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The Impact of Long-Short Speculators on the Volatility of Agricultural Commodity Futures Prices

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Abstract

Departing from the lively discussion about the Masters' hypothesis, this paper examines whether increasing activities of long-short speculators in commodity futures markets have a stabilizing or destabilizing impact on price movements. Our analysis covers five agricultural commodities traded in the US market over the period from 2006 to 2017. We conclude that long-short speculators do not destabilize commodity prices. Instead, we find evidence that activities of long-short speculators reduce volatility in the markets under scrutiny.

Keywords: Commodity Futures Markets, GARCH models, Long-short Speculators

1. Introduction

Over the past decade, the causes and consequences of the increasing financialization of commodity markets have been controversially discussed in the academic literature and public debate. This discussion was caused by unprecedented price fluctuations in a wide range of commodity markets. Between 2006 and 2011, commodity prices increased rapidly, exhibiting pronounced price spikes and sharp reversals in 2007/08 as well as 2011. Since 2013, an overall continuing decline in prices is observable across a broad spectrum of commodities. At the same time, commodity futures have become increasingly utilized

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by financial investors, due to their diversification benefits and strength in inflation hedging (Miffre and Brooks, 2013). The synchronized rise in commodity prices, trading volume and open interest held by financial investors have caused a heated debate on speculation as the major driver of these exceptional commodity price movements and has resulted in the implementation of new regulatory measures (Paulson et al., 2013).

The empirical literature on speculation in commodity markets and the public debate is mainly focused on commodity index traders (CITs), which emerged as notable market participants at the same time as commodity markets became increasingly volatile. While the empirical literature predominantly rejects the so-called Masters hypothesis (e.g. Stoll and Whaley, 2010; Irwin and Sanders, 2011, 2012; Hamilton and Wu, 2015; Brunetti and Reiffen, 2014), the role of classical speculators, also referred to as long-short investors, received significantly less attention. This is particularly remarkable, since the investment strategies of CITs and long-short speculators are substantially different and therefore, may have a varying impact on market outcomes. In contrast to CITs, which typically buy and hold long positions in nearby futures contracts under consideration of predefined and publicised roll-over strategies, long-short speculators are prone to beat the market with selection and timing (Brunetti and Reiffen, 2014; Etienne et al., 2014).

Theoretical work on speculation does not provide an unambiguous answer whether speculative trading stabilizes or destabilizes (commodity) prices. The traditional theory, as for example put forward by Friedman (1953), comes to the conclusion that trading activities of speculators stabilize prices by buying if the price is low and selling if the price is high. If speculators bought if the price is high and sold if the price is low, they would destabilize prices but would sooner or later leave the market (Friedman, 1953; De Long et al., 1990). Contradicting conclusions are reached by theoretical work on herding, noise traders and speculative bubbles. These theoretical considerations provide a framework in which speculative trading may destabilize prices (Brunetti et al., 2016). For instance, De Long et al. (1990) demonstrate that rational speculators can drive prices away from their fundamental level by anticipating the price impact of positive feedback traders.[1]

To the present, very few papers have empirically investigated the impact of long-short speculators on commodity futures markets. The majority of studies examines the general influence of speculation on commodity markets and does not differentiate between distinct trader types (e.g. Kim, 2015; Manera et al., 2013, 2016; Büyükşahin and Harris, 2011; Alquist and Gervais, 2013) or focuses on CITs (e.g. Irwin and Sanders, 2012, 2011; Gilbert and Pfuderer, 2014; Hamilton and Wu, 2015). As Miffre and Brooks (2013), Büyükşahin and Robe (2014) and Brunetti et al. (2016) our analysis is focused on long-short speculation. However, the existing literature is expanded by examining the impact of long-short speculation on commodity price volatility in agricultural commodity markets and by investigating, whether market liquidity alters the influence of long-short speculators. The empirical analysis is based on the implementation of GARCH models that take into account two different measures of long-short speculators' activities using the non-commercial trader category of the CFTC's Supplemental Commitment of Traders (SCOT) report. Moreover, we consider several macroeconomic determinants of agricultural commodity prices to specify the mean equation. Our empirical approach permits conclusion regarding the effects of long-short speculation and macroeconomic factors on price movements.

The remainder of this paper is structured as follows: In Section 2, the measures for long-short speculators' activities and the underlying data are presented. After that the methodology is introduced in Section 3. The empirical application of the previously presented testing procedures occurs in Section 4. Section 5 displays a variety of robustness checks. Finally, Section 6 concludes.

[1] A comprehensive survey of theoretical considerations and empirical findings with respect to the (de)stabilizing impact of speculative activities on prices is provided by Miffre and Brooks (2013) and Brunetti et al. (2016).

2. Measure construction and data description

To calculate a measure for the activity of long-short speculators, publicly available positions data provided in the CFTC's SCOT reports are utilized. The advantage of using the SCOT reports lies in the fact that this report explicitly differentiates between non-commercial, commercial, commodity index and non-reporting traders.[2] As highlighted, for example, by Alquist and Gervais (2013) and Manera et al. (2016), the empirical literature commonly interprets non-commercial traders as speculators and traders in the commercial category as hedgers. Since the SCOT reports further differentiate the non-commercial category into index traders and other trader types, we refer to the non-commercial less index traders as classical or long-short speculators.

It needs to be highlighted that traders classified as non-commercials are not the only group holding speculative positions. The index fund category consists of traders which in the disaggregated COT reports would, at least partially, be classified as speculators (Sanders and Irwin, 2011a), but due to differences in the underlying trading strategy, not as long-short speculators. The non-reporting category captures all traders, whose position size does not exceed the threshold defined by the CFTC regardless of the underlying trading strategy. It seems plausible that several traders, classified as non-reporting, hold speculative positions and could be classed as non-commercial or long-short speculators.

