

Chemnitz University of Technology
Faculty of Economics and Business Administration
Thüringer Weg 7
09107 Chemnitz, Germany

Phone +49 (0)371 531 26000

Fax +49 (0371) 531 26019

<https://www.tu-chemnitz.de/wirtschaft/index.php.en>

wirtschaft@tu-chemnitz.de

Long-short speculator sentiment in agricultural commodity markets*

Oliver Borgards[†]

Robert L. Czudaj[‡]

January 26, 2022

Abstract

This paper tests the hypothesis that long-short speculators are able to generate short-term investment returns based on their sentiment for twelve agricultural commodity futures. For this purpose, we dynamically model the equidirectional trading of long and short commodity futures of long-short speculators as a proxy for their market sentiment. We find evidence that the sentiment period returns are considerably positive and differ significantly from neutral sentiment periods for all commodities which underlines the sentiment's relevance. In line with the empirical literature, we can reject the argument of price manipulation as the price continues to develop into the direction of the sentiment period although long-short speculators trade non-directionally in the following. We rather indicate the existence of a short-term time-series momentum effect, which can be robustly identified without the requirement to define an external model parameter. From the superior sentiment-based momentum returns, we conclude that long-short speculators have valuable, exclusive information, which cannot be replicated by observing their trading activity with a time lag of eight trading days. We also find that a sentiment-based momentum strategy generates significantly higher returns than the long-short speculators have realized in the fifteen-year sample period which we attribute to the complexity of the long-short speculators' investment strategies.

Keywords: [commodities, time-series momentum, sentiment, long-short speculators, commitment of traders, price manipulation]

JEL classification: [G11, G14, G15, C18]

*Thanks for valuable comments on a previous draft of the paper are due to the participants of the research seminar in Chemnitz.

[†]Chemnitz University of Technology, Department of Economics and Business, Chair for Empirical Economics, Thüringer Weg 7, Chemnitz D-09126, Germany

[‡]Ludwig-Maximilians-University Munich, Department of Mathematics, Computer Science and Statistics, Chair for Statistics and Econometrics, Akademiestr. 1/I, D-80799 Munich, Germany and Chemnitz University of Technology, Department of Economics and Business, Chair for Empirical Economics, Thüringer Weg 7, Chemnitz D-09126, Germany, E-mail: robert-lukas.czudaj@wirtschaft.tu-chemnitz.de

1 Introduction

For thousands of years, people have been consuming and trading natural resources, in particular agricultural products, as a prerequisite for human and economic development. However, in the recent decades commodity markets have changed fundamentally. Initially developed for producers and processors of the physical assets, the early agricultural commodity markets can be characterized by a lack of liquidity and transparency as investors were not able to efficiently invest in them. In the early days of commodity investing, the academic literature shares the view that investors who were speculating on the price development of commodities follow the trading activity of hedgers (see (Working, 1953), Working (1954), Working (1960) and Working (1962)). With the advent of the financialization of commodity markets in the last decades, the enabling of direct investments into commodities goes hand in hand with an increasing number of complex and innovative financial products with the primary intention of portfolio diversification and inflation hedging (Domanski and Heath, 2007). In particular, the introduction of commodity indices was a significant catalyst for change in the commodity markets. As a consequence of rising volumes into passive commodity products and accompanying increasing agricultural commodity prices, the G20 announced food security as one of the world's priorities, suspecting newer speculative-oriented market participants such as commodity index traders (i.e. long-only money managers who track the performance of a commodity index) and long-short speculators (i.e. investors who speculate on increasing or decreasing commodity prices with commodity derivatives) to negatively influence commodity prices.

The empirical literature on speculation in commodity markets was initiated by the political and regulatory discussion of the Master's hypothesis (Masters and White, 2008) which accused the significantly increased inflows of commodity index funds for the increase in commodity prices. Concentrated on the commodity index trader's influence, the empirical literature unambiguously rejects the Master's hypothesis and shows that they do not have a significant impact on commodity prices, but provide liquidity to the financial commodity markets (see Sanders et al. (2010), Irwin and Sanders (2011), Irwin and Sanders (2012), Brunetti and Reiffen (2014), Palazzi et al. (2020) and Maria et al. (2020)). The majority of the empirical literature on speculation in the commodity markets discusses the impact of financialization as well as the role of speculators without considering a specific trader group. As a result, the largest part of the empirical literature also comes to the same conclusion (see Often and Wisen (2013), Manera et al. (2013), Kim (2015), Mayer et al. (2017), Boyd et al. (2018), Fishe and Smith (2019), Wimmer et al. (2021)). In the context of the increasing world population, this political and ethical discussion about the world's most essential resources remains vivid and primarily concentrates on index-tracking market players to our surprise. On the contrary, only a minor part of the empirical literature

examines the role of classical speculators like hedge funds which opportunistically exploit investment opportunities with long or short directional trades based on their information. The empirical literature predominantly confirms the prevailing view on the role of speculators also for long-short traders (see Miffre and Brooks (2013), Buyuksahin and Robe (2014), Brunetti et al. (2016), Bohl and Sulewski (2019), Bohl et al. (2021)). Since the investment motive of long-short traders differs considerably from that of commodity index traders, the question on the role of their information-based sentiment in this legitimate discussion about price influence remains. This motivates us to provide a comprehensive analysis of the long-short speculator's sentiment which is the key driver in their investment process. To the best of our knowledge, this is the first study which uses the long-short speculators' open interest as a proxy for their market sentiment to examine price dynamics as well as price influence. From the perspective of an investor, our results are highly relevant. On the one hand, they show the validity of their information and the resulting price dynamics. On the other hand, they extend the empirical literature's view on price manipulation by providing valuable insights whether their information-driven investment style has an effect on agricultural commodity prices. Hence, our motivation is to analyze if long-short speculators as the smallest trader group in the commodity markets besides producers, processors and passive investors have a measurable impact on agricultural commodity prices.

In order to assess the relevance of the long-short speculator's information, we use periods of equidirectional trading defined as buying long and selling short futures contracts (long sentiment) and vice versa (short sentiment) as a proxy for their sentiment on twelve agricultural commodity futures. The open interest of futures is particularly suitable for the development of a sentiment indicator as it can be regarded as the commodity futures market's cash flow. Increasing or decreasing open interest can be a signal when certain market participants are entering or leaving the market and may give clues to market direction. In addition, our open interest based sentiment proxy also offers the benefit that we are able to rely on data on a higher frequency compared to survey based indicators, which would at best be available at a monthly frequency. Initially, we compare the commodity's log returns in long or short sentiment periods with those of neutral sentiment periods. Since equidirectional trading can impact the price itself, we also consider how the commodity price evolves subsequent to long or short sentiment periods. We can reject the argument of price manipulation, if the commodity price immediately halts or reverts back directly after the long or short sentiment period. We also test the exclusiveness of the long-short speculators information by replicating a sentiment-modeled momentum strategy based on publicly available open interest data of long-short speculators. Finally, we compare the risk-return characteristics of an exclusive and a publicly available, modeled sentiment-based trading strategy with the realized ex-post returns of the long-short speculators over a fifteen-year sample period.

We contribute to the empirical literature by studying short-term price dynamics on the basis of the

long-short speculators' sentiment in agricultural commodity markets. In contrast, the vast majority of the existing literature studies the speculative behavior of commodity index traders, in particular if they have a negative impact on the agricultural commodity prices as one of the earth's most essential resources. We instead concentrate on long-short speculators representing a group of investment managers who have probably the clearest investment intentions as they predominantly enter directional trades to follow their opportunistic investment strategies (Etienne et al., 2014). We also contribute by modeling investor sentiment dynamically as a period of equidirectional trading without the requirement to define external parameters. Since it is not reasonable to quantify investor sentiment as a proxy of the long-short speculators' future price expectations with external parameters, the corresponding findings might be biased when relying on such an approach. To the best of our knowledge, this is the first study that also tests the time-series momentum effect on commodity markets by dynamically considering the long-short speculator's sentiment as the initializing formation period. Consequently, our work extends the empirical literature by illustrating price dynamics during and after varying periods of consistent trading activity for a broad range of agricultural commodities over more than a decade.

We find evidence that the sentiment of long-short speculators is highly relevant in agricultural commodity markets. Defining long (short) sentiment dynamically as a period in which long-short speculators consistently buy (sell) long futures contracts and sell (buy) short futures contracts, we find that the log returns in long (short) sentiment periods are positive (negative) and significantly different from zero for all commodities. On the contrary, the log returns in neutral sentiment periods do not differ significantly from zero. Since we are able to regularly confirm these results over the entire sample period, our findings underline the directional sentiment's importance. Furthermore, since the commodity prices predominantly move further into the direction of the sentiment period, we are able to reject the argument of price manipulation because long-short speculators do not trade consistently anymore. When applying our results to the concept of time-series momentum, a long or short sentiment period would represent a formation period which is followed by a corresponding momentum period. Therefore, our results strongly support the time-series momentum effect as the momentum periods returns are significantly different from zero for most of the commodities.

