.101)			(0.424)	(0.862)
	Positive	−10.106**	1.356		Positive	−3.315***	−0.574
		(5.228)	(3.545)			(0.817)	(1.267)
Rough rice	Negative	−3.757***	1.021	Gold	Negative	−6.588***	−2.538***
		(0.829)	(1.115)			(0.877)	(0.465)
	Positive	−5.621	−3.753		Positive	−12.173***	0.599
		(3.241)	(2.594)			(2.893)	(1.069)
Soybean	Negative	−10.864***	−1.710***	Platinum	Negative	−0.171	−0.347
		(0.840)	(0.640)			(0.484)	(0.446)
	Positive	−10.634***	−1.299		Positive	−8.525***	1.325
		(4.182)	(1.429)			(2.625)	(1.106)
Soybean meal	Negative	−7.359***	−0.978	Silver	Negative	−8.926***	0.728
		(0.723)	(0.671)			(1.038)	(0.937)
	Positive	−9.391***	−2.044		Positive	−14.762***	2.005
		(3.293)	(1.734)			(4.270)	(2.333)
Soybean oil	Negative	−9.363***	−0.114	Feeder cattle	Negative	−8.017***	−0.572
		(0.769)	(0.818)			(0.554)	(0.498)
	Positive	−12.115***	0.461		Positive	−1.831	0.690
		(1.946)	(1.589)			(1.676)	(1.055)
Wheat	Negative	−29.246***	2.612	Live cattle	Negative	−0.318	−2.077***
		(2.876)	(1.598)			(0.595)	(0.575)
	Positive	−16.230***	−8.992**		Positive	1.336	2.309**
		(4.822)	(3.768)			(1.269)	(1.173)
Cocoa	Negative	1.556	−1.079	Crude oil	Negative	11.261***	−11.074***
		(0.912)	(1.357)			(1.863)	(1.416)
	Positive	−26.819***	−6.428		Positive	−9.842***	7.452***
		(9.069)	(5.506)			(3.272)	(2.731)
Coffee	Negative	−14.456***	−1.721**	Heating oil	Negative	17.457***	5.901***
		(1.100)	(0.786)			(1.118)	(2.114)
	Positive	−4.845*	−6.338***		Positive	−17.718***	−5.493
		(2.508)	(2.324)			(2.926)	(4.058)
Cotton	Negative	−7.827***	1.146*	Natural gas	Negative	−0.351	−18.850***
		(0.810)	(0.678)			(4.492)	(4.267)
	Positive	0.638	−4.003***		Positive	−77.527***	−16.388
		(5.147)	(1.870)			(26.955)	(13.895)

Note: the table reports multinomial logistic regression (Equation 5) results between the dependent variable that indicates a positive/negative bubble (indicator variable takes 1 for a negative bubble, 2 for a positive bubble and zero otherwise), and net long positions held by money managers (β_1) and the interactive dummy variable representing commodity-specific liquidity (β_2). A negative (positive) bubble is when the nearby futures price is in a decreasing (increasing) trend over the 1-week period prior to the detected bubble. Standard errors are given in parenthesis while, ***,**,* represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 4: Multinomial Logit Model: Funding liquidity and speculation