To quantify the trading activities of long-short speculators, two measures based on open interest positions held by non-commercial traders are used, which are frequently applied in the empirical literature. Motivated by Aulerich et al. (2014), the total open interest of long-short speculators is utilized as a proxy for their speculative activity:

$$S_{i,t}^{Total} = NCS_{i,t} + NCL_{i,t} + SNC_{i,t} \cdot NR_{i,t}, \tag{1}$$

[2] For a detailed characterization of the SCOT reports as well as the relationship between legacy, disaggregated and supplemental commitments of traders report see, for example, Irwin and Sanders (2012) and Gilbert and Pfuderer (2014).

where $NCS_{i,t}$ denotes short positions held by classical speculators (non-commercials less index traders) in market i at time t and $NCL_{i,t}$ the long positions held by this group. To account for long-short speculators classified as non-reporting traders, we follow Sanders et al. (2010) and Kim (2015) by assuming that non-reporting trader show the same distribution pattern as observed in the group of reporting traders and allocate them accordingly. Therefore, the share of non-commercial trader at total open interest $OI_{i,t}$ is denoted by $SNC_{i,t} = (NCS_{i,t} + NCL_{i,t})/(2 \cdot OI_{i,t})$. $NR_{i,t}$ describes the total positions held by non-reporting traders.

In line with Manera et al. (2016), the share of long-short speculators at the total open interest is used as a robustness check:

$$S_{i,t}^{Share} = \frac{NCS_{i,t} + NCL_{i,t} + SNC_{i,t} \cdot NR_{i,t}}{2 \cdot OI_{i,t}}. \tag{2}$$

Although the SCOT reports are frequently applied in the academic literature on speculation in commodity markets, they have several limitations and drawbacks. The low data frequency is one major disadvantage of the CFTC reports, which are published on a weekly basis. Testing procedures may fail to find an impact of position changes on commodity prices since significant position and price changes can occur in a short period of time.[3] Additional limitations arise from the underlying trader classification. This classification is made on the basis of the major trading strategy which the individual trader is following and all positions held by this trader are then classified, for example as non-commercial or index related (Gilbert and Pfuderer, 2014). Such a clear distinction seems to be problematic, keeping in mind that traders from all categories can hold speculative positions or hedge their risk exposure. Results of Ederington and Lee (2002) as well as Dewally et al. (2013) indicate that this distinction especially with respect to the commercial category is insufficient. Nevertheless, for

[3]Few studies use daily data from the CFTC's Large Trader Reporting System (e.g. Brunetti and Büyükşahin, 2009; Sanders and Irwin, 2011b; Büyükşahin and Harris, 2011; Büyükşahin and Robe, 2014; Brunetti et al., 2016), but this database is not publicly available.

practical reasons and with respect to the lack of more adequate data, such a proceeding seems unavoidable (Alquist and Gervais, 2013; Manera et al., 2016). Despite these limitations, several studies utilize either the legacy, the disaggregated or the supplemental commitment of traders reports in absence of more appropriate data.

Data on futures prices for five agricultural commodities traded at the Chicago Board of Trade (CBOT), the Intercontinental Exchange (ICE) and the Kansas City Board of Trade (KCBT) are collected from Thomson Reuters Datastream. To investigate whether market liquidity alters the influence of speculation on price movements, the three most liquid agricultural futures markets considered by the CFTC and the two most illiquid markets are examined.[4] The most liquid markets are CBOT corn and soybeans as well as ICE sugar, the most illiquid are the ICE coffee and KCBT wheat markets.[5] The analysis covers the period from April 2006 to December 2017. To match the position data provided by the CFTC, Tuesday-to-Tuesday logarithmic price differences are calculated. In the case that a Tuesday is not a trading day, the settlement price of the preceding trading day is used. Continuous futures prices series as provided by Thomson Reuters are used, which are constructed by switching the contract on the first trading day of the expiring month.

The influence of macroeconomic factors on commodity price movements is controversially discussed in the academic literature. We control for these factors

[4]Concerning commodities covered by the CFTC, illiquidity is always a relative term. In comparison to some commodity futures where a trade does not take place at all trading days (e.g. Adämmer et al., 2016), futures covered by the CFTC are highly liquid. Comparing commodities covered by the CFTC, it becomes obvious that commodities like KCBT wheat are significantly less liquid as, for example, ICE sugar, whereby liquidity is measured by total open interest (see Table 1).

[5]To measure the liquidity of a market and based on this, to construct a ranking, the total amount of open interest during the investigation period of an individual agricultural futures market is used (e.g. Miffre and Brooks, 2013). To check the robustness of the ranking, a set of sub-rankings is constructed to investigate whether the results change if total open interest in a given year are examined.

following among others Brooks et al. (2015), Chevallier (2009), Manera et al. (2013, 2016) and Kim (2015). We use data on the S&P 500 to capture the influence of the general economic development and the 3-month treasury bill rate to account for effects caused by monetary policy decisions. Furthermore, data on oil prices and the US dollar exchange rate are utilized. The empirical application is based on the Trade Weighted US Dollar Index, which is a weighted average of the US dollar exchange rates of key US trading partners. The use of oil prices and the US dollar exchange rate in the context of (agricultural) commodity markets is, for example, motivated by Chen et al. (2010) and Nazlioglu and Soytas (2012). All data on macroeconomic factors are obtained from Thomson Reuters Datastream.

Summary statistics for all variables used in the analysis and the results of unit root tests are provided in Table 1. To test the stationarity properties of the underlying time series the augmented Dickey and Fuller (1981) (ADF) is applied. From Table 1 it becomes obvious that futures prices, macroeconomic factors and the measure of speculators' activities are non-stationary in levels. Stationarity is achieved by calculating logarithmic price differences for each variable, which approximate continuously compounded returns.