As a conclusion, we suppose that long-short speculators rather own valuable information in form of their investment strategies which they use to exploit short-term price movements. Our results also clearly show that the commodity price initially remains persistent at the beginning of a momentum period but then decays. We therefore conclude that a sentiment period can be understood as a kind of price impulse based on the valuable information of the long-short speculators. The price impulse in the form of equidirectional trading then initiates a time-series momentum effect which weakens the more the price moves away from the original equilibrium price. Moreover, we find that the replication of a

sentiment-based trading strategy by observing the open interest of the long-short speculators with a time lag of 8 trading days leads to considerably lower returns which are not significantly different from zero or even negative. As the time-lag represents the beginning of a directional sentiment period, our results let us to conclude that in particular the beginning of a sentiment period is a substantial but exclusive stimulus that can have a sustainable impact on the subsequent price development. Finally, we show that the returns of an exclusive sentiment-based momentum strategy considerably outperform the realized ex-post returns of the long-short speculators over the entire sample period. Although surprising at first glance, the difference can be explained with the higher complexity of a long-short speculator's investment strategy. The complexity involves hedging requirements, information asymmetries, different investment horizons and negative market impact effects which are not considered in our modeled sentiment strategy. Nevertheless, our findings provide valuable information for the risk management of individual investment managers to better assess commodity price dynamics. As we clearly provide evidence that long-short speculators do not manipulate commodity prices in line with the existing literature, our findings are an important signal that investment managers who predominantly act opportunistically, follow ethically correct investment practices.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on speculation in the commodity markets. Section 3 outlines the data and the methodology used in this study. In Section 4, we present and discuss the results of our empirical findings. Section 5 offers concluding remarks.

2 Review of the literature

The structural change of the agricultural commodity markets in the early 2000s, also changed the academic discussion fundamentally. Previously, the commodity markets were primarily hedgers-driven, in which market participants who were actively engaged in the physical commodity markets (i.e. producers and processors) were hedging the prices of their commodities with futures contracts (hereinafter hedgers). In the traditional view, investors who were speculating on the price development of commodities (hereinafter speculators) follow the trading activity of hedgers (see Working (1953), Working (1954), Working (1960) and Working (1962)). In the course of the financialization of commodity markets in the first decade of the new millennium, investors and individuals could now invest in a broad range of commodities with over-the-counter (OTC) swaps, exchange-traded funds (ETF) and exchange-traded notes (ETN) without having to own the commodities themselves (Domanski and Heath, 2007). This resulted in a sharp increase in trading volume on commodity futures exchanges and established new speculative-oriented market participants such as commodity index traders (i.e. long-only money

managers who track the performance of a commodity index) and long-short speculators (i.e. investors who speculate on increasing or decreasing commodity prices with commodity derivatives). Therefore, the more recent empirical literature examines whether Working's hypothesis is still valid and whether the financial commodity markets are now speculators-driven.

The emergence of the empirical literature on speculation in the commodity markets was initiated by the political and regulatory discussion of the Master's hypothesis. The Master's hypothesis is based on the hedge fund manager Michael W. Masters, who harshly supposed that the significantly increased inflows of commodity index funds are the reason for the sharp increase in commodity prices between 2007 and 2008 and their divergence from fundamental values (Masters and White, 2008). The empirical literature was enabled to examine the Master's hypothesis by the extension of the Commodity Futures Trading Commission's (CFTC) Supplemental Commitment of Traders (SCOT) report to the traditional Commitment of Traders (COT) reports.¹ It further splits the speculators' open interest for 12 agricultural commodity markets into commodity index traders and long-short traders starting in 2006. This now allowed for a closer examination of long-only commodity index traders and their impact on commodity prices. Sanders et al. (2010) show that the relative share of commodity index traders in open interest is stable between 2006 and 2008, concluding that the increased inflows are the response to a rising hedging demand.

Irwin and Sanders (2011) criticize the underlying data as well as the methodological approaches of previous empirical studies that find a significant impact of commodity index trader's futures positions on commodity future prices. Irwin and Sanders (2012) examine the Master's hypothesis using Fama-MacBeth cross-sectional regression tests as well as Granger causality tests. In both studies, they are unable to find a direct impact of commodity index traders' futures positions on returns as well as on volatility so that they reject the Master's hypothesis as one of the first. Brunetti and Reiffen (2014) use a theoretical equilibrium model of trader behavior to show that commodity index traders reduce hedging costs. After empirically validating their model with the commodity index trader's futures positions, they conclude that commodity index traders provide an important counterparty for hedgers by providing liquidity and do not influence commodity prices directly. Palazzi et al. (2020) use linear and non-linear regressions to find out whether speculators in general and commodity index traders in particular influence

¹The COT report provides a breakdown of each Tuesday's open interest for futures markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC. The legacy COT report differentiates between commercials (i.e. producers and processors of the commodities, hedgers), non-commercials (i.e. money managers, speculators) and non-reporting traders (small investors, residuals of the open interest). The disaggregated COT report further splits up commercials into the group of processors/producers and swap dealers as well as non-commercials into managed money and other reportables. See Irwin and Sanders (2012) for a detailed description of the trader groups in the legacy, disaggregated und supplemental COT reports of the CFTC.

commodity futures prices or whether they follow the price movement. As a result, they find no cause and effect relationship, so that the Master's hypothesis can be rejected ultimately. Maria et al. (2020) investigate the influence of commodity index trading activity on commodity futures prices using Granger causality tests during the period 2006 to 2017. They confirm the previous empirical studies that the spike in commodity prices in 2007 to 2008 and the period thereafter is not due to speculative behavior of commodity index traders. In summary, the empirical literature unambiguously rejects the Master's hypothesis and shows that commodity index traders do not have a significant impact on commodity prices, but provide liquidity to the financial commodity markets.

The vast majority of the empirical literature on speculation in the commodity markets discusses the impact of financialization as well as the role of speculators without considering a specific trader group from the SCOT report. Instead, they predominantly model the activity of hedgers and speculators with open interest from the traditional legacy and disaggregated COT reports. Sanders et al. (2010) note that the group of speculators (i.e. money managers and other reportables) that can be modeled from both reports cannot be assigned to a clear trader group, so that the different intentions (i.e. directional trading, hedging, index-tracking) partially overlap. However, the majority of that part of the empirical literature also comes to the same conclusion as the studies on the Master's hypothesis. Boyd et al. (2018) examine the findings of a large number of empirical studies on the role of commodity speculators and their price impact during the financialization period. They clearly conclude that speculators provide liquidity to hedgers while finding no evidence of destabilization as well as price distortion in commodity markets initiated by speculators. Wimmer et al. (2021) analyze more than 50 research articles that study the relationship between commodity prices and speculative behavior using Granger causality tests. They point out that either speculative behavior in the agricultural, energy, and metal markets cannot be detected or Granger causality tests are not able to quantify the relationship well enough.

Often and Wisen (2013) also investigate this relationship using Granger causality tests and show that hedgers in particular have a greater impact on prices in certain commodity markets (e.g. live cattle) than swap dealers or producers. As well as Often and Wisen (2013), Manera et al. (2013) model speculative behavior by Working's Speculative Index (Working, 1960), which measures the excessiveness of speculation as a ratio calculated by measuring the amount by which speculation exceeds commercial hedging needs, divided by commercial open interest. Using dynamic conditional correlation (DCC) multivariate GARCH models, they show that financial speculation cannot explain the returns of 5 agricultural commodities. Kim (2015) examines the impact of financialization on commodity prices as well as on their volatility as a proxy for market stability. As a result, speculators do not destabilize commodity spot prices, but tend to contribute to lower volatility and increased price efficiency associated with greater liquidity. Mayer et al. (2017) investigate the same intention with bi-directional

Granger causality tests and an EGARCH volatility analysis for metal commodity markets and show that non-commercials in particular do not influence commodity prices and volatility. On the other hand, an influence in sub-samples such as booms and crises can be observed for both commercials and non-commercials, while the effect is greater for long futures positions. Fishe and Smith (2019) show that money managers including speculators tend to follow commodity prices according to their assessment of the future price development having no price-influencing impact.

To our surprise, only a minor part of the empirical literature examines the role of classical speculators based on the open interest of long-short traders from the CFTC's SCOT report. Long-short speculators (i.e., hedge fund managers) use their information in the form of selection and timing strategies to enter directional long or short trades, which means that their intentions differ considerably from those of the commodity index traders (Etienne et al., 2014). By replicating various hedge fund strategies with price data of 27 commodity futures in the period from 1992 to 2011, Miffre and Brooks (2013) demonstrate that long-short speculators tend to have no significant impact on volatility as well as on the diversifiability of their commodity investments. Buyuksahin and Robe (2014) use daily open interest data of 17 commodity futures from the CFTC's non-public large trader reporting system. They show that the correlation of commodity and equity index returns increases with increasing trading activity of long-short speculators. In the context of the commodity financialization, these traders therefore have an impact on the diversifiability of commodities, which cannot be observed for swap dealers and commodity index traders. Brunetti et al. (2016) use the same non-public data set and confirm the prevailing view of the empirical literature on the role of speculators also for long-short speculators. Showing a negative correlation between the futures positions and the volatility of crude oil, natural gas and corn, they provide evidence that long-short speculators stabilize commodity futures markets and inject liquidity into them. Bohl and Sulewski (2019) study long-short speculators of corn, soybeans, sugar, coffee, and wheat futures for the period from 2006 to 2017 to determine whether their trading activity has an impact on volatility and thus on price stability. Using GARCH models, they estimate conditional volatility and conclude that long-short speculators either have no impact on volatility or even reduce it. Bohl et al. (2021) examine how speculative activity affects informational efficiency of commodity futures markets and find evidence for a significant negative relation between speculative activity and the degree of informational efficiency. A subsequent analysis shows that the results are mainly driven by traditional long-short speculators while the influence of index trader is insignificant.