Commodity	Bubble	β_1	β_2	Commodity	Bubble	β_1	β_2
Corn	Negative	-11.685^{***}	-0.399	Sugar	Negative	-17.203^{***}	11.096^{***}
		(0.975)	(0.709)			(1.758)	(1.483)
	Positive	-7.042^{***}	-2.203		Positive	-15.358^{*}	2.202
		(2.525)	(1.840)			(8.590)	(5.861)
Oats	Negative	-1.786^{**}	0.386	Copper	Negative	0.604	-1.867^{**}
		(0.744)	(0.890)			(0.506)	(0.743)
	Positive	-34.829^{***}	28.023^{***}		Positive	-2.397^{**}	-2.005
		(10.518)	(5.850)			(1.000)	(1.300)
Rough rice	Negative	-3.116^{***}	-0.349	Gold	Negative	-5.357^{***}	0.015
		(0.898)	(0.961)			(0.751)	(0.447)
	Positive	-9.012^{***}	4.353^{**}		Positive	-9.108^{***}	-0.875
		(3.400)	(2.471)			(2.533)	(1.193)
Soybean	Negative	-9.026^{***}	-3.292^{***}	Platinum	Negative	0.611	-1.399^{***}
		(0.876)	(0.599)			(0.520)	(0.388)
	Positive	-11.192^{***}	0.507		Positive	-8.403^{***}	3.315^{***}
		(4.294)	(1.366)			(3.158)	(1.163)
Soybean meal	Negative	-7.236^{***}	0.949	Silver	Negative	-7.093^{***}	-2.169^{***}
		(0.726)	(0.630)			(1.058)	(0.749)
	Positive	-10.936^{***}	-1.916		Positive	-13.550^{***}	-4.128^{*}
		(3.285)	(1.708)			(4.873)	(2.594)
Soybean oil	Negative	-8.914^{***}	-2.588^{***}	Feeder cattle	Negative	-6.280^{***}	-3.124^{***}
		(0.849)	(0.707)			(0.583)	(0.495)
	Positive	-12.002^{***}	-0.552		Positive	-4.035^{**}	-0.563
		(2.227)	(1.539)			(1.721)	(1.116)
Wheat	Negative	-26.983^{***}	-5.500^{***}	Live cattle	Negative	4.992^{***}	-7.301^{***}
		(2.948)	(1.529)			(0.907)	(0.777)
	Positive	-22.877^{***}	3.310		Positive	3.913	-1.610
		(5.145)	(3.418)			(2.116)	(1.792)
Cocoa	Negative	-0.122	2.671^{**}	Crude oil	Negative	29.849^{***}	-20.499^{***}
		(0.953)	(1.276)			(2.493)	(1.849)
	Positive	-24.298^{***}	9.552		Positive	-0.408	-7.403^{*}
		(6.512)	(5.877)			(5.183)	(4.304)
Coffee	Negative	-13.733^{***}	-0.116	Heating oil	Negative	18.520^{***}	-2.290
		(1.106)	(0.737)			(1.420)	(1.753)
	Positive	0.985	2.542		Positive	-17.511^{***}	2.878
		(4.141)	(1.697)			(4.613)	(4.171)
Cotton	Negative	-6.146^{***}	-2.851^{***}	Natural gas	Negative	-11.507^{***}	13.834^{***}
		(0.774)	(0.552)			(3.972)	(4.951)
	Positive	2.872	0.896		Positive	-81.632^{***}	22.447
		(4.634)	(1.368)			(25.947)	(20.723)

Note: the table reports multinomial logistic regression (Equation 6) results between the dependent variable that indicates a positive/negative bubble (indicator variable takes 1 for a negative bubble, 2 for a positive bubble and zero otherwise), and net long positions held by money managers (β_1) and the interactive dummy variable representing funding liquidity constraints (β_2). A negative (positive) bubble is when the nearby futures price is in a decreasing (increasing) trend over the 1-week period prior to the detected bubble. Standard errors are given in parenthesis while, ***,**,* represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 5: Net long positions held by money managers

	Bearish market conditions				Bullish market conditions			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Corn	0.077	0.047	0.048	0.058	0.063	0.094	0.087	0.109
Oats	0.078	0.039	0.034	0.035	0.061	0.096	0.068	0.056
Rough rice	0.023	0.001	-0.001	-0.012	0.011	0.043	0.036	0.048
Soybean	0.118	0.099	0.088	0.101	0.110	0.130	0.107	0.119
Soybean meal	0.132	0.100	0.079	0.091	0.117	0.146	0.122	0.131
Soybean oil	0.064	0.038	0.058	0.070	0.049	0.080	0.100	0.096
Wheat	0.008	-0.009	-0.010	-0.006	-0.001	0.033	0.013	0.043
Cocoa	0.111	0.089	0.121	0.121	0.101	0.124	0.140	0.124
Coffee	0.029	-0.001	0.041	0.037	0.014	0.065	0.074	0.080
Cotton	0.150	0.132	0.144	0.152	0.143	0.164	0.157	0.165
Sugar	0.089	0.067	0.053	0.057	0.078	0.093	0.087	0.081
Copper	0.051	0.011	0.002	-0.013	0.040	0.058	0.026	0.010
Gold	0.222	0.199	0.200	0.212	0.211	0.230	0.236	0.244
Platinum	0.277	0.223	0.255	0.248	0.261	0.287	0.304	0.331
Silver	0.148	0.124	0.119	0.123	0.138	0.150	0.155	0.155
Feeder cattle	0.122	0.098	0.104	0.094	0.107	0.161	0.142	0.161
Live cattle	0.180	0.172	0.169	0.172	0.178	0.176	0.170	0.156
Crude oil	0.073	0.066	0.073	0.067	0.071	0.072	0.078	0.072
Heating oil	0.050	0.037	0.026	0.025	0.044	0.048	0.051	0.045
Natural gas	0.040	0.034	0.028	0.025	0.038	0.037	0.031	0.028