3. Methodology

Initially proposed by Bollerslev (1986) and Taylor (1987), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are frequently applied in financial econometrics. The mean equation is composed of a set of macroeconomic control variables, namely the return of the S&P 500 index ($sp500_t$), the 3-month US treasury bill secondary market rate ($tbill_t$), the US dollar exchange rate ($exrate_t$) and the WTI crude oil spot price (oil_t). Since the impact of futures speculation on the volatility of commodity returns is examined, the measure $s_{i,t}$ is incorporated into the variance equation as an explanatory regressor (Kim, 2015; Manera et al., 2016).

With respect to the macroeconomic variables included into the mean equation, it is expected that the parameter on the S&P 500 as a proxy for the general economic development exhibits a positive sign. The US treasury bill, which serves as the risk free rate, is assumed to have a negative influence on commodity prices. Additionally, the exchange rate is assumed to exert a negative influence on the commodity prices under scrutiny. The commodities covered in the analysis are traded in US dollar, therefore it is anticipated that an appreciation of the US dollar will lead to a depreciation of commodity prices. The weakness of the US dollar is one of the most frequently discussed explanatory factors behind the commodity price spikes around 2008 (e.g. Nazlioglu and Soytas, 2012; Etienne et al., 2014). Finally, it is assumed that the oil price will affect agricultural commodity prices positively, through higher production and transport costs as well as increasing demand for biofuels (e.g. Nazlioglu and Soytas, 2012). Preliminary tests indicate that a GARCH(1,1) specification is appropriate. Accordingly, the mean equation is represented by:

$$r_{t,i} = \alpha_0 + \beta_2 sp500_t + \beta_3 tbill_t + \beta_4 exrate_t + \beta_5 oil_t + \eta_{i,t}, \tag{3}$$

with $\eta \sim N(0, \sigma_t^2)$. The return of each individual futures price series is defined as $r_{i,t} = [ln(F_{i,t}) - ln(F_{i,t-1})] \times 100$, where $F_{i,t}$ denotes the futures price of commodity i at time t. The variance equation is given by the following formula:

$$\sigma_{i,t}^2 = \delta_0 + \delta_1 \eta_{i,t-1}^2 + \delta_2 \sigma_{i,t-1}^2 + \delta_3 s_{i,t}. \tag{4}$$

The conditional volatility is denoted by $\sigma_{i,t}^2$. The ARCH effect is described by the parameter δ_1 in the variance equation and the GARCH effect is denoted by δ_2. ARCH and GARCH estimates are expected to be positive, while ensuring that their sum is smaller than one ($\delta_1 + \delta_2 < 1$). These restrictions ensure covariance stationarity and that the conditional variance is always non-negative. The interpretation of the parameter of interest is straightforward. A destabilizing impact of long-short speculation on commodity price volatility is indicated if a positive parameter estimate is obtained for δ_3. In contrast, a negative estimate indicates a stabilizing influence of speculative activities.

4. Empirical application

First, we estimate the models based on total open interest of long-short speculators (Equation 1) to investigate their impact on commodity price volatility. The estimates for the mean and variance equation are presented in Table 2. The S&P 500 as a proxy for the influence of the general economic development does not have a significant influence on the majority of the examined commodities, with the exception of coffee. The positive estimates obtained for coffee may be explained by findings of Creti et al. (2013). The authors show that the correlation between the S&P 500 and coffee increases during stock price rises. The results do not indicate a significant impact of the three-month treasury bill rate on commodity price movements for four out of five commodities (a weakly significant estimate is obtained for corn). These findings are in line with Manera et al. (2013). In contrast, a significant positive influence of oil prices on agricultural commodities is observed in all markets under scrutiny. The parameter estimates for the US dollar exchange rate are all negative and highly significant at the 1% level. Therefore, the results are in line with the predictions and findings of the literature on fundamental factors of commodity price movements (e.g. Nazlioglu and Soytas, 2012; Etienne et al., 2014; Manera et al., 2013, 2016).

The time-invariant level of conditional volatility, measured through the constant in the variance equation, is solely significant for coffee and wheat. The restrictions imposed to ensure covariance stationarity and a positive conditional variance are met by all commodities. The ARCH estimates range between 0.06 for corn and 0.162 for soybeans, whereas the GARCH estimates are commonly close to one (between 0.699 for coffee and 0.886 for sugar). The estimated volatility persistence ($\delta_1 + \delta_2$) ranges between 0.78 and 0.959 and the resulting half-life of volatility shocks is between approximately 3 and 17 weeks.[6] Therefore, the results show significant signs of shock persistence.

The parameter δ_3 measures the effect of speculators' activity on returns

[6]The half-life of a volatility shock is defined as $ln(0.5)/ln(\delta_1 + \delta_2)$ (Zivot, 2009).

volatility. Significantly negative estimates for δ_3 are obtained for all commodities examined. This observation implies that speculative activities of long-short speculators calm returns volatility.

Since these results are potentially influenced by the choice of the measure for speculators' activities, the previous analysis is replicated by using the market share of long-short speculators (Equation 2) as an alternative measure. The results of the estimated GARCH models using the market share of long-short speculators are presented in Table 3. The results of the mean equation generally comply with the previous analysis. In line with the estimation based on total open interest, every restriction on the GARCH model ($\delta_1 > 0$, $\delta_2 > 0$ and $\delta_1 + \delta_2 < 1$) is satisfied by all commodities examined. Again, the estimates of δ_2 are close to one, whereas the estimates of δ_1 are commonly below 0.1, with the expectation of soybeans, providing a strong indication for the persistence of volatility shocks. Accordingly, the half-life of shocks ranges between approximately 2 and 18 weeks. The parameter estimates for δ_3 are all negative and highly significant. These observations support the previous results and provide indication that long-short speculators' activities calm returns volatility in the examined markets.

