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Speculators and time series momentum in commodity futures markets

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Abstract

In this paper, we analyze the relationship between speculators in commodity futures markets and generic time series momentum (TSMOM) traders as well as the impact of this relationship on the subsequent TSMOM strategy performance. We find strong empirical evidence across all commodity markets that speculators in commodity markets tend to trade a TSMOM strategy, which confirms the results found by Boos and Grob (*Journal of Financial Markets* 64, 100774). On the basis of this result, we also ascertain whether the degree of such alignment has an impact on the performance of the TSMOM strategy. We find that there is weak, but statistically significant and robust evidence to suggest that the higher the degree of alignment between speculators and a generic TSMOM strategy, the lower the realized performance of trading TSMOM in these markets. Albeit we find little evidence that this can be exploited in a dynamic investment strategy, this negative relationship suggests that if a Commodity Trading Advisor (CTA) trades commodity futures markets which are less commonly traded by other CTAs, these markets may not only increase the internal diversification of their fund but these markets may also have a higher TSMOM Sharpe ratio by themselves. Consequently, our analysis provides valuable insights into improving the portfolio construction of CTAs.

KEYWORDS

commitment of traders, commodities, momentum, speculative crowding

JEL CLASSIFICATION

G11, Q02

1 | INTRODUCTION

Commodities can offer distinct diversification benefits to investors as they tend not to be highly correlated to traditional asset classes. However, commodities may also exhibit certain features such as a very high volatility or a negative roll yield which need to be considered when constructing a portfolio that includes an allocation to commodities (see Fernandez-Perez et al., 2016; Levine et al., 2018; Skiadopoulos, 2012). Specifically, adding individual commodity markets long-only to an existing portfolio may have limit benefit. For instance, Vinzelberg and Auer (2014) show that

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adding crude oil futures does not improve key statistics of typical stocks and bonds portfolios. Therefore, it can prove useful to not invest 'buy&hold' into commodities but trade them in an active investment strategy such as alternative risk premia, see e.g. Fuertes et al. (2015), Miffre (2016) and Markwat et al. (2020). One of the most studied alternative risk premia is time series momentum (TSMOM) also known as trend-following (Moskowitz et al., 2012),¹ which is typically traded by so-called Commodity Trading Advisors (CTA). Essentially, TSMOM dictates to hold a long exposure in an asset if its price has been increasing and vice versa for short positions. Erb and Harvey (2006) argue that whilst holding commodities long-only does not necessarily generate equity-like returns there is evidence to suggest that historically long-short investment strategies such as momentum were profitable. Georgopoulou and Wang (2017) show that much of mutual fund performance in equities and also in commodities can be explained by TSMOM. Clare et al. (2014) find that combining TSMOM with cross-sectional momentum for commodity futures yields even higher risk-adjusted returns. The popularity of momentum trading is owed to its persistence (e.g. Geczy & Samonov, 2016) and resilience (e.g. Foltice & Langer, 2015). Consequently, when constructing portfolios, Stadtmüller et al. (2024) argue in favour of a core portfolio which is enhanced by a satellite investment with a fixed allocation to commodity futures momentum.

The presence of TSMOM traders in commodity futures markets has been investigated extensively. Regressing the returns of two broad CTA indices on the returns of a generic multi-asset TSMOM strategy Hurst et al. (2017) find significantly positive coefficient estimates which suggests that CTAs indeed predominately trade TSMOM. Using futures across all asset classes Fan et al. (2020) find that speculative pressure as a factor can help to explain the cross-section of returns after controlling for a number of alternative risk premia across all sectors but fixed income. Lutzenberger (2014) shows that in addition to TSMOM predictability also other exogenous variables can help forecasting the returns of commodity futures. More recently, the academic debate has focussed on the relationship between speculators in commodity futures and TSMOM. For instance, Borgards and Czudaj (2022) show that the changes in speculative open interest have forecasting power for the returns of the underlying market as well as their relationship with momentum. In the same direction Boos and Grob (2023) hypothesize that speculators in commodity futures are trend-followers and show that regressions which explain the changes in net speculative open interest by generic TSMOM positions have substantial explanatory power across commodity markets. They also estimate the average momentum filter weights traded by speculators using a penalized regression.