Note: the table reports net long positions of money managers scaled by open interest when, (a) market & funding liquidity is high ($D_{com} = 0$ and $D_{fun} = 0$), (b) market liquidity is low ($D_{com} = 1$), (c) funding liquditiy is low ($D_{fun} = 1$) and (d) when both market liquidity and funding liquidity are low ($D_{com} = 1$ and $D_{fun} = 1$). Markets are considered bearish (bullish) when the nearby futures price is in a decreasing (increasing) trend over the past 1-week period.

Table 6: Multinomial Logit Model: Speculation under Market and Funding liquidity shortage

Commodity	Bubble	β_1	β_2	Commodity	Bubble	β_1	β_2
Corn	Negative	-11.338^{***}	-4.029^{***}	Sugar	Negative	-13.160^{***}	4.980^{**}
		(0.940)	(0.927)			(1.662)	(2.093)
	Positive	-7.457^{***}	-2.624		Positive	-10.793	7.151
		(2.385)	(2.017)			(9.627)	(5.149)
Oats	Negative	-1.430^{**}	-1.054	Copper	Negative	-0.214	1.496
		(0.595)	(1.413)			(0.396)	(1.206)
	Positive	-11.437^{**}	5.974^{*}		Positive	-2.983^{***}	-2.459
		(5.288)	(3.950)			(0.748)	(1.598)
Rough rice	Negative	-3.618^{***}	0.909	Gold	Negative	-7.109^{***}	-2.334^{***}
		(0.804)	(1.432)			(0.864)	(0.593)
	Positive	-5.836	-2.207		Positive	-11.964^{***}	1.441
		(3.233)	(2.818)			(2.828)	(1.280)
Soybean	Negative	-11.079^{***}	-3.249^{***}	Platinum	Negative	-0.186	-0.451
		(0.836)	(0.829)			(0.479)	(0.541)
	Positive	-10.925^{***}	-2.517		Positive	-8.706^{***}	1.997
		(4.132)	(1.809)			(2.634)	(1.292)
Soybean meal	Negative	-7.612	0.360	Silver	Negative	-8.875^{***}	-1.011
		(0.711)	(0.957)			(1.043)	(1.207)
	Positive	-9.512^{***}	0.165		Positive	-15.144^{***}	2.903
		(3.281)	(2.338)			(4.274)	(2.800)
Soybean oil	Negative	-9.224^{***}	-1.159	Feeder cattle	Negative	-7.822^{***}	-2.615^{***}
		(0.760)	(0.973)			(0.546)	(0.594)
	Positive	-12.161^{***}	0.786		Positive	-1.755	1.053
		(1.949)	(1.793)			(1.654)	(1.169)
Wheat	Negative	-28.035^{***}	-0.874	Live cattle	Negative	-0.111	-3.952^{***}
		(2.819)	(1.923)			(0.589)	(0.630)
	Positive	-18.068^{***}	-12.865^{***}		Positive	1.741	1.297
		(4.852)	(5.659)			(1.251)	(1.231)
Cocoa	Negative	0.533	11.306^{***}	Crude oil	Negative	12.154^{***}	-16.100^{***}
		(0.843)	(3.818)			(1.887)	(1.534)
	Positive	-27.866^{***}	4.181		Positive	-8.849^{***}	4.998^{*}
		(8.922)	(8.490)			(3.245)	(2.818)
Coffee	Negative	-14.693^{***}	-2.078^{**}	Heating oil	Negative	17.830^{***}	7.714^{***}
		(1.090)	(0.994)			(1.073)	(2.718)
	Positive	-5.928^{**}	-1.985		Positive	-18.807^{***}	-2.474
		(2.484)	(2.345)			(2.892)	(4.526)
Cotton	Negative	-7.811^{***}	2.576^{***}	Natural gas	Negative	-6.956	1.950
		(0.805)	(1.016)			(4.016)	(7.129)
	Positive	-0.882	-3.895		Positive	-84.913^{***}	-7.021
		(4.933)	(2.451)			(26.543)	(27.205)