Summarizing the empirical results, we do not find evidence for a destabilizing impact of long-short speculators' activities on commodity price volatility in any of the commodity markets examined. Instead, the results of the GARCH model indicate a stabilizing effect of long-short speculation for the commodities under scrutiny independent of the market liquidity. Furthermore, the results are in line with current academic literature on the stabilization hypothesis (e.g. Miffre and Brooks, 2013; Kim, 2015; Manera et al., 2013, 2016).

5. Robustness analysis

Nevertheless, the results may be affected by the choice of the underlying model specifications, the construction of the underlying measure of speculators' activities and the investigation period. To enhance the robustness of our results, the current analysis is expanded through several robustness checks. First, we test whether excluding non-reporting traders from the measure of speculators' activities may alter the results. Second, the results are validated by investigating whether the influence of long-short speculators differs during high or low price periods. Finally, the results of different model specifications are examined to ensure that these are unaffected by changes in the underlying model. Therefore, different controls in the variance equation of the GARCH model are applied.

5.1. Non-Reporting traders

Long-short speculators whose position size does not exceed the reporting level are classified as non-reporting traders. In the initial analysis, it is assumed that the proportion of long-short speculators in the reporting category is comparable to the proportion of classical speculators in the non-reporting category. To test whether the results are affected by an incorrect assignment of non-reporting traders, the initial analysis is replicated under the assumption that none of them are long-short speculators. The results are displayed in Table 4. The estimated coefficients for the measures of speculators' activities are comparable to the results of the initial analysis in sign and magnitude, providing indication that the results are unaffected by the in- or exclusion of non-reporting traders.

5.2. Subsamples

After agricultural commodity prices increased dramatically during the early phases of the examination period, exhibiting pronounced spikes and crashes, a continuing decline in prices and volatility is observable in recent years. Hence, the calming influence of long-short speculation on volatility indicated by the initial analysis could potentially be explained by the long-lasting decline in prices and volatility during past years. To test whether the influence of long-short speculation varies in phases with exceptionally high prices, controls for these periods are incorporated into the model. High price periods are identified by using a two-regime Markov switching model. Based on the results of the Markov model, a regime dummy variable is constructed. The dummy variable takes on one, if the results of the Markov switching model indicate a high price regime and zero otherwise. The initial variance equation is expanded by including the regime dummy and an interaction term. The interaction term is defined as interaction between the speculation measure and the price regime dummy.

The results indicate that volatility in general is significantly increased during high price periods across all commodities as indicated by the significantly positive estimates obtained for the regime dummy. Nevertheless, significantly negative estimates are obtained for the speculation measure. This indicates a calming influence of long-short speculators' activities regardless of the measure used or the underlying price regime. Solely, the weak positive interaction term observed for corn by using S^{Total} indicates a rise in volatility caused by speculators' activities during high price periods. The results are presented in Table 5 and Table 6.

5.3. GARCH model specifications

The influence of the macroeconomic controls could affect commodity price volatility. For example, several studies indicate the presence of volatility spillovers from energy to agricultural commodity markets (e.g. Du et al., 2011; Nazlioglu and Soytas, 2012; Nazlioglu et al., 2013; Ji and Fan, 2012). Accordingly, we incorporate returns of the macroeconomic controls not only in the mean but also into the variance equation to take these effects into account. An additional possible misspecification is the lack of consideration of inventories and seasonality. Inventories of storable commodities are shown to affect prices and volatility (e.g. Peterson and Tomek, 2005). To account for changes in inventories, beginning and ending stocks of Hard Red Winter Wheat as provided by the United States Department of Agriculture are utilized. We construct a dummy variable, which takes on one if the difference between the beginning and ending stock is positive and zero otherwise. Agricultural commodities are known to exhibit seasonality and the lack of consideration of seasonality may lower the quality of results. To ensure clarity of presentation and with respect to the attention wheat received in the debate on speculation in commodity markets, the analysis is restricted to wheat.

Table 7 and 8 displays the results for seven different specifications of the variance equation and an unaltered mean equation. It becomes obvious that the initial results are nearly unaffected by variations of the variance equation, regardless of the underlying speculation measure. The parameter estimates for S^{Total} and S^{Share} are all highly significant, negative and comparable in their magnitude.

The previous analysis is extended by including spread positions of long-short speculators as reported by the CFTC into the initial measures of speculators' activities. Highly significant negative parameter estimates are obtained for S^{Total}_{Spread} and S^{Share}_{Spread}, supporting the initial inference that long-short speculation reduces volatility. An additional extension is to differentiate between long, short and spread positions held by non-commercial trader. By decomposing the initial measure into NC_{long},NC_{short} and NC_{spread}, the overall results are not altered. Significantly negative parameter estimates are observed for the measures based on the short positions, whereas long and spread positions are not significantly different from zero.

Since the results from the comprehensive robustness analysis for wheat need not to hold for other commodities, we replicate the previous analysis in reduced form for the remaining commodities. Table 9 displays the results. The robustness analysis is based on two models incorporating macroeconomic factors. The first model uses S^{Share} and the second model considers spreading positions, using S^{Share}_{Spread}. Table 9 indicates negative and insignificant estimates for both speculation measures examining soybeans and sugar. With respect to coffee, a positive and highly significant estimate is obtained. Examining corn and incorporating macroeconomic factors into the variance equation leads to an non-converging GARCH model, therefore we could not report results for corn.

In conclusion, the initial results, as described in Section 4, are robust towards changes in the econometric specification, the definition of the underlying measures of speculators' activities and the examination period in most cases. Inconclusive results are obtained for coffee only.