In summary, the empirical literature largely agrees that speculators, either as a specific (i.e. commodity index traders and long-short speculators) or as a non-specific group of money managers, do not destabilize commodity markets and provide liquidity to them as the main counterparty of hedgers. To the best of our knowledge, this is the first study which uses the long-short speculators' open interest as

a proxy for their market sentiment to examine price dynamics as well as price influence and also tests the time-series momentum effect on the commodity markets by dynamically considering the long-short speculator's sentiment as the initializing formation period.

3 Data and methodology

3.1 Data

We source the open interest data on the basis of the Commodity Futures Trading Commission's (CFTC, <https://www.cftc.gov>) Supplement Commodity Index Trader (SCOT) report. It contains the long and short futures positions of three trader groups (non-commercials, index traders and long-short speculators) for 12 agricultural commodities during the sample period from 01/03/2006 to 12/29/2020, recorded as of Tuesday of each week. The commodity futures are wheat, corn, soybeans, soybean oil, soybean meal, cotton, cocoa, sugar, coffee, lean hogs, live cattle and feeder cattle. In addition, we use the daily close prices of the futures contract with the shortest maturity (front contract) for the same dates as the weekly open interest data in order to be able to observe futures positioning and prices at identical times. The price data was obtained from the Chicago Mercantile Exchange (CME, <https://www.cmegroup.com>) and the Intercontinental Exchange (ICE, <https://www.theice.com>). Table 1 shows the descriptive statistics of the weekly close price log returns as well as the average open interest proportion of the long-short speculator's futures positioning. It shows that the log returns of most of the commodities are mildly skewed to the left, which indicates that downturns are steeper than upturns. Excess kurtosis can only be observed for a few commodities. With an average open interest proportion between 10% and 21%, the long-short speculators are the smallest of the three trader groups.

*** Insert Table 1 about here ***

3.2 Methodology

We model the speculator's sentiment based on long and short futures contracts held by long-short speculators from the Commodity Futures Trading Commission's SCOT report. Long-short speculators use their information primarily to enter into directional, speculative trades, while commercials (i.e. producers and processors) predominantly hedge the price of their agricultural commodities and commodity index

traders track the price performance of the underlying commodity index². We therefore assume that the returns achieved by long-short speculators reflect the quality of the information incorporated in the investment strategies. We further assume that long-short speculators have particularly valuable information if they simultaneously buy long futures contracts c^{long} (i.e. $c_t^{\text{long}} > c_{t-1}^{\text{long}}$) and sell short futures contracts c^{short} (i.e. $c_t^{\text{short}} < c_{t-1}^{\text{short}}$) in a period t , which we hereafter refer to as long sentiment and conversely as short sentiment. On the other hand, if they buy or sell long and short futures contracts at the same time, the investment manager sentiment is not uniform (hereafter referred to as neutral sentiment).

*** Insert Figure 1 about here ***

Figure 1 exemplary shows the price time series of the corn futures front contract and the long and short sentiment periods projected onto it at the respective price levels p_t^{long} and p_t^{short} . A blue (red) outlined point marks the time t when the long-short speculators bought long (short) futures contracts c^{long} (c^{short}) and sold short (long) futures contracts compared to the previous week $t - 1$. To evaluate the quality of investment manager sentiment, we consider the log returns $\Delta p_t^{\text{long sentiment}}$ and $\Delta p_t^{\text{short sentiment}}$ of the corn futures' front contract prices p for the same weekly periods t . We also define the log returns of the neutral sentiment periods $\Delta p_t^{\text{neutral sentiment}}$, which are shown as non-outlined points in Figure 1:

$$\Delta p_t^{\text{long sentiment}} = \log(p_t^{\text{long}}) - \log(p_{t-l-1}^{\{\text{neutral, short}\}}) \quad \text{if } p_{t-l}^{\text{long}} \quad \text{and} \quad p_{t+1}^{\{\text{neutral, short}\}}, \quad (1)$$

$$\Delta p_t^{\text{short sentiment}} = \log(p_t^{\text{short}}) - \log(p_{t-l-1}^{\{\text{neutral, long}\}}) \quad \text{if } p_{t-l}^{\text{short}} \quad \text{and} \quad p_{t+1}^{\{\text{neutral, long}\}}, \quad (2)$$

$$\Delta p_t^{\text{neutral sentiment}} = \log(p_t^{\text{neutral}}) - \log(p_{t-l-1}^{\{\text{long, short}\}}) \quad \text{if } p_{t-l}^{\text{neutral}} \quad \text{and} \quad p_{t+1}^{\{\text{long, short}\}}, \quad (3)$$

where the parameter l represents the length of the consecutive sentiment periods and

$$p_t^{\text{long}} = c_t^{\text{long}} > c_{t-1}^{\text{long}} \quad \text{and} \quad c_t^{\text{short}} < c_{t-1}^{\text{short}}, \quad (4)$$

$$p_t^{\text{short}} = c_t^{\text{long}} < c_{t-1}^{\text{long}} \quad \text{and} \quad c_t^{\text{short}} > c_{t-1}^{\text{short}}, \quad (5)$$

²For a more detailed description of the different trader groups and their differences, please see Irwin and Sanders (2012) and Robe and Roberts (2019) in particular for agricultural markets.

$$p_t^{\text{neutral}} = \left\{ c_t^{\text{long}} > c_{t-1}^{\text{long}} \quad \text{and} \quad c_t^{\text{short}} > c_{t-1}^{\text{short}} \right\} \quad \text{or} \quad \left\{ c_t^{\text{long}} < c_{t-1}^{\text{long}} \quad \text{and} \quad c_t^{\text{short}} < c_{t-1}^{\text{short}} \right\}. \quad (6)$$

If investment managers have valuable information about the short-term price development of the respective commodities, we expect the log returns $\Delta p_t^{\text{long sentiment}}$ ($\Delta p_t^{\text{short sentiment}}$) to develop positively (negatively) in long (short) sentiment periods and to differ significantly from zero. We also expect that in neutral sentiment periods the log returns $\Delta p_t^{\text{neutral sentiment}}$ do not differ significantly from zero. If these observations hold, this may have two implications. On the one hand, long-short speculators may have valuable information to predict the short-term price development. Second, they may influence the price itself (price manipulation) by trading futures contracts in the same direction. The argument of price manipulation is invalidated if the price continues to increase (decrease) after one ($l=1$) or more consecutive ($l>1$) long (short) sentiment periods.

We therefore define long (short) sentiment-momentum as a long (short) sentiment period that is extended to the next short (long) sentiment period. In Figure 1, the long (short) sentiment-momentum periods are each projected as blue (red) points on the price time series of the corn futures front contract. Again, we calculate the log returns of the corresponding sentiment-momentum periods $\Delta p_{t,i}^{\text{long sentiment-momentum}}$ as well as $\Delta p_{t,i}^{\text{short sentiment-momentum}}$ and compare them with the log returns of the long and short sentiment periods. The respective sentiment-momentum periods are defined as

$$\Delta p_{t,i}^{\text{long sentiment-momentum}} = \log(p_{t+i}^{\{\text{long, neutral}\}}) - \log(p_{t-l-1+i}^{\{\text{short}\}}) \quad \text{if} \quad p_{t-l}^{\{\text{long, neutral}\}} \quad \text{and} \quad p_{t+1}^{\{\text{short}\}}, \quad (7)$$

$$\Delta p_{t,i}^{\text{short sentiment-momentum}} = \log(p_{t+i}^{\{\text{short, neutral}\}}) - \log(p_{t-l-1+i}^{\{\text{long}\}}) \quad \text{if} \quad p_{t-l}^{\{\text{short, neutral}\}} \quad \text{and} \quad p_{t+1}^{\{\text{long}\}}, \quad (8)$$

where i is a lag parameter defined as $i=0$ for the original, non-lagged sentiment-momentum periods. We expect that the log returns of the sentiment-momentum periods $\Delta p_{t,0}^{\text{long sentiment-momentum}}$ and $\Delta p_{t,0}^{\text{short sentiment-momentum}}$ differ significantly from the sentiment periods $\Delta p_t^{\text{long sentiment}}$ and $\Delta p_t^{\text{short sentiment}}$, so that we can conclude that long-short speculators have valuable information to be able to predict the short-term price development in a sustainable way.