Given the ample evidence that speculators in commodity futures trade a trend-following strategy, we address the following question: Does the degree of speculative crowding among CTAs in a commodity market have an impact on the performance of a trend-following strategy in that market? Rather than using generic measures speculative crowding e.g. the fraction of speculators in all traders, we use a novel measure which is tailored to the specific problem. We consider how closely aligned the net speculative open interest in any given commodity market is to the positions of a generic trend-following strategy. Consequently, our work builds upon Boos and Grob (2023) who empirically show that the changes in net speculative open interest can be explained by the changes in a generic trend-following signal. They report high out-of-sample R^2 for all markets and estimate the weights which the average CTA would have applied. Our work is closely related to theirs but we focus predominately on the consequences of such alignment between speculators and TSMOM traders. Essentially, we use the degree of alignment as measure of speculative crowding. The more speculators trade TSMOM the closer their aggregate net positioning should be to a generic trend-following position. In contrast to standard metrics, such as e.g. the proportion of speculators to all open interest, this measure is more informative as it specifically test how similar the positions of speculators to the positions of a TSMOM strategy. If speculators were on aggregate aligned with a specific trading strategy such as momentum this could potentially have a more profound impact than merely generic measures of speculative activity because alignment requires different speculators to trade in the same direction at the same time. The underlying hypothesis is that if too many CTAs trend-follow a commodity market in a similar fashion the expected returns of this strategy diminish. The possible reasons could be the increased risk of reversals and tail risks (e.g. Barroso et al., 2022; Brown et al., 2022).² The consequences of such strategy alignment could both pose a systemic risk but could also impact the performance of trading that strategy.

The majority of the literature focusses on the systemic risk aspect. Whether speculators in commodity markets cause price impact has been famously alleged by Masters and White (2008) whose hypothesis that long-only speculators in commodity futures were the main driver behind the 2007–2008 price spike has been tested empirically by Irwin and Sanders (2012) who found no evidence in favour of this hypothesis. Boyd et al. (2018) review the impact of the financialization of commodity futures and conclude that speculators have little impact on price distortions but that they predominately provide liquidity to hedgers. Brooks et al. (2015) investigate extreme price moves in commodity markets and find little, if any, evidence that these were caused by speculative bubbles. On the contrary, using informational efficiency as a measure of market quality, Bohl et al. (2021) find empirical evidence that the higher the speculative activity in a commodity market, the lower on average the quality of that market. Decomposing price shocks to commodity futures into a

permanent and a transitory component, Haase et al. (2019) find no empirical evidence that speculators cause long-term price impact. Haase et al. (2016) summarize a large number of studies on this subject in a meta-analysis and find that there is no conclusive evidence neither for nor against the hypothesis that speculators drive commodity market prices. However, Haase et al. (2017) find some empirical evidence that speculators in commodity markets can Granger-cause market volatility, whilst Kim (2015) find that speculative futures trading does not destabilize commodity markets. In another meta-analysis of a large number of published studies Wimmer et al. (2021) find that the null hypothesis of non-causality cannot be rejected.

More toward the direction of our work are studies that relate the degree of speculative crowding to strategy performance. For instance, Baltas (2019) investigates the impact of crowding in risk premia strategies including momentum. His results suggest that the impact of crowding can be either beneficial or not depending on whether the investment strategy is convergent (e.g. mean-reversion trading) or divergent (e.g. momentum trading). Focussing specifically on trend-following Bollen et al. (2021) investigate whether those CTAs that perform more similar to their peers under- or outperform them. They find that similarity to the peer group is associated on average with higher performance. Building a heterogeneous agent model, He and Li (2015) investigate the relationship between different types of traders. They find that when momentum traders are more active in a market, momentum strategies with a short horizon tend to stabilize the market and may be more profitable. Carter and Revoredo-Giha (2023) attribute a degeneration in CTA returns in commodity futures to the financialization of such markets. In contrast to the aforementioned analyses, we focus on the differences between individual commodity markets with regards to the relationship between speculative crowding and trend-following performance. This can provide a useful guide to investment managers to adjust their weighting (or even inclusion) of markets in their strategy.

In Figure 1, an example is given to illustrate the hypothesized relationship between speculators and CTAs. It shows the time series of the (normalized) net speculative position for the Arabica Coffee futures together with the corresponding (normalized) positions of a generic TSMOM strategy. It can be seen that these appear to be closely related.

Investigating the trading behavior in futures contracts using the CFTC commitment of traders data has been done in financial markets, too. For instance, using the S&P 500 index future Smales (2016) finds that speculators and small traders reveal some ability to forecast future returns.