6. Conclusion

Motivated by repeated spikes and crashes in agricultural commodity prices, we investigate whether long-short speculators' trading activities impact on the volatility of commodity prices. By focusing on this trader type, which had been given little attention in the current academic literature on commodity price volatility, this paper contributes to the ongoing debate on commodity futures speculation.

Conditional volatility is approximated using a GARCH model while controlling for a potential influence of different macroeconomic factors. The analysis covers the three most liquid and the two most illiquid agricultural commodity markets listed in the SCOT reports and therefore provides evidence, whether the impact of long-short speculators positions varies with the market liquidity. The GARCH model estimations strongly indicate that long-short speculators have either no or a calming effect on conditional volatility regardless of the underlying speculation measure and market liquidity.

The results are consistent with the current academic literature, which generally finds a calming influence of speculation in commodity markets, and broadly confirm the theoretical predictions. These findings have important policy implications. Since speculation could affect the functionality of commodity markets positively, regulatory measures should be implemented with caution to maintain the positive aspects of adequate speculation. Regulatory measures introduced to limit an assumed harmful impact of speculators may be counterproductive concerning the volatility of agricultural commodity prices. This conclusion is in accordance with Sanders et al. (2010).

Additional research efforts seem to be necessary to answer the question, whether speculation in all its forms and manifestations is harmful or beneficial. Current research on the impact of market participants (e.g. CITs, long-short speculators) is commonly based on and potentially influenced by the highly aggregated, weekly position data provided by the CFTC, which is currently the best public available data source. We strongly recommend policy makers to provide more disaggregated data at higher frequencies as currently available, before implementing potentially premature regulatory measures.

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Table 1: Summary statistics and unit-root tests

		Summary statistics				Unit-Root test statistics	
		Mean	Std.dev.	Min	Max	Level	log first-diff.
Corn	Return	0.067	4.442	-20.878	18.410	-2.05	-26.445^{***}
	S^{Share}	0.136	0.037	0.054	0.220	-2.644^{*}	-16.769^{***}
	S^{Total}	479990.565	145862.585	185365.266	820227.438	-2.552	-15.38^{***}
	OI^{Total}	1762391.196	262106.324	1091888.000	2573509.000	-3.662^{***}	-5.908^{***}
Soybeans	Return	0.088	3.582	-15.184	10.677	-2.444	-25.645^{***}
	S^{Share}	0.136	0.030	0.056	0.214	-4.071^{***}	16.129^{***}
	S^{Total}	213033.609	75587.797	56401.352	403488.094	-2.804^{*}	-15.716^{***}
	OI^{Total}	775241.667	192206.093	379052.000	1302943.000	-3.111^{**}	-5.733^{***}
Sugar	Return	-0.033	4.846	-18.819	20.318	-1.394	-24.709^{***}
	S^{Share}	0.127	0.049	0.048	0.243	-5.492^{***}	-22.863^{***}
	S^{Total}	243967.179	102889.998	99523.609	484588.375	-3.502^{***}	-15.666^{***}
	OI^{Total}	962306.507	163107.850	604290.000	1535068.000	-2.244	-7.387^{***}
Coffee	Return	0.022	4.325	-14.489	17.663	-2.190	-25.015^{***}
	S^{Share}	0.158	0.046	0.070	0.280	-2.732^{*}	-17.877^{***}
	S^{Total}	63617.960	23049.472	25652.273	136983.266	0.111	-17.444^{***}
	OI^{Total}	199578.371	33936.189	111943.000	284067.000	0.572	-5.078^{***}
Wheat	Return	0.002	4.419	-16.373	20.181	-2.127	-25.259^{***}
	S^{Share}	0.220	0.059	0.102	0.385	-3.169^{**}	-15.334^{***}
	S^{Total}	80597.908	43705.504	18055.088	228597.156	-2.310	-15.636^{***}
	OI^{Total}	174030.789	53184.214	80581.000	345716.000	-2.893^{**}	-7.463^{***}
Macro factors	S& P 500	1582.751	451.982	696.330	2681.470	1.13	-26.061^{***}
	T-Bill	0.954	1.600	-0.010	5.050	-2.616^{*}	-18.788^{***}
	ExRate	106.983	9.057	93.949	128.963	-0.699	-24.13^{***}
	Oil	75.355	23.370	27.960	141.060	-2.853^{*}	-5.721^{***}

Notes: Own calculation based on data obtained from Thomson Reuters Datastream and the Supplemental Commitment of Traders (SCOT) reports provided by the US Commodity Futures Trading Commission (CFTC). Selection of the lag length for the ADF test is based on the AIC. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table 2: GARCH regressions based on S^{Total}

	Corn	Soybeans	Sugar	Wheat	Coffee
			Mean equation		
S&P 500	-0.006	0.107	-0.014	0.091	0.172^{**}
	(0.088)	(0.070)	(0.102)	(0.084)	(0.082)
T-Bill	0.013^{*}	0.003	0.008	0.003	-0.008
	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)
ExRate	-1.189^{***}	-0.951^{***}	-0.955^{***}	-1.528^{***}	-1.280^{***}
	(0.291)	(0.214)	(0.317)	(0.244)	(0.284)
Oil	0.118^{***}	0.090^{***}	0.131^{***}	0.084^{***}	0.108^{***}
	(0.041)	(0.024)	(0.046)	(0.032)	(0.037)
Constant	0.074	0.189	-0.067	-0.041	-0.021
	(0.175)	(0.119)	(0.184)	(0.156)	(0.164)
			Variance equation		
S^{Total}	-0.138^{***}	-0.099^{***}	-0.129^{***}	-0.115^{***}	-0.053^{**}
	(0.037)	(0.027)	(0.037)	(0.018)	(0.021)
Constant	-0.255	0.138	-0.468	0.726^{**}	1.172^{**}
	(0.523)	(0.422)	(0.515)	(0.319)	(0.535)
ARCH	0.060^{***}	0.162^{***}	0.073^{***}	0.105^{***}	0.081^{**}
	(0.023)	(0.043)	(0.014)	(0.037)	(0.038)
GARCH	0.883^{***}	0.708^{***}	0.886^{***}	0.730^{***}	0.699^{***}
	(0.040)	(0.070)	(0.018)	(0.058)	(0.131)
Sum (G)ARCH	0.943	0.87	0.959	0.835	0.78
Half-life	11.811	4.977	16.557	3.844	2.79
AIC	3457.148	3126.31	3562.045	3425.253	3407.768
BIC	3496.84	3166.002	3601.736	3464.944	3447.459