If the log returns of the sentiment-momentum periods actually differ significantly from the ones of the sentiment periods, it is interesting from the perspective of an external trader whether he can also achieve a positive return by trading the long and short sentiment-momentum periods one week later after observing this trading behavior. It should be noted that the open interest data of the SCOT report refers to a Tuesday, while the report is released on the subsequent Friday at 3:30 p.m. Eastern standard

time. This means that an external trader can only open a position on Friday at the close price, so that his replicated sentiment momentum strategy has a time lag of 8 trading days in total ($i=8$). Accordingly, we calculate the log returns of the lagged sentiment momentum periods $\Delta p_{t,8}^{\text{long sentiment-momentum}}$ and $\Delta p_{t,8}^{\text{short sentiment-momentum}}$ with the close prices of Friday or the subsequent Monday, respectively, if Friday is an U.S. exchange holiday. An external trader would not only be able to enter a position 8 trading days later, but also to close a position 8 trading days later, so that we expect their log returns to be at least partially different from those of the sentiment and sentiment-momentum periods. If the lagged sentiment-momentum log returns are absolutely lower and significantly different from those in the sentiment and sentiment-momentum periods, it indicates that during the time lag a significant part of the exclusive information is priced into the commodities by the long-short speculators. Accordingly, the beginning of a sentiment period would represent a meaningful price impulse, which would have a noticeable impact on the short-term price development.

4 Empirical findings

The results of our analysis are discussed in three steps. In the first step, we investigate whether long and short sentiment periods differ from neutral sentiment periods to show whether the equidirectional trading of long-short speculators can be attributed to valuable information. Since equidirectional trading can impact the price itself, we further examine in the second step how the prices of the commodity futures evolve subsequent to the long and short sentiment periods (sentiment-momentum). In the third step, we show whether the possibly valuable information of long-short speculators can be profitably exploited by a time-lagged replication of the sentiment-momentum strategy (sentiment-momentum-lagged). Table 2 presents the mean log returns as well as the standard deviations of the individual sentiment, sentiment-momentum and sentiment-momentum-lagged periods, while Table 3 shows them cumulatively over the entire sample period. Figure 2 compares the log return development of the three time-normalized sentiment periods graphically for each commodity.

*** Insert Table 2 about here ***

*** Insert Table 3 about here ***

*** Insert Figure 2 about here ***

First, long and short sentiment periods differ significantly from neutral sentiment periods in which long-short speculators do not trade in equivalent directions. Table 2 shows that for all commodities the mean log returns of the long (short) sentiment periods are positive (negative) and significantly different from zero at the 1% significance level. In contrast, for almost all commodities the log returns of the neutral sentiment periods are not significantly different from zero. Since the standard deviations are comparable for long, short and neutral sentiment periods, we can conclude that the larger log returns of the long and short sentiment periods are not caused by abrupt price jumps. Furthermore, long-short speculators regularly initiate directional sentiment periods, as those are equally distributed over the entire sample period and occur on average every 6 weeks per commodity (calculated as the total number of observations divided by the number of observed sentiment periods per commodity). Table 3 shows that the maximum drawdowns of the cumulated neutral sentiment returns are considerably higher (in negative terms) which is a consequence of the lower log returns that are more sensitive to price fluctuations. We assume that the more favorable risk profile of the directional sentiment periods leads to a higher confidence that the underlying information of their trades is valuable. Our findings can therefore be attributed to two possible explanations. On the one hand, long-short speculators can form an opinion (or sentiment) about the commodity's short-term price development on the basis of their information, which they implement as directional trades. Provided that the price of the commodity develops according to their sentiment, they are reinforced in the value of their information and repeat this process. On the other hand, their random, equidirectional trading can impact the price itself. Therefore, in case the commodity price does not continue to move in the same direction directly after a sentiment period, it is plausible that the price was randomly impacted by the long-short speculator's trading activity during the sentiment period. Conversely, we can reject the argument of active influencing the commodity price in case it continues to develop in the direction of the sentiment period (sentiment-momentum). We would instead conclude that long-short speculators have valuable information on the future price development.

Second, commodity futures which are held beyond the long and short sentiment periods always have higher returns than when they are closed out at the end of the sentiment period. Table 2 shows that the sentiment-momentum log returns for almost all commodities (the only exception is cocoa short) are higher than those of the sentiment periods. The log returns even differ considerably from the log returns of the sentiment periods for the majority of commodities for both long and short sentiment-momentum periods which is shown by the statistical significance of the S-SM differences in Table 2. As a conclusion, we rule out the possibility that the equidirectional trading of the long-short speculators is a random act.

Since the price continues to increase (decrease) after the end of a long (short) sentiment period, even though the long-short speculators no longer trade in the same direction, we conclude that they do not influence the price notably. Our findings are consistent with the empirical literature on speculation in commodity markets presented in Section 2. The empirical literature broadly agrees that speculators in general and long-short speculators in particular do not influence the commodity price but stabilize it by injecting liquidity and being the hedger's counterparty. Furthermore, the low percentage of long and short open interest in relation to the total open interest in Table 1 suggests that long-short speculators, as the smallest trader group in the SCOT report, do not have the necessary impact to influence the price sustainably. As a more plausible alternative, we hypothesize that long-short speculators confidently make use of their valuable information as a result on their extensive research efforts.

Third, the higher log returns of the sentiment-momentum periods indicate a short-term time-series momentum effect for almost all agricultural commodities. The momentum effect is one of the most extensively documented financial anomalies (see De Long et al. (1990), De Long et al. (1990), Jegadeesh and Titman (1993), Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999)) and can be explained by the psychological behavior of investors (see Tversky and Kahneman (1974), De Long et al. (1990), Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999) and Grinblatt and Han (2005)). Time-series momentum means that the past performance of an asset price tends to continue in the future (Moskowitz et al., 2012). According to Moskowitz et al. (2012), time series momentum is a defined period of time (holding or momentum period) in which the price of an asset moves in the same direction as in an immediately preceding, defined period of time (lookback or formation period). If we consider a sentiment period as a formation period, the difference to the sentiment-momentum period represents the momentum period. While the majority of the empirical literature examines the concept of time-series momentum on the basis of a set of parameters, our approach does not require a parameter as a sentiment period is defined as the equidirectional trading of long-short speculators. We therefore conclude that our findings are robust to external market changes which requires parameter-based methods to vary their external parameters in order to consistently confirm the results. In addition to the significantly higher log returns discussed above, Table 2 also shows that the standard deviations in sentiment-momentum periods are higher compared to those in the sentiment periods for all commodities and directions. These can be explained by an initially persistent but then decaying price development after the sentiment period, which can be more intuitively obtained from Figure 2. Figure 2 shows that the coarse-dotted lines of the long (short) sentiment-momentum periods (with the exception of cocoa short) are always above (below) the solid lines of the sentiment periods. Here, the lines' differences represent the time-series momentum effect. In addition, for all commodities and directions the slope of the sentiment-momentum line decreases over time or, as in the case of cocoa and the meat markets, even tends to the sentiment

period line again. From the decaying price dynamics during a sentiment-momentum period, we conclude that a sentiment period can be understood as a kind of price impulse based on the valuable information of a long-short speculator. The price impulse in the form of equidirectional trading then initiates a time-series momentum effect. As the commodity price continues to increase or decrease beyond the sentiment period, the time-series momentum effect weakens as the price might have already moved away from the original equilibrium price.

Fourth, trading the sentiment-momentum period with a time lag (sentiment-momentum-lagged) by externally observing the open interest of the long-short speculators leads to considerably lower log returns than in the sentiment and sentiment-momentum periods. Table 2 shows that the mean log returns in sentiment-momentum-lagged periods are not significantly different from zero or even negative for all commodities and directions. Table 3 shows that only for 8 (7) commodities the cumulative log returns are positive in long (short) sentiment-momentum-lagged periods, while the maximum drawdown as a measurement of the loss risk is significantly higher for all commodities than in sentiment and sentiment-momentum periods. Replicating the sentiment-momentum strategy implies that a trader needs to derive the open interest data of the long-short speculators from the SCOT report. As the data of the publicly available SCOT report refers to the previous Tuesday, but is published on Friday of the following week, a trader receives a signal to enter and exit a commodity futures position only 8 trading days later than the reference date of the open interest. The time lag of 8 trading days always represents the initial period of a new sentiment period. As discussed in the section above, their log returns are significantly different to zero which means that a trader generally misses both a favorable entry into and a favorable exit from a commodity futures position. Our results let us to conclude that the beginning of a sentiment period is a substantial stimulus that can have a sustainable impact on the subsequent price development. We extend our findings in the way that long-short speculators have valuable, exclusive information that cannot be exploited by the time delayed observation of their open futures positions. For this reason, forecasting the price stimulus (i.e. the first period of a sentiment period after a contrary sentiment-momentum period) seems to be particularly worthwhile in perspective.

*** Insert Table 4 about here ***

Finally, we further investigate how the time-lagged, publicly available sentiment-momentum-lagged trading strategy and the non-lagged, exclusive sentiment-momentum trading strategy perform in comparison to the realized ex-post returns of the long-short speculators. Table 4 shows the cumulative and

weekly mean returns in USD as well as the risk figures for all three strategies under the assumption that only one futures contract is bought or sold per trade. For example, in case a trader observes from the publicly available SCOT report that the long-short speculators were buying (selling) coffee futures long contracts and selling (buying) coffee futures short contracts in aggregate, he would buy (sell) one coffee futures long (short) contract. If he would have processed this strategy over the entire fifteen-year sample period, he then would have realized a gross loss of 104,625.00 USD. In contrast, long-short speculators who have the information at least for themselves more than a week earlier, can trade instantly and would have made a gross profit of 657,787.50 USD in the same period. Surprisingly at first, however, long-short speculators have achieved an ex-post return of 19,322.45 USD which is significantly lower than the sentiment-momentum strategy. Table 4 confirms our previously discussed findings that the returns of our sentiment-momentum trading strategy are positive and significantly different from zero for all commodities. Furthermore, the time-lagged sentiment-momentum strategy generates a positive return for only 41% of the commodities which are largely not significantly different from zero.