Note: the table reports multinomial logistic regression (Equation 7) results between the dependent variable that indicates a positive/negative bubble (indicator variable takes 1 for a negative bubble, 2 for a positive bubble and zero otherwise), and net long positions held by money managers (β_1) and the interactive dummy variable representing both market and funding liquidity constraints (β_2). A negative (positive) bubble is when the nearby futures price is in a decreasing (increasing) trend over the 1-week period prior to the detected bubble. Standard errors are given in parenthesis while, ***,**,* represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 7: Multinomial Logit Model: Relative liquidity (market) and speculation

Commodity	Bubble	β_1	β_2	Commodity	Bubble	β_1	β_2
Corn	Negative	−11.699***	−0.658	Sugar	Negative	−12.117***	−2.734***
		(0.944)	(0.793)			(1.693)	(1.031)
	Positive	−8.824***	2.206		Positive	−6.782	−8.116**
		(2.314)	(1.686)			(9.468)	(3.461)
Oats	Negative	−1.149*	−1.502	Copper	Negative	0.248	−1.146
		(0.636)	(1.035)			(0.430)	(0.801)
	Positive	−9.278*	−0.515		Positive	−3.348***	−0.752
		(5.133)	(3.524)			(0.749)	(1.409)
Rough Rice	Negative	−3.365***	−0.608	Gold	Negative	−7.423***	1.217**
		(0.840)	(1.087)			(0.856)	(0.559)
	Positive	−5.752*	−0.519		Positive	−11.899***	0.402
		(3.238)	(2.335)			(2.838)	(1.302)
Soybean	Negative	−11.193***	−0.336	Platinum	Negative	−0.242	0.001
		(0.840)	(0.664)			(0.483)	(0.452)
	Positive	−11.647***	1.123		Positive	−8.907***	1.455
		(4.173)	(1.428)			(2.669)	(1.145)
Soybean meal	Negative	−7.681***	0.560	Silver	Negative	−8.794***	−0.475
		(0.716)	(0.728)			(1.048)	(0.857)
	Positive	−9.043***	−2.249		Positive	−14.294***	−1.885
		(3.312)	(1.959)			(4.379)	(2.520)
Soybean oil	Negative	−9.509***	0.533	Feeder cattle	Negative	−8.196***	0.057
		(0.770)	(0.838)			(0.556)	(0.508)
	Positive	−12.395***	1.482		Positive	−1.849	1.634
		(1.963)	(1.582)			(1.659)	(1.093)
Wheat	Negative	−27.269***	−3.692**	Live cattle	Negative	−0.976*	0.073
		(2.853)	(1.634)			(0.582)	(0.628)
	Positive	−19.113***	−2.285		Positive	1.648	1.711
		(5.025)	(3.232)			(1.254)	(1.288)
Cocoa	Negative	2.054**	−2.700**	Crude oil	Negative	7.679***	−1.646
		(0.934)	(1.280)			(1.769)	(1.527)
	Positive	−27.446***	2.000		Positive	−8.306**	3.983
		(8.808)	(4.147)			(3.206)	(2.943)
Coffee	Negative	−14.619***	−1.103	Heating oil	Negative	18.936***	−0.418
		(1.100)	(0.784)			(1.160)	(1.953)
	Positive	−5.473**	−1.848		Positive	−17.738***	−6.947
		(2.536)	(1.735)			(2.848)	(4.443)
Cotton	Negative	−7.727***	0.503	Natural gas	Negative	−2.836	−11.514***
		(0.814)	(0.657)			(4.343)	(4.284)
	Positive	−0.190	−1.392		Positive	−76.429***	−28.380*
		(4.968)	(1.476)			(27.734)	(15.040)