Notes: The GARCH models are estimated using S^{Total} (Equation 1) as measure for long-short speculators' activity. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 3: GARCH regressions based on S^{Share}

	Corn	Soybeans	Sugar	Wheat	Coffee
			Mean equation		
S&P 500	-0.014	0.106	-0.005	0.111	0.169**
	(0.086)	(0.070)	(0.102)	(0.083)	(0.083)
T-Bill	0.014*	0.003	0.008	0.003	-0.008
	(0.007)	(0.003)	(0.006)	(0.006)	(0.006)
ExRate	-1.187***	-0.945***	-0.969***	-1.509***	-1.252***
	(0.290)	(0.216)	(0.313)	(0.247)	(0.277)
Oil	0.117***	0.088***	0.126***	0.081**	0.099***
	(0.041)	(0.023)	(0.046)	(0.032)	(0.036)
Constant	0.086	0.141	-0.068	-0.032	-0.039
	(0.172)	(0.116)	(0.180)	(0.158)	(0.155)
			Variance equation		
S^{Share}	-0.163***	-0.098***	-0.160***	-0.114***	-0.082***
	(0.040)	(0.031)	(0.037)	(0.019)	(0.016)
Constant	-0.701	-0.070	-0.814	0.762**	1.405***
	(0.533)	(0.475)	(0.601)	(0.321)	(0.336)
ARCH	0.053***	0.166***	0.070***	0.098***	0.093**
	(0.020)	(0.043)	(0.012)	(0.036)	(0.038)
GARCH	0.903***	0.731***	0.893***	0.737***	0.600***
	(0.031)	(0.065)	(0.016)	(0.060)	(0.103)
Sum (G)ARCH	0.956	0.897	0.963	0.835	0.693
Half-life	15.404	6.377	18.385	3.844	1.89
AIC	3456.109	3129.483	3558.68	3431.356	3389.651
BIC	3495.801	3169.174	3598.371	3471.048	3429.342

Notes: The GARCH models are estimated using S^{Share} (Equation 2) as measure for long-short speculators' activity. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 4: GARCH regressions S^{Total} and S^{Share} excluding all non-reporting traders

	Corn	Soybeans	Sugar	Wheat	Coffee
			Variance equation S^{Total}		
S^{Total}	-0.134***	-0.099***	-0.130***	-0.111***	-0.052**
	(0.036)	(0.027)	(0.036)	(0.017)	(0.022)
Constant	-0.198	0.137	-0.534	0.694**	1.115**
	(0.512)	(0.422)	(0.517)	(0.329)	(0.559)
ARCH	0.061***	0.163***	0.072***	0.105***	0.081**
	(0.023)	(0.044)	(0.013)	(0.036)	(0.038)
GARCH	0.879***	0.707***	0.890***	0.737***	0.713***
	(0.041)	(0.071)	(0.016)	(0.058)	(0.130)
AIC	3457.293	3126.388	3562.215	3427.373	3408.129
BIC	3496.985	3166.079	3601.907	3467.065	3447.821
			Variance equation S^{Share}		
S^{Share}	-0.163***	-0.098***	-0.161***	-0.115***	-0.082***
	(0.040)	(0.032)	(0.037)	(0.018)	(0.016)
Constant	-0.656	-0.054	-0.818	0.690**	1.399***
	(0.520)	(0.471)	(0.599)	(0.326)	(0.340)
ARCH	0.054***	0.167***	0.069***	0.093***	0.094**
	(0.020)	(0.044)	(0.012)	(0.035)	(0.039)
GARCH	0.901***	0.729***	0.894***	0.751***	0.601***
	(0.031)	(0.066)	(0.016)	(0.057)	(0.104)
AIC	3455.924	3129.448	3558.831	3431.58	3390.11
BIC	3495.616	3169.139	3598.523	3471.272	3429.801

Notes: The GARCH models are estimated using S^{Total} and S^{Share} as measure for long-short speculators' activity by assuming none trader in the non-reporting category is a long-short speculator. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 5: GARCH regressions based on S^{Total} controlling for price regimes