On the contrary, the realized ex-post returns of the long-short speculators are predominantly positive, but only for soybeans and soybean oil they differ significantly from zero. At this point we meet up with the complexity of long-short investment strategies in reality. While long-short speculators mostly enter directional trades based on their information, they also partially hedge their directional positions with futures contracts (see Bohl and Sulewski (2019)).³ Hedging strategies incorporate the opposite trading of futures contracts which results in a lowered impact of the strategy since the net futures position is lower than in the case of absence of hedging the position. This argument cannot be examined directly because the CFTC's SCOT report makes no distinction between hedging positions and directional trades. However, the consistent lower standard deviations and maximum drawdowns for almost all commodities in Table 4 show that the lowered net position as a consequence of the fund's risk management and hedging activities clearly reduces the risk of an investment strategy. We further hypothesize that the ex-post net position of the long-short speculators is considerably less responsive than the net positions of our modeled investment strategies, which change its directional bias within one week. Figure 1 in Section 3.2 illustrates the dynamics of the ex-post net futures position exemplary for the corn futures price. At the beginning of the longer long sentiment-momentum period from June to November 2020, the long-short speculator's net position is negative and only becomes positive as from October 2020, when the price of corn futures has already developed significantly into a positive direction. This means that a long-short speculator incurred a loss during the longest part of the sentiment-momentum period,

³Mellios et al. (2016) also argue that the convenience yield has an important impact on speculation and hedging positions in commodity futures markets and the interaction among time-varying risk premia determines the magnitude and the sign of these positions.

although he has correctly forecasted the price development of the corn futures and has subsequently reduced his negative net position by buying more long contracts than short contracts.

We therefore assume that some long-short speculators have informational advantages and change their directional bias earlier than others. This hypothesis can only be presumed because the SCOT report only allows us to obtain the aggregated open futures positions of all long-short speculators. Consequently, we are not able to derive conclusions about any individual long-short asset manager's trading activity. We also consider that their investment strategies have a longer-term investment horizon, so that the net futures positions are simply maintained for longer. Commodity investment strategies are commonly based on fundamental, commodity-specific factors which have an effect on the commodities' shorter- and longer-term supply and demand like crop results, weather conditions or consumer price trends like an increased demand of plant-based proteins (see also Keenan (2020)). In contrast to our algorithmic, technically-oriented sentiment-momentum strategies, the majority of the commodity investment managers follow an opportunistic approach which commonly has a longer-term investment horizon. Furthermore, as most of the commodity investment funds are highly capitalized, a rapid directional change of the fund's net position is often associated with a disadvantageous market impact. An immediate buy or sell of a significant volume of futures positions would therefore lead to market distortions, which would have a potentially negative impact on the sustainable price development. However, the significant differences between the non-lagged and lagged sentiment-momentum periods show that both trading strategies require a timely trade execution which is usually technically not feasible for a largely capitalized commodity investment fund. In summary, hedging requirements, information asymmetries, longer investment horizons and negative market impact effects may explain the lower ex-post returns of the long-short speculators compared to our modeled sentiment-momentum strategy.

5 Conclusion

Our paper tests the hypothesis that long-short speculators are able to generate short-term investment returns based on their sentiment. We use the equidirectional trading activity of long-short speculators as a proxy for their sentiment on twelve agricultural commodity futures. In the first step, we compare the commodity futures returns in periods with a long or short sentiment with those of a neutral sentiment to derive the sentiment's relevance. As equidirectional trading can impact the commodity price itself, we measure how the commodity price evolves directly after a long or short sentiment period. In case the commodity price continues to develop in the direction of the sentiment period, we can reject the argument of price manipulation and hypothesize that long-short speculators of agricultural commodities have valuable information. Finally, we investigate whether the replication of a sentiment-based trading

strategy can be profitably applied for a trader who is only able to retroactively derive the investment manager's sentiment.

We find that the log returns in long (short) sentiment periods are positive (negative) and significantly different from zero for all commodities which is not the case for each neutral sentiment period. The regular occurrence over the entire sample period shows the sentiment periods' relevance. We also find for all commodities and directions that the future prices continue to develop into the direction of the sentiment period. As a consequence we can reject the argument of price manipulation as the price moves further in the direction of the sentiment period although the long-short speculators have partially oppositely directed open futures positions. We therefore suppose that long-short speculators have valuable information which they use to exploit shorter-term price movements. Our results indicate the existence of a short-term time-series momentum effect. Transferring the definition of time-series momentum to our application, a sentiment period represents the formation period which is directly followed by the momentum period (Moskowitz et al., 2012). As both the sentiment and momentum periods are modeled dynamically on the basis of the long-short speculator's futures positions, our results do not require an external parameter which makes them robust to external market changes during the sample period. Furthermore, we provide evidence that the valuable information of the long-short speculators is exclusive which means that an external trader is not able to replicate the log returns of the sentiment-momentum periods from the long-short speculators. Finally, we conclude that our modeled, sentiment-based momentum strategy generates a significantly higher return in comparison to the realized ex-post returns of the long-short speculators. The differences can be explained with the complexity of the investment managers' strategies such as hedging requirements, information asymmetries, longer investment horizons and negative market impact effects.

We contribute to the empirical literature on speculation on commodity markets by studying speculative price dynamics on the basis of investor sentiment. Contrary to numerous empirical studies which concentrate on the speculative behavior of commodity index traders (in particular on the Master's hypothesis), we examine the equidirectional trading effects of long-short speculators. Since long-short speculators aim to enter directional trades based on their information, their sentiment serves as an observable proxy for the value of their information. Although our modeled sentiment strategy can only be derived from the aggregated group of long-short speculators, our findings provide valuable information for the risk management of individual investment managers to better assess commodity price dynamics. Moreover, since we clearly reject the argument of manipulating commodity prices, we conclude that long-short speculators ethically correctly invest in agricultural commodities, representing the most essential food resources of our planet. As our modeled sentiment forms a valuable but not observable proxy for the long-short speculators' information, future research might also analyze its inner dynamics. Finally,

we would suggest to concentrate more on the behavior of long-short speculators as they represent the trader group of the CFTC reports that probably have the clearest investment intentions.

References

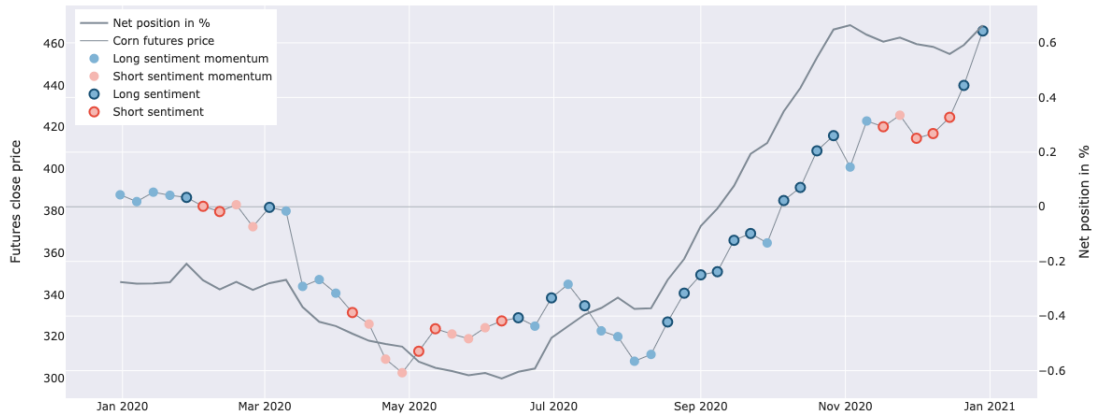
- Barberis, N., Shleifer, A., and Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3):307–343.
- Bohl, M. T., Pütz, A., and Sulewski, C. (2021). Speculation and the informational efficiency of commodity futures markets. *Journal of Commodity Markets*, 23:100159.
- Bohl, M. T. and Sulewski, C. (2019). The impact of long-short speculators on the volatility of agricultural commodity futures prices. *Journal of Commodity Markets*, 16:100085.
- Boyd, N. E., Harris, J. H., and Li, B. (2018). An update on speculation and financialization in commodity markets. *Journal of Commodity Markets*, 10:91–104.
- Brunetti, C., Büyükşahin, B., and Harris, J. H. (2016). Speculators, prices, and market volatility. *Journal of Financial and Quantitative Analysis*, 51(5):1545–1574.
- Brunetti, C. and Reiffen, D. (2014). Commodity index trading and hedging costs. *Journal of Financial Markets*, 21:153–180.
- Buyuksahin, B. and Robe, M. A. (2014). Speculators, commodities and cross-market linkages. *Journal of International Money and Finance*, 42:38–70.
- Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *Journal of Finance*, 53(6):1839–1885.
- De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4):703–738.
- De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, 45(2):379–395.
- Domanski, D. and Heath, A. (2007). Financial investors and commodity markets. *BIS Quarterly Review*, March:53–67.
- Etienne, X. L., Irwin, S. H., and Garcia, P. (2014). Bubbles in food commodity markets: Four decades of evidence. *Journal of International Money and Finance*, 42:129–155.