The contribution of this work can be summarized as follows. First, after replicating some of the key results of Boos and Grob (2023), we introduce the corresponding regression estimates as measure of alignment among speculators. This measure is specifically tailored to the empirical observation that the predominant part of speculators in commodity futures pursue a trend-following strategy. Second, we find that the performance of trend-following a commodity market is negatively correlated to the degree of the estimated alignment. However, we also find that this effect appears to be predominately contemporaneous though and thus it is unlikely that it can be exploited profitably in a dynamic trading strategy. This negative relationship suggests that if a CTA adds new commodity markets which are less commonly traded by other CTAs relative to other speculators, such markets do not only increase the internal diversification of the portfolio but may also tend to

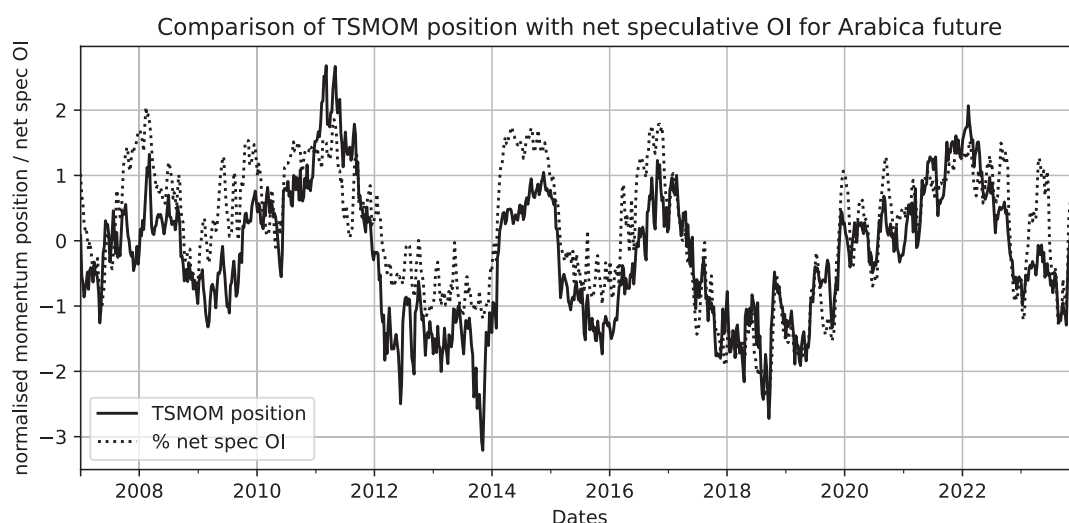


FIGURE 1 Example of similarity between net speculative OI and trend-following position. Time series of trend-following positions and the % net speculative open interest scaled by their own volatility (fixed) for Arabica Coffee futures.

individually perform superior in a TSMOM strategy. This finding may explain why more and more CTAs launch so-called 'alternative markets' programs which trade more exotic and less commonly traded commodity futures markets.

This paper is structured as follows. In the next section, we discuss the data and methodology that we use for our analyses. In the third section, some statistics are provided that allow to better understand the relationship between the different categories of commodity traders. The fourth section contains the main empirical results. The fifth section provides some robustness analyses to support the key findings. In the sixth section, we discuss whether the findings can be used profitably in an investment strategy. The final section concludes.

2 | DATA AND EMPIRICAL STRATEGY

2.1 | Data

We collect data for $n = 26$ commodity futures markets. The sample period is from January 2006 to December 2023 and is limited by the historical availability of the disaggregated open interest (OI) data from the Commodity Futures Trading Commission (CFTC).³ All data are retrieved from Bloomberg.

The contracts with their basic properties are shown in Table 1. Most markets are in the agricultural sector. With the exceptions of lean hogs and feeder cattle all contracts are physically settled.

TABLE 1 The table shows the contract specification for the commodity futures series we consider.