	Corn	Soybeans	Sugar	Wheat	Coffee
			Mean equation		
S&P 500	-0.007	0.106	-0.018	0.099	0.179^{**}
	(0.086)	(0.068)	(0.090)	(0.084)	(0.082)
T-Bill	0.012^{*}	0.002	0.009	0.003	-0.007
	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)
ExRate	-1.116^{***}	-0.951^{***}	-1.023^{***}	-1.542^{***}	-1.259^{***}
	(0.281)	(0.207)	(0.279)	(0.249)	(0.285)
Oil	0.115^{***}	0.089^{***}	0.128^{***}	0.082^{**}	0.106^{***}
	(0.038)	(0.023)	(0.042)	(0.033)	(0.037)
Constant	0.119	0.210^{*}	-0.089	-0.069	0.009
	(0.167)	(0.123)	(0.181)	(0.155)	(0.163)
			Variance equation		
S^{Total}	-0.208^{***}	-0.107^{***}	-0.114^{***}	-0.097^{***}	-0.058^{***}
	(0.050)	(0.034)	(0.035)	(0.022)	(0.021)
Dummy	1.212^{***}	0.496^{*}	0.691^{**}	-0.485^{*}	0.382^{*}
	(0.458)	(0.281)	(0.270)	(0.276)	(0.208)
Interaction	0.163^{*}	0.015	0.044	-0.040	0.028
	(0.088)	(0.043)	(0.058)	(0.038)	(0.050)
Constant	-0.923	-0.005	0.673^{**}	0.854^{**}	1.361^{***}
	(0.670)	(0.442)	(0.340)	(0.337)	(0.493)
ARCH	0.071^{***}	0.149^{***}	0.146^{***}	0.104^{***}	0.069^{*}
	(0.023)	(0.043)	(0.039)	(0.038)	(0.040)
GARCH	0.878^{***}	0.708^{***}	0.718^{***}	0.742^{***}	0.638^{***}
	(0.032)	(0.070)	(0.058)	(0.059)	(0.148)
AIC	3451.452	3126.115	3561.473	3425.714	3408.61
BIC	3499.964	3174.627	3609.985	3474.226	3457.121

Notes: The GARCH models are estimated using S^{Total} (Equation 1) as measure for long-short speculators' activity. We control for a potentially varying impact of long-short speculators' activities depending on the underlying price regime. The dummy takes on one during high price regimes and zero otherwise. The interaction term is defined as regime dummy times speculation measure. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 6: GARCH regressions based on S^{Share} controlling for price regimes

	Corn	Soybeans	Sugar	Wheat	Coffee
			Mean equation		
S&P 500	-0.016	0.104	-0.008	0.111	0.184**
	(0.086)	(0.069)	(0.090)	(0.083)	(0.079)
T-Bill	0.013*	0.002	0.008	0.004	-0.008
	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)
ExRate	-1.148***	-0.948***	-1.033***	-1.547***	-1.192***
	(0.283)	(0.208)	(0.277)	(0.249)	(0.274)
Oil	0.114***	0.086***	0.124***	0.078**	0.094***
	(0.039)	(0.023)	(0.041)	(0.032)	(0.036)
Constant	0.132	0.158	-0.074	-0.063	-0.054
	(0.177)	(0.121)	(0.177)	(0.157)	(0.156)
			Variance equation		
S^{Share}	-0.204***	-0.117***	-0.140***	-0.099***	-0.082***
	(0.041)	(0.041)	(0.034)	(0.026)	(0.015)
Dummy	1.143***	0.651*	0.914***	-0.583*	0.490***
	(0.384)	(0.337)	(0.320)	(0.313)	(0.190)
Interaction	0.100	0.031	0.080	-0.056	0.062
	(0.079)	(0.048)	(0.075)	(0.040)	(0.038)
Constant	-1.169**	-0.286	0.227	0.600	1.732***
	(0.534)	(0.515)	(0.424)	(0.378)	(0.299)
ARCH	0.055***	0.151***	0.137***	0.096***	0.086**
	(0.019)	(0.044)	(0.037)	(0.034)	(0.042)
GARCH	0.899***	0.731***	0.759***	0.789***	0.449***
	(0.027)	(0.064)	(0.057)	(0.057)	(0.134)
AIC	3452.433	3128.36	3559.570	3432.17	3384.856
BIC	3500.945	3176.872	3608.082	3480.682	3433.368

Notes: The GARCH models are estimated using S^{Share} (Equation 2) as measure for long-short speculators' activity. We control for a potentially varying impact of long-short speculators' activities depending on the underlying price regime. The dummy takes on one during high price regimes and zero otherwise. The interaction term is defined as regime dummy times speculation measure. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 7: Wheat GARCH regressions for several specifications using measures based on total open interest

	1	2	3	4	5	6	7
S^{Total}	-0.070***	-0.090***	-0.089***	-0.097***	-0.110***		
	(0.022)	(0.023)	(0.022)	(0.022)	(0.018)		
S^{Total}_{Spread}							-0.104***
							(0.022)
NC^{Total}_{long}						0.002	
						(0.018)	
NC^{Total}_{short}						-0.062***	
						(0.009)	
NC^{Total}_{spread}						-0.002	
						(0.012)	
D.Regime	-0.303	-0.463*	-0.447*	-0.485*			
	(0.237)	(0.275)	(0.268)	(0.276)			
Interaction	-0.048	-0.045	-0.047	-0.040			
	(0.036)	(0.038)	(0.038)	(0.038)			
ExRate	-0.299	-0.256	-0.266		-0.241		
	(0.262)	(0.329)	(0.330)		(0.304)		
Oil	-0.054	-0.034	-0.037		-0.046		
	(0.036)	(0.047)	(0.047)		(0.043)		
Inventory	-0.077	-0.074					
	(0.186)	(0.208)					
D.Q2	0.435						
	(0.291)						
D.Q3	0.331						
	(0.272)						
D.Q4	-0.305						
	(0.289)						
Constant	1.281***	0.940**	0.868**	0.854**	0.726**	1.074***	0.973***
	(0.368)	(0.373)	(0.340)	(0.337)	(0.321)	(0.288)	(0.360)
ARCH	0.096**	0.097***	0.098***	0.104***	0.100***	0.111***	0.113***
	(0.042)	(0.036)	(0.036)	(0.038)	(0.035)	(0.040)	(0.040)
GARCH	0.644***	0.741***	0.744***	0.742***	0.734***	0.667***	0.694***
	(0.086)	(0.060)	(0.059)	(0.059)	(0.057)	(0.072)	(0.077)
AIC	3426.860	3430.384	3428.508	3425.714	3427.561	3422.23	3435.301
BIC	3501.833	3492.126	3485.840	3474.226	3476.073	3470.742	3474.992