- Fishe, R. P. and Smith, A. (2019). Do speculators drive commodity prices away from supply and demand fundamentals? *Journal of Commodity Markets*, 15:100078.
- Grinblatt, M. and Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, 78(2):311–339.
- Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6):2143–2184.
- Irwin, S. H. and Sanders, D. R. (2011). Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy*, 33(1):1–31.
- Irwin, S. H. and Sanders, D. R. (2012). Testing the Masters Hypothesis in commodity futures markets. *Energy Economics*, 34(1):256–269.
- Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48(1):65–91.
- Keenan, M. (2020). *Advanced Positioning, Flow and Sentiment Analysis in Commodity Markets*. John Wiley & Sons, Ltd, 2nd edition.
- Kim, A. (2015). Does futures speculation destabilize commodity markets? *Journal of Futures Markets*, 35(8):696–714.
- Manera, M., Nicolini, M., and Vignati, I. (2013). Financial speculation in energy and agriculture futures markets: A multivariate garch approach. *Energy Journal*, 34(3):55–81.
- Maria, G. S., Giovanni, V., and Mattia, V. (2020). Did index trader and swap dealer activity produce a bubble in the agricultural commodity market? *African Journal of Business Management*, 14(1):9–24.
- Masters, W. M. and White, A. (2008). The Accidental Hunt Brothers: How institutional investors are driving up food and energy prices. Technical report.
- Mayer, H., Rathgeber, A., and Wanner, M. (2017). Financialization of metal markets: Does futures trading influence spot prices and volatility? *Resources Policy*, 53:300–316.
- Mellios, C., Six, P., and Lai, A. N. (2016). Dynamic speculation and hedging in commodity futures markets with a stochastic convenience yield. *European Journal of Operational Research*, 250(2):493–504.
- Miffre, J. and Brooks, C. (2013). Do long-short speculators destabilize commodity futures markets? *International Review of Financial Analysis*, 30:230–240.

- Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.
- Often, E. M. and Wisen, C. H. (2013). Disaggregated commitment of traders. *Journal of Applied Business Research*, 29(5):1381–1400.
- Palazzi, R. B., Figueiredo Pinto, A. C., Klotzle, M. C., and De Oliveira, E. M. (2020). Can we still blame index funds for the price movements in the agricultural commodities market? *International Review of Economics and Finance*, 65:84–93.
- Robe, M. A. and Roberts, J. S. (2019). Who holds positions in agricultural futures markets. *SSRN Electronic Journal*, June.
- Sanders, D. R., Irwin, S. H., and Merrin, R. P. (2010). The adequacy of speculation in agricultural futures markets: Too much of a good thing? *Applied Economic Perspectives and Policy*, 32(1):77–94.
- Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131.
- Wimmer, T., Geyer-Klingenberg, J., Hütter, M., Schmid, F., and Rathgeber, A. (2021). The impact of speculation on commodity prices: A Meta-Granger analysis. *Journal of Commodity Markets*, 22:100148.
- Working, H. (1953). Futures trading and hedging. *American Economic Review*, 43(3):314–343.
- Working, H. (1954). Whose markets? Evidence on some aspects of futures trading. *Journal of Marketing*, 19(1):1–11.
- Working, H. (1960). Speculation on hedging markets. *Food Research Institute Studies*, 1:185–220.
- Working, H. (1962). New concepts concerning futures markets and prices. *American Economic Review*, 62:432–459.

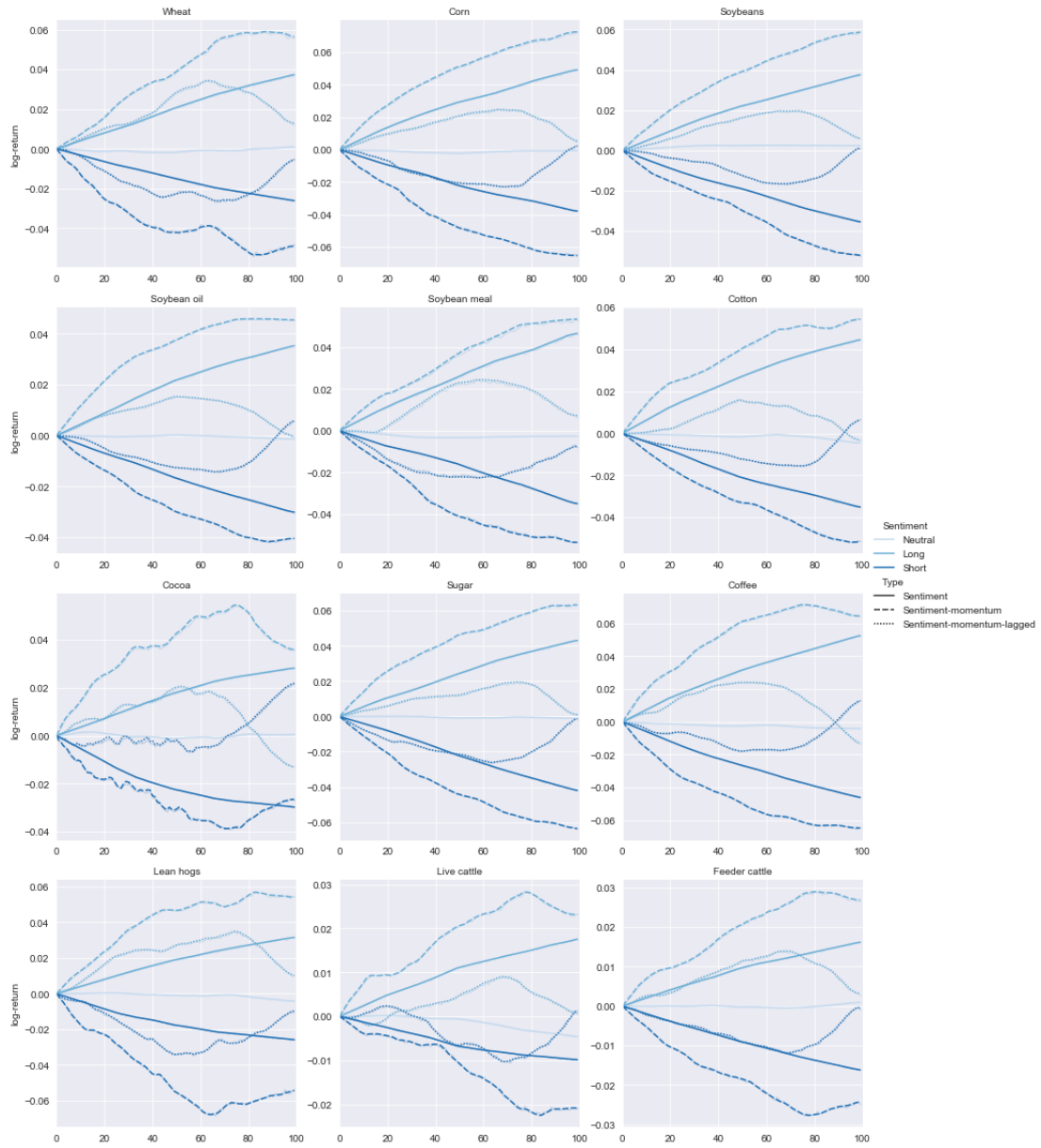
Figures

Figure 1: Sentiment periods of long-short speculators



Note: The blue (red) outlined points mark the end of weekly long (short) sentiment periods in which long-short speculators increase their long (short) corn futures positions and decrease their short (long) corn futures positions. The non-outlined points mark the end of weekly neutral sentiment periods in which long-short speculators increase or decrease their long and short corn futures positions simultaneously. A blue (red) non-outlined point means that the weekly period follows a recent long (short) sentiment period (sentiment momentum). All sentiment and sentiment momentum periods are projected to the price time series of the corn's front contract futures for the period from December 31, 2019 to December 29, 2020. The dark grey line marks the long-short speculator's net futures position in percent of its open interest. A net position of 1.0 (-1.0) means that the long-short speculator's open interest is made up of long (short) positions only.

Figure 2: Mean log returns of the various sentiment periods



Note: The solid lines mark the mean log return development for long (mid blue), short (dark blue) and neutral (light blue) sentiment periods while the dotted lines represent the sentiment-momentum (coarse-dotted) as well as the lagged sentiment-momentum (fine-dotted) periods. All sentiment periods are normalized to the length of 100 weeks.