Name	Ticker	Cash settled	Exchange	Sector	Sub-sector
Crude	CL1	N	New York Mercantile Exchange	Energies	Energies
NatGas	NG1	N	New York Mercantile Exchange	Energies	Energies
HeatingOil / ULSD	HO1	N	New York Mercantile Exchange	Energies	Energies
Gasoline	XB1	N	New York Mercantile Exchange	Energies	Energies
Copper	HG1	N	Commodity Exchange, Inc.	Metals	Industrials
Gold	GC1	N	Commodity Exchange, Inc.	Metals	Precious
Silver	SI1	N	Commodity Exchange, Inc.	Metals	Precious
Platinum	PL1	N	New York Mercantile Exchange	Metals	Precious
Palladium	PA1	N	New York Mercantile Exchange	Metals	Precious
Wheat	W 1	N	Chicago Board of Trade	Ags	Grains and Oilseeds
Corn	C 1	N	Chicago Board of Trade	Ags	Grains and Oilseeds
Soybean	S 1	N	Chicago Board of Trade	Ags	Grains and Oilseeds
SoybeanMeal	SM1	N	Chicago Board of Trade	Ags	Grains and Oilseeds
SoybeanOil	BO1	N	Chicago Board of Trade	Ags	Grains and Oilseeds
Coffee	KC1	N	ICE Futures US Softs	Ags	Softs
Sugar	SB1	N	ICE Futures US Softs	Ags	Softs
Cotton	CT1	N	ICE Futures US Softs	Ags	Softs
Cocoa	CC1	N	ICE Futures US Softs	Ags	Softs
Lumber	LB1	N	Chicago Mercantile Exchange	Ags	Softs
Juice	JO1	N	ICE Futures US Softs	Ags	Softs
LiveCattle	LC1	N	Chicago Mercantile Exchange	Ags	Livestock
LeanHogs	LH1	Y	Chicago Mercantile Exchange	Ags	Livestock
FeederCattle	FC1	Y	Chicago Mercantile Exchange	Ags	Livestock
HardWinterWheat	KW1	N	Chicago Board of Trade	Ags	Grains and Oilseeds
SpringWheat	MW1	N	Minneapolis Grain Exchange	Ags	Grains and Oilseeds
Rough rice	RR1	N	Chicago Board of Trade	Ags	Grains and Oilseeds

Source: Bloomberg.

For each of the futures contracts, we obtain daily end-of-day closing prices. As each futures contract expires at a fixed date, we generate a continuous series of prices for each market by rolling every contract either on its last trading date or on the first business day of the expiration month, whichever is earlier. Ratio adjustments are applied backward in history. With these adjustments, there is no price-jump from rolls but the carry return is earned (or paid) continuously (Kojien et al., 2018). Thus, using ratio adjustments for the rolls between contracts allows to compute logarithmic returns simply as difference between the logarithm of the adjusted prices.

Futures do not require a full investment but are traded on margin accounts for which only an initial and a variation margin have to be posted. We assume that the futures position is fully collateralized, so that the returns can be interpreted as standard excess returns.

The OI data is originally provided by the CFTC on a weekly basis in the ‘Disaggregated Commitment of Traders Report’. The report contains the aggregate long and short positioning of reportable market participants in futures markets which are classified in four categories: swap dealers, producers, money managers and others. In plain terms, ‘swap dealers’ are primarily investment banks who act as market makers; ‘producers’ are all market participants who are involved with the physical underlying of the futures contract, i.e. buyers or sellers of the actual commodity; ‘money managers’ are asset management firms who hold positions to speculate on the future price development and thus are subsequently labeled ‘speculators’; finally, ‘others’ are any traders who do not fall into any of the previous categories. The OI data is published on Fridays for Tuesday’s holdings. As we are interested in explaining alignment we use the Tuesday timestamps. We use the futures-only data and ignore options as CTAs tend trade the former. The original OI data is sampled in lots and is mapped to USD positions by multiplying the number of lots with the corresponding contract value.⁴

Net and gross OI for each commodity market $i = 1, \dots, n$ and each category of trader, $\text{cat} \in \{\text{prod}, \text{swap}, \text{spec}, \text{other}\}$, are defined as

$$\begin{aligned} OI_{i,t}^{\text{net,cat}} &= OI_{i,t}^{\text{long,cat}} - OI_{i,t}^{\text{short,cat}} \text{ and} \\ OI_{i,t}^{\text{gross,cat}} &= OI_{i,t}^{\text{long,cat}} + OI_{i,t}^{\text{short,cat}}, \end{aligned} \quad (1)$$

respectively and can be interpreted as the net and gross aggregate positioning of speculative traders in a given market. For comparability we normalize both by the aggregate gross OI, i.e. for net OI we have

$$OI_{i,t}^{\% \text{net,cat}} = \frac{OI_{i,t}^{\text{net,cat}}}{\sum_{\text{cat} \in \{\text{prod}, \text{swap}, \text{spec}, \text{other}\}} OI_{i,t}^{\text{gross,cat}}}. \quad (2)$$

In order to have well-defined statistics, both $OI_{i,t}^{\% \text{net,cat}}$ and $OI_{i,t}^{\% \text{gross,cat}}$ are normalized by the gross OI.