Notes: The GARCH models are estimated using speculation measures incorporating non-reporting traders. Variables with a leading "D." are defined as dummy variables. The dummy takes on one during high price regimes and zero otherwise. The interaction term is defined as regime dummy times speculation measure. All macroeconomic controls are defined as returns. The inventory dummy takes on one during years in which the ending stock exceeds the beginning stock and zero otherwise. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 8: Wheat GARCH regressions for several specifications using measures based on the share at total open interest

	1	2	3	4	5	6	7
S^{Share}	-0.079***	-0.095***	-0.092***	-0.099***	-0.110***		
	(0.026)	(0.026)	(0.027)	(0.026)	(0.019)		
S^{Share}_{Spread}							-0.134***
							(0.032)
NC^{Share}_{long}						0.012	
						(0.026)	
NC^{Share}_{short}						-0.060***	
						(0.009)	
NC^{Share}_{spread}						-0.007	
						(0.017)	
D.Regime	-0.325	-0.536*	-0.535*	-0.583*			
	(0.274)	(0.304)	(0.312)	(0.313)			
Interaction	-0.037	-0.054	-0.061	-0.056			
	(0.044)	(0.042)	(0.041)	(0.040)			
ExRate	-0.343	-0.309	-0.321		-0.275		
	(0.344)	(0.349)	(0.358)		(0.290)		
Oil	-0.061	-0.037	-0.041		-0.047		
	(0.042)	(0.046)	(0.046)		(0.039)		
Inventory	-0.152	-0.128					
	(0.205)	(0.222)					
D.Q2	0.568						
	(0.362)						
D.Q3	0.178						
	(0.322)						
D.Q4	-0.337						
	(0.358)						
Constant	0.891**	0.708*	0.592	0.600	0.752**	1.271***	1.512***
	(0.430)	(0.427)	(0.392)	(0.378)	(0.336)	(0.252)	(0.299)
ARCH	0.093**	0.089***	0.091***	0.096***	0.093***	0.123***	0.131**
	(0.036)	(0.033)	(0.033)	(0.034)	(0.034)	(0.043)	(0.051)
GARCH	0.737***	0.787***	0.790***	0.789***	0.741***	0.619***	0.560***
	(0.068)	(0.057)	(0.056)	(0.057)	(0.059)	(0.078)	(0.104)
AIC	3431.993	3435.91	3434.226	3432.17	3432.742	3425.069	3433.68
BIC	3506.966	3497.652	3491.558	3480.682	3481.254	3473.581	3473.372

Notes: The GARCH models are estimated using speculation measures incorporating non-reporting traders. Variables with a leading "D." are defined as dummy variables. The dummy takes on one during high price regimes and zero otherwise. The interaction term is defined as regime dummy times speculation measure. All macroeconomic controls are defined as returns. The inventory dummy takes on one during years in which the ending stock exceeds the beginning stock and zero otherwise. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.

Table 9: Robustness Analysis using Macro factors and spreads

	Soybeans	Sugar	Coffee	Soybeans	Sugar	Coffee
			Mean equation			
S&P500	0.115	-0.021	0.156*	0.115	-0.021	0.156*
	(0.071)	(0.108)	(0.089)	(0.071)	(0.108)	(0.089)
T-Bill	0.004	0.007	-0.007	0.004	0.007	-0.007
	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)	(0.006)
ExRate	-1.027***	-0.928***	-1.163***	-1.027***	-0.928***	-1.163***
	(0.219)	(0.324)	(0.289)	(0.219)	(0.324)	(0.289)
Oil	0.097***	0.125***	0.112***	0.097***	0.125***	0.112***
	(0.028)	(0.046)	(0.037)	(0.028)	(0.046)	(0.037)
Constant	0.111	-0.087	-0.110	0.111	-0.087	-0.110
	(0.123)	(0.180)	(0.159)	(0.123)	(0.180)	(0.159)
			Variance equation			
S^{Share}	-0.082	0.187	0.123**			
	(0.082)	(0.145)	(0.054)			
ExRate	-0.486	-0.694	0.040	-0.486	-0.694	0.040
	(0.478)	(0.581)	(0.249)	(0.478)	(0.581)	(0.249)
Oil	-0.073	0.035	0.008	-0.073	0.035	0.008
	(0.049)	(0.118)	(0.031)	(0.049)	(0.118)	(0.031)
S^{Share}_{Spread}				-0.082	0.187	0.123**
				(0.082)	(0.145)	(0.054)
Constant	0.019	-0.756	1.434***	0.019	-0.756	1.434***
	(0.411)	(0.705)	(0.445)	(0.411)	(0.705)	(0.445)
ARCH	0.170***	0.070***	0.125**	0.170***	0.070***	0.125**
	(0.045)	(0.014)	(0.049)	(0.045)	(0.014)	(0.049)
GARCH	0.732***	0.898***	0.586***	0.732***	0.898***	0.586***
	(0.065)	(0.021)	(0.145)	(0.065)	(0.021)	(0.145)
Sum (G)ARCH	0.902	0.968	0.711	0.902	0.968	0.711
Half-Life	6.720	21.312	2.032	6.720	21.312	2.032
AIC	3138.943	3566.946	3415.939	3138.943	3566.946	3415.939
BIC	3187.455	3615.458	3464.450	3187.455	3615.458	3464.450

Notes: The GARCH models are estimated using S^{Share} (Equation 2) and S^{Share}_{Spread} as measure for long-short speculators' activity. We control for a potentially varying impact of long-short speculators' activities depending on the underlying macro economic factors. ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively. Standard errors are provided in parentheses.