Tables

Table 1: **Descriptive statistics**

Commodity	Mean	Median	SD	Minimum	Maximum	Skewness	Kurtosis	No. obs.	Long OI %	Short OI %	Sample Period
Wheat	0.00074	-0.00178	0.04492	-0.17625	0.16909	0.23481	0.82690	782	0.2132	0.1724	01/03/2006 - 12/29/2020
Corn	0.00096	0.00206	0.04228	-0.25553	0.23255	-0.19068	4.04113	782	0.1317	0.1113	01/03/2006 - 12/29/2020
Soybeans	0.00095	0.00196	0.03416	-0.20049	0.12031	-0.52429	2.54083	782	0.1423	0.1005	01/03/2006 - 12/29/2020
Soybean oil	0.00079	0.00054	0.03207	-0.11597	0.14310	0.03212	1.12830	782	0.1602	0.1433	01/03/2006 - 12/29/2020
Soybean meal	0.00015	-0.00100	0.03944	-0.29350	0.14666	-0.93769	8.46808	404	0.1607	0.1293	04/02/2013 - 12/29/2020
Cotton	0.00042	0.00044	0.04253	-0.28964	0.16153	-0.71166	5.63051	782	0.1923	0.1030	01/03/2006 - 12/29/2020
Cocoa	0.00062	0.00094	0.04017	-0.16719	0.16840	0.04935	1.25533	782	0.2144	0.1450	01/03/2006 - 12/29/2020
Sugar	0.00008	-0.00077	0.04774	-0.22989	0.15835	-0.08654	1.66787	782	0.1333	0.1091	01/03/2006 - 12/29/2020
Coffee	0.00018	-0.00043	0.04432	-0.14489	0.19934	0.23585	0.90913	782	0.1458	0.1575	01/03/2006 - 12/29/2020
Lean hogs	0.00005	0.00166	0.05437	-0.24099	0.23114	-0.22991	3.24713	782	0.1794	0.1260	01/03/2006 - 12/29/2020
Live cattle	0.00019	0.00158	0.02626	-0.14223	0.11666	-0.56224	3.27677	782	0.2043	0.1023	01/03/2006 - 12/29/2020
Feeder cattle	0.00026	0.00154	0.02418	-0.11783	0.13702	-0.06550	3.23120	782	0.2122	0.1660	01/03/2006 - 12/29/2020

Note: The table reports the mean, median, standard deviation (SD), minimum value, maximum value, skewness, kurtosis and the number of observations (No. obs.) for the 1 week close price log changes of the 12 commodities. Long and short open interest (OI) % represent the long-short speculator's mean proportion of the total open interest, respectively.

Table 2: Return, standard deviation and return difference of the individual sentiment periods

Commodity	Direction	Mean return, statistical significance, no. observations			Standard deviation			Delta, statistical significance		
		S	SM	SML	S	SM	SML	S-SM	S-SML	SM-SML
Wheat	Long	0.03735 *** (111)	0.05647 *** (77)	0.01285 ns (77)	0.05727	0.0815	0.08213	-0.01912 *	0.03346 ***	0.05258 ***
	Short	-0.02607 *** (145)	-0.04916 *** (78)	-0.00527 ns (78)	0.04949	0.10983	0.10755	0.02309 **	-0.02604 ***	-0.04913 ***
	Neutral	0.00103 ns (179)	-	-	0.05724	-	-	-	-	-
Corn	Long	0.04927 *** (132)	0.07262 *** (92)	0.00525 ns (92)	0.05774	0.10121	0.09493	-0.02335 **	0.04667 ***	0.07002 ***
	Short	-0.03786 *** (152)	-0.06547 *** (92)	0.00214 ns (91)	0.0585	0.09626	0.09625	0.02761 ***	-0.04039 ***	-0.068 ***
	Neutral	-0.00051 ns (178)	-	-	0.04701	-	-	-	-	-
Soybeans	Long	0.0376 *** (146)	0.05868 *** (101)	0.00593 ns (101)	0.03587	0.06209	0.06783	-0.02108 ***	0.03639 ***	0.05747 ***
	Short	-0.03537 *** (149)	-0.05197 *** (101)	0.00117 ns (101)	0.0413	0.0653	0.06142	0.0166 **	-0.03726 ***	-0.05386 ***
	Neutral	0.0024 ns (172)	-	-	0.0356	-	-	-	-	-
Soybean oil	Long	0.03527 *** (145)	0.04543 *** (103)	-0.00027 ns (103)	0.03735	0.04968	0.05502	-0.01015 *	0.03298 ***	0.04313 ***
	Short	-0.0301 *** (144)	-0.04046 *** (103)	0.00584 ns (103)	0.04802	0.06714	0.06301	0.01036 ns	-0.03145 ***	-0.04181 ***
	Neutral	-0.00137 ns (179)	-	-	0.03278	-	-	-	-	-
Soybean meal	Long	0.04659 *** (66)	0.05348 *** (50)	0.00723 ns (50)	0.07279	0.07962	0.06513	-0.0069 ns	0.03987 ***	0.04676 ***
	Short	-0.03494 *** (83)	-0.05345 *** (51)	-0.00742 ns (51)	0.04553	0.07737	0.09116	0.01852 *	-0.03253 ***	-0.05104 ***
	Neutral	-0.00264 ns (86)	-	-	0.02949	-	-	-	-	-
Cotton	Long	0.04455 *** (136)	0.05438 *** (99)	-0.00332 ns (99)	0.0501	0.09659	0.08389	-0.00983 ns	0.04866 ***	0.05849 ***
	Short	-0.03508 *** (143)	-0.0517 *** (99)	0.00643 ns (99)	0.0425	0.0803	0.07876	0.01663 **	-0.03952 ***	-0.05614 ***
	Neutral	-0.00444 ns (175)	-	-	0.05219	-	-	-	-	-
Cocoa	Long	0.02814 *** (120)	0.03569 *** (68)	-0.01309 ns (68)	0.04222	0.08235	0.06729	-0.00756 ns	0.03445 ***	0.04201 ***
	Short	-0.02974 *** (98)	-0.02653 *** (67)	0.02187 *** (67)	0.04667	0.06258	0.05698	-0.00321 ns	-0.03584 ***	-0.03263 ***
	Neutral	0.00059 ns (163)	-	-	0.06402	-	-	-	-	-
Sugar	Long	0.04316 *** (151)	0.0634 *** (102)	0.00098 ns (102)	0.05662	0.10037	0.09275	-0.02024 **	0.04775 ***	0.06799 ***
	Short	-0.04195 *** (150)	-0.0636 *** (101)	-0.00114 ns (101)	0.0573	0.08884	0.08637	0.02165 **	-0.03848 ***	-0.06013 ***
	Neutral	-0.00114 ns (196)	-	-	0.04928	-	-	-	-	-
Coffee	Long	0.05247 *** (133)	0.06451 *** (91)	-0.01304 * (91)	0.05522	0.07642	0.07002	-0.01204 ns	0.05753 ***	0.06957 ***
	Short	-0.04601 *** (133)	-0.06464 *** (91)	0.01276 * (91)	0.0455	0.07421	0.07193	0.01863 **	-0.04951 ***	-0.06814 ***
	Neutral	-0.00415 ns (189)	-	-	0.04894	-	-	-	-	-
Lean hogs	Long	0.03159 *** (119)	0.05428 *** (71)	0.01043 ns (71)	0.06298	0.12474	0.12089	-0.02268 *	0.02373 ***	0.04642 ***
	Short	-0.02578 *** (115)	-0.0543 *** (71)	-0.00961 ns (71)	0.06559	0.12615	0.11914	0.02852 **	-0.02477 ***	-0.05329 ***
	Neutral	-0.0041 ns (187)	-	-	0.08075	-	-	-	-	-
Live cattle	Long	0.01756 *** (125)	0.02323 *** (73)	0.00062 ns (73)	0.03424	0.05601	0.05509	-0.00567 ns	0.01815 ***	0.02382 ***
	Short	-0.00989 *** (123)	-0.0209 *** (74)	0.00131 ns (74)	0.02707	0.06297	0.06858	0.01101 *	-0.01188 ***	-0.02288 ***
	Neutral	-0.00462 * (186)	-	-	0.03714	-	-	-	-	-
Feeder cattle	Long	0.01618 *** (120)	0.02689 *** (72)	0.00313 ns (72)	0.02781	0.05267	0.05357	-0.0107 *	0.0148 ***	0.02551 ***
	Short	-0.01617 *** (119)	-0.02426 *** (73)	-0.00044 ns (73)	0.03007	0.05967	0.05407	0.00809 ns	-0.01526 ***	-0.02335 ***
	Neutral	0.00093 ns (180)	-	-	0.03214	-	-	-	-	-

Note: The table shows the mean return, number of observations (in parentheses), standard deviation and the delta of the respective mean returns for the individual long and short sentiment periods (S), sentiment-momentum periods (SM) and sentiment-momentum-lagged periods (SML) as well as for the neutral sentiment periods. The statistical significance of the mean return indicates whether the sample mean return is equal to zero. The delta statistical significance shows the result of a t-test that calculates whether two given sentiment periods have identical mean returns. The asterisks represent the level of significance, where ***, **, * indicates that the test statistic is significant at the 1%, 5% and 10% level, respectively, while ns means that the test statistic is not significant.