2.2 | Generic momentum signals and positions

There are two main types of momentum strategies: time series momentum (TSMOM) which takes directional net exposures, see Moskowitz et al. (2012), and cross-sectional momentum (XSMOM) which is generally net cash or risk neutral, see Jegadeesh and Titman (1993). Albeit a number of works have discussed the latter (e.g. Shen et al., 2007) we focus on the former because it is the predominant strategy employed by many CTAs (Hurst et al., 2013).

To compare the net speculative positioning with the positions of a generic TSMOM strategy we need to specify a baseline momentum model. We define the TSMOM signal s_{it} at time $t = 1, \dots, T$ for each market $i = 1, \dots, n$, in accordance with Levine and Pedersen (2016) as the market return over the preceding 260 business days normalized by the corresponding estimate of volatility, i.e.

$$s_{it} = \frac{r_{it}^{\text{1year}}}{\hat{\sigma}_{it}^{\text{1year}}}. \quad (3)$$

Fan and Zhang (2024) highlight the importance of risk managing the positions in individual commodity markets in risk premia strategies. Thus, the positions of a TSMOM strategy are typically scaled inversely proportional to volatility (see e.g. Harvey et al., 2021),

$$p_{it} = \frac{\sigma^{\text{target}}}{\hat{\sigma}_{it}} s_{it}. \quad (4)$$

where we set $\sigma^{\text{target}} = 10\%$ per annum⁵ and we also use the RiskMetrics (1996) standard for $\hat{\sigma}_{it}$.

In the robustness section, we discuss the sensitivity of the key results to these specifications. In particular, we test the impact of applying a forecast function to the signal, e.g. the sign function which is often used in the literature (e.g. Moskowitz et al., 2012), and the impact of using a ‘slower’ position scaling, which may be relevant in practice.

2.3 | Measuring the alignment between speculators and momentum traders

We hypothesize that speculators in commodity futures markets trade TSMOM as described by the generic strategy in the previous subsection. To test this hypothesis empirically, we follow Boos and Grob (2023) and estimate a regression where the changes in the net speculative OI are explained by changes in the positions of a generic TSMOM strategy. While we base our primary empirical model on theirs, we deviate in three regards, though. First, in this work, the trend-following position is volatility-scaled, which has been highlighted by Kim et al. (2016) as a significantly contributing factor to TSMOM performance and consequently is used in practice by many CTAs, which is relevant to this work. Second, we use weekly data on both sides of the regression as we do not aim to back out average filter weights but explain changes in the speculative positioning. Lastly, we normalize the variables of both sides of the regression by their corresponding standard deviation. This renders both sides of the regressions dimensionless so that the coefficient estimates can be interpreted in terms of standard deviations and are consequently comparable across markets. Thus, the model specification reads

$$\Delta \tilde{OI}_{it}^{\% \text{net, spec}} = \beta_{0,i}^{\Delta} + \beta_{1,i}^{\Delta} \Delta \tilde{p}_{it} + \epsilon_{it}^{\Delta} \quad (5)$$

where $OI_{it}^{\% \text{net, spec}}$ is defined in (2) and the positions of the TSMOM strategy p_{it} are defined in (4). Variables which are super-scripted by a tilde $\tilde{\cdot}$ denote the corresponding variable divided by its own volatility, i.e. for instance for the TSMOM positions the normalization is $\tilde{p}_{it} = p_{it} / \text{std}(p_{it})$.

In addition, we also use a specification in levels, which entails the issue of high autocorrelation in the regressor but may still provide some additional information. Thus, we also estimate

$$\tilde{OI}_{it}^{\% \text{net, spec}} = \beta_{0,i} + \beta_{1,i} \tilde{p}_{it} + \epsilon_{it}. \quad (6)$$

It should be noted that the levels regression (6) uses highly autocorrelated variables which by construction are stationary though. The trend-following positions as defined in (4) use a scaled version of the lagged 1-year market return. The differencing in (5) has the advantage of removing the high autocorrelation but also removes the level information though. Clearly, both regressions are related but still have their distinct advantages and disadvantages so that we use both in the empirical analysis.