Note: the table reports multinomial logistic regression (Equation 8) results between the dependent variable that indicates a positive/negative bubble (indicator variable takes 1 for a negative bubble, 2 for a positive bubble and zero otherwise), and net long positions held by money managers (β_1) and the interactive dummy variable representing relative liquidity (β_2). A negative (positive) bubble is when the nearby futures price is in a decreasing (increasing) trend over the 1-week period prior to the detected bubble. Standard errors are given in parenthesis while, ***,**,* represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 8: Multinomial Logit Model: Relative liquidity (oil) and speculation

Commodity	Bubble	β_1	β_2	Commodity	Bubble	β_1	β_2
Corn	Negative	−11.754***	−0.527	Sugar	Negative	−12.486***	−1.419
		(0.938)	(0.814)			(1.687)	(1.051)
	Positive	−7.807***	−2.700		Positive	−10.029	1.052
		(2.314)	(1.931)			(9.238)	(2.618)
Oats	Negative	−1.738***	0.925	Copper	Negative	0.227	−0.984
		(0.627)	(1.109)			(0.436)	(0.781)
	Positive	−8.907*	−2.820		Positive	−3.856***	1.092
		(5.035)	(4.181)			(0.781)	(1.290)
Rough Rice	Negative	−3.669***	0.704	Gold	Negative	−6.933***	−1.056***
		(0.827)	(1.176)			(0.866)	(0.480)
	Positive	−6.130**	2.014		Positive	−11.860***	−0.144
		(3.240)	(2.310)			(2.842)	(1.110)
Soybean	Negative	−11.046***	−0.873	Platinum	Negative	−0.195	−0.201
		(0.842)	(0.642)			(0.485)	(0.442)
	Positive	−10.705***	−2.853*		Positive	−8.409***	0.311
		(4.144)	(1.512)			(2.622)	(1.145)
Soybean meal	Negative	−7.486***	−0.339	Silver	Negative	−8.922***	0.310
		(0.725)	(0.674)			(1.050)	(0.839)
	Positive	−9.397***	−1.360		Positive	−14.564***	−0.531
		(3.294)	(1.739)			(4.256)	(2.299)
Soybean oil	Negative	−8.981***	−1.955**	Feeder cattle	Negative	−8.221***	0.140
		(0.771)	(0.816)			(0.556)	(0.507)
	Positive	−11.869***	−1.022		Positive	−1.589	−0.154
		(1.933)	(1.617)			(1.666)	(1.127)
Wheat	Negative	−27.845***	−0.997	Live cattle	Negative	−1.409***	2.327***
		(2.856)	(1.599)			(0.567)	(0.733)
	Positive	−16.484***	−11.599***		Positive	1.987	0.673
		(4.845)	(3.951)			(1.227)	(1.534)
Cocoa	Negative	1.180	0.357	Crude oil	Negative	7.240***	0.000
		(0.895)	(1.451)			(1.715)	(0.000)
	Positive	−24.410***	−8.087		Positive	−7.265***	0.000
		(8.535)	(5.990)			(3.109)	(0.000)
Coffee	Negative	−14.652***	−0.831	Heating oil	Negative	18.878***	−0.235
		(1.104)	(0.784)			(1.134)	(2.012)
	Positive	−7.004***	1.673		Positive	−18.632***	−3.472
		(2.575)	(1.696)			(2.852)	(4.514)
Cotton	Negative	−7.889***	1.596**	Natural gas	Negative	−1.518	−14.349***
		(0.808)	(0.699)			(4.431)	(4.240)
	Positive	−1.269	−6.366***		Positive	−73.485***	−28.112**
		(5.113)	(2.303)			(27.946)	(14.730)

Note: the table reports multinomial logistic regression (Equation 9) results between the dependent variable that indicates a positive/negative bubble (indicator variable takes 1 for a negative bubble, 2 for a positive bubble and zero otherwise), and net long positions held by money managers (β_1) and the interactive dummy variable representing funding constraints (β_2). A negative (positive) bubble is when the nearby futures price is in a decreasing (increasing) trend over the 1-week period prior to the detected bubble. Standard errors are given in parenthesis while, ***,**,* represent statistical significance at 1%, 5% and 10% levels, respectively.