Table 3: Return, standard deviation and maximum drawdown of the total sentiment periods

Commodity	Direction	Cumulated return			Standard deviation			Maximum drawdown		
		S	SM	SML	S	SM	SML	S	SM	SML
Wheat	Long	4.14605	4.34817	0.98931	1.08888	1.1052	0.26553	-0.12501	-0.2672	-0.52407
	Short	-3.78035	-3.83446	-0.41118	1.14407	1.18922	0.31231	0.25093	0.42978	0.6463
	Neutral	0.18437	-	-	0.15342	-	-	-0.66118	-	-
Corn	Long	6.50356	6.68114	0.48324	1.80895	1.9552	0.28177	-0.08228	-0.17419	-0.89617
	Short	-5.75503	-6.02326	0.19515	1.71683	1.86748	0.18842	0.09757	0.21324	0.7575
	Neutral	-0.09065	-	-	0.1641	-	-	-0.81193	-	-
Soybeans	Long	5.48935	5.92633	0.59872	1.57866	1.70084	0.15791	-0.06138	-0.18671	-0.40045
	Short	-5.27016	-5.24908	0.118	1.65658	1.70042	0.16645	0.11337	0.20105	0.64316
	Neutral	0.41303	-	-	0.19216	-	-	-0.34355	-	-
Soybean oil	Long	5.11477	4.67892	-0.02759	1.3529	1.35252	0.23246	-0.10235	-0.19175	-0.92002
	Short	-4.33451	-4.16775	0.60134	1.41046	1.3312	0.14099	0.19556	0.24418	0.62346
	Neutral	-0.2456	-	-	0.15365	-	-	-0.75641	-	-
Soybean meal	Long	3.07471	2.67409	0.3617	0.90892	0.78212	0.18751	-0.15087	-0.14988	-0.44124
	Short	-2.89971	-2.72616	-0.37855	0.85307	0.83081	0.28573	0.11903	0.18613	0.49384
	Neutral	-0.22707	-	-	0.1313	-	-	-0.4313	-	-
Cotton	Long	6.05841	5.38333	-0.32908	1.77716	1.58308	0.23222	-0.17411	-0.46065	-1.01479
	Short	-5.01603	-5.11863	0.6364	1.46042	1.49142	0.29507	0.12592	0.19562	1.14167
	Neutral	-0.77768	-	-	0.2742	-	-	-0.94745	-	-
Cocoa	Long	3.37648	2.42718	-0.89002	0.87412	0.59266	0.37661	-0.08937	-0.32309	-1.33611
	Short	-2.91472	-1.77766	1.46522	0.79808	0.53297	0.4662	0.14675	0.61146	1.64155
	Neutral	0.09582	-	-	0.25224	-	-	-0.97099	-	-
Sugar	Long	6.51688	6.46687	0.09983	2.00891	1.93346	0.30096	-0.10799	-0.29143	-1.26826
	Short	-6.29209	-6.42348	-0.11501	1.93515	1.88949	0.13232	0.23946	0.28097	0.60831
	Neutral	-0.22267	-	-	0.13393	-	-	-0.58291	-	-
Coffee	Long	6.97868	5.87025	-1.18621	2.05153	1.79562	0.46372	-0.08503	-0.21633	-1.6672
	Short	-6.11942	-5.88229	1.16156	1.89315	1.80452	0.37058	0.11445	0.19825	1.3729
	Neutral	-0.78391	-	-	0.1649	-	-	-0.87943	-	-
Lean hogs	Long	3.7598	3.85371	0.74056	0.96091	1.15707	0.29398	-0.29	-0.57632	-0.54697
	Short	-2.96518	-3.85526	-0.682	0.93611	1.17029	0.36888	0.26666	0.42946	0.62184
	Neutral	-0.76716	-	-	0.28306	-	-	-1.30691	-	-
Live cattle	Long	2.19504	1.6956	0.0455	0.63837	0.52323	0.09318	-0.17445	-0.19036	-0.45361
	Short	-1.21638	-1.54641	0.09689	0.30357	0.46413	0.21404	0.12859	0.21224	0.85283
	Neutral	-0.85919	-	-	0.34847	-	-	-1.04077	-	-
Feeder cattle	Long	1.94201	1.93593	0.22515	0.57368	0.56944	0.15102	-0.13523	-0.20439	-0.3933
	Short	-1.92441	-1.77117	-0.03248	0.55075	0.48405	0.11451	0.10456	0.33222	0.55562
	Neutral	0.168	-	-	0.11099	-	-	-0.37405	-	-

Note: The table shows the cumulated return, standard deviation and maximum drawdown for the total long and short sentiment periods (S), sentiment-momentum periods (SM) and sentiment-momentum-lagged periods (SML) as well as for the neutral sentiment periods.

Table 4: Ex-post long-short speculator and sentiment strategy returns

Commodity	Strategy	Cumulated return	Mean return, statistical significance	Standard deviation	Maximum drawdown
Cocoa	ex-post	-1,250.60	-1.43387 ns	355.97	-9,282.55
Coffee	ex-post	19,322.45	23.4142 ns	1,080.04	-26,431.10
Corn	ex-post	14,649.42	18.76304 ns	406.58	-8,419.71
Cotton	ex-post	39,934.16	51.14501 ns	1,197.49	-32,967.00
Soybean meal	ex-post	2,790.48	6.99488 ns	444.37	-8,889.60
Soybean oil	ex-post	22,802.47	28.98189 ***	271.82	-2,572.84
Soybeans	ex-post	51,518.11	66.26471 **	942.20	-15,574.81
Sugar	ex-post	12,195.53	15.1218 ns	645.50	-12,035.98
Wheat	ex-post	15,532.32	20.82319 ns	730.33	-17,367.30
Feeder cattle	ex-post	24,409.29	31.45627 ns	610.22	-6,796.18
Lean hogs	ex-post	-11,260.64	-14.2137 ns	604.83	-20,469.20
Live cattle	ex-post	18,938.92	24.19006 ns	520.24	-9,465.57
Cocoa	sentiment-momentum	108,630.00	138.91304 ***	1,003.84	-16,420.00
Coffee	sentiment-momentum	657,787.50	841.16049 ***	2,370.14	-29,437.50
Corn	sentiment-momentum	283,200.00	362.14834 ***	934.66	-4,275.00
Cotton	sentiment-momentum	388,835.00	497.23146 ***	1,872.20	-20,160.00
Soybean meal	sentiment-momentum	191,260.00	473.41584 ***	1,417.97	-14,400.00
Soybean oil	sentiment-momentum	205,860.00	263.24808 ***	752.40	-5,586.00
Soybeans	sentiment-momentum	592,362.50	757.4968 ***	1,797.58	-16,975.00
Sugar	sentiment-momentum	246,915.20	315.74834 ***	943.23	-5,958.40
Wheat	sentiment-momentum	251,987.50	322.23465 ***	1,377.37	-11,550.00
Feeder cattle	sentiment-momentum	243,592.50	311.49936 ***	1,679.89	-46,775.00
Lean hogs	sentiment-momentum	239,030.00	305.66496 ***	1,516.52	-15,210.00
Live cattle	sentiment-momentum	143,352.00	183.31458 ***	1,168.43	-14,260.00
Cocoa	sentiment-momentum-lagged	-59,120.00	-75.60102 **	1,010.55	-66,040.00
Coffee	sentiment-momentum-lagged	-104,625.00	-133.79156 ns	2,507.68	-128,756.25
Corn	sentiment-momentum-lagged	14,837.50	18.97379 ns	1,002.20	-23,425.00
Cotton	sentiment-momentum-lagged	-28,580.00	-36.54731 ns	1,936.83	-63,650.00
Soybean meal	sentiment-momentum-lagged	32,300.00	79.9505 ns	1,494.31	-21,980.00
Soybean oil	sentiment-momentum-lagged	-7,740.00	-9.8977 ns	796.89	-28,890.00
Soybeans	sentiment-momentum-lagged	25,287.50	32.33696 ns	1,950.55	-51,300.00
Sugar	sentiment-momentum-lagged	9,396.80	12.01637 ns	994.37	-29,489.60
Wheat	sentiment-momentum-lagged	57,275.00	73.24169 ns	1,412.69	-21,487.50
Feeder cattle	sentiment-momentum-lagged	13,812.50	17.66304 ns	1,708.32	-48,047.50
Lean hogs	sentiment-momentum-lagged	43,872.00	56.1023 ns	1,545.89	-27,382.00
Live cattle	sentiment-momentum-lagged	-4,348.00	-5.5601 ns	1,182.91	-52,848.00

Note: The table shows the cumulated return, mean return, standard deviation and maximum drawdown of the ex-post long-short speculator's futures trading as well as the sentiment-momentum and sentiment-momentum-lagged strategy in US-dollar for the period from January 3, 2006 to December 29, 2020. The ex-post long-short speculator return is calculated as the futures return of all long-short speculator's long and short futures positions divided by the open interest in order to approximate the total investment result on the basis of one futures contract. In the same way, the strategies' return time series are also simulated with the trading of one long or short futures contract. The statistical significance of the mean return indicates whether the sample mean return is equal to zero. The asterisks represent the level of significance, where ***, **, * indicates that the test statistic is significant at the 1%, 5% and 10% level, respectively, while ns means that the test statistic is not significant.