A statistically significant estimate for β_1^{Δ} or β_1 , respectively, would suggest that the aggregate speculators in that market behave similar to a time series momentum trader as defined in section 2.2. We also compute out-of-sample R_{OS}^2 (Campbell & Thompson, 2008), which compares the mean squared error (MSE) from the prediction of the regression to the MSE of using the historical average as prediction, i.e. for instance for (5)

$$R_{i,OS}^2 = 1 - \frac{\sum_{t=\tau}^T (y_{it} - \hat{y}_{it})^2}{\sum_{t=\tau}^T (y_{it} - \bar{y}_{it})^2}, \quad i = 1, \dots, n \quad (7)$$

where $y_{it} = \Delta \tilde{OI}_{it}^{\% \text{net, spec}}$ for (5) and $y_{it} = \tilde{OI}_{it}^{\% \text{net, spec}}$ for (6) and the predictors \hat{y}_t and \bar{y}_t use data up to time $t - 1$. As the prediction is out-of-sample a minimum estimation window size τ for the regression needs to be specified which we set to the equivalent of 4 years of observations. All statistical significance tests for these regressions are based on the stationary bootstrap by Politis and Romano (1994).

3 | MARKET STRUCTURE

3.1 | Who trades with whom?

We first ascertain which categories of traders in commodity futures trade with each other. To this end, we correlate the contemporaneous weekly changes in the corresponding net open interest for each combination of categories. A negative relationship suggests that as one category of traders builds up a net position, the other category reduces its position and thus on aggregate can be interpreted as trading activity between these two categories. Table 2 shows the average correlations by sector. In all sectors, the most pronounced correlation is found between speculators and producers, which economically suggests that speculators tend to bet against the hedges from producers. In agriculturals, this correlation has by far the largest magnitude whilst in the other two sectors all correlations are clearly negative which indicates speculators also trade with swap dealers and others traders.

Overall, these results are in line with Boos and Grob (2023) who use a variance decomposition and find that producers are the dominant counterparty to TSMOM traders.

3.2 | Positioning and performance by category of trader

Next, we investigate the average positioning of each category of traders and the associated performance. Figure 2 shows the box plots of the aggregate net OI percentages. On average producers have held short positions and hence have in tendency hedged their existing physical long exposures whilst market makers and speculators have been predominately long and thus taken the opposite side of the hedges.

We now estimate the aggregate performance of each category of traders. The net OI of each category serves as proxy for the aggregate positioning which we assume to be approximately constant over the following week due to the lack of higher frequency data. We compare the performance of all categories together with the TSMOM strategy. For a fair comparison we allow the latter to update its positions also only once a week on Tuesdays. The positions of all markets are scaled with an ex ante forecast of volatility to target an annualized level of 10%. The results are shown in Table 3.

All realized volatilities are well below 10% due to the diversification within each of the portfolios. Overall, the positions of the generic TSMOM strategy outperform all categories of traders. With the exception of energies, the same is true for all individual sectors. Interestingly, speculators actually realize a negative performance overall whilst the other categories of traders and the TSMOM strategy realize positive performances over the sample period. The reason for the poor performance of speculators is a positive bias in the speculators' positions compared to the other categories of traders, see Figure 2, and also compared to the TSMOM strategy. An explanation for this bias could be the presence of long-only commodity speculators who hold fairly static long exposures to provide investors with protection against commodity price inflation by investing in or in alignment with commodity indices, for instance the S&P GSCI. By contrast, TSMOM models have held overall short positions on average for each market. This is a sensible result given that most commodities tend to trade in contango, so that the negative roll yield will cause a negative drag in the signal definition (3).⁶

4 | SPECULATORS AND MOMENTUM TRADERS

4.1 | Are speculators momentum traders?

We hypothesize that speculators on aggregate trade a strategy that is similar to the generic TSMOM strategy presented in section 2.2, which we test in two steps. First, we test for positive autocorrelation in the changes of the net

TABLE 2 Average Pearson correlations of the weekly changes in net open interest among different categories of traders.

Sector	Prod/swap	Prod/spec	Prod/other	Swap/spec	Swap/other	Spec/other
All	−0.04	−0.81	0.04	−0.21	−0.04	−0.38
Ags	−0.20	−0.86	−0.02	−0.00	−0.09	−0.32
Energies	0.05	−0.66	0.14	−0.45	0.01	−0.58
Metals	0.44	−0.77	0.15	−0.74	0.05	−0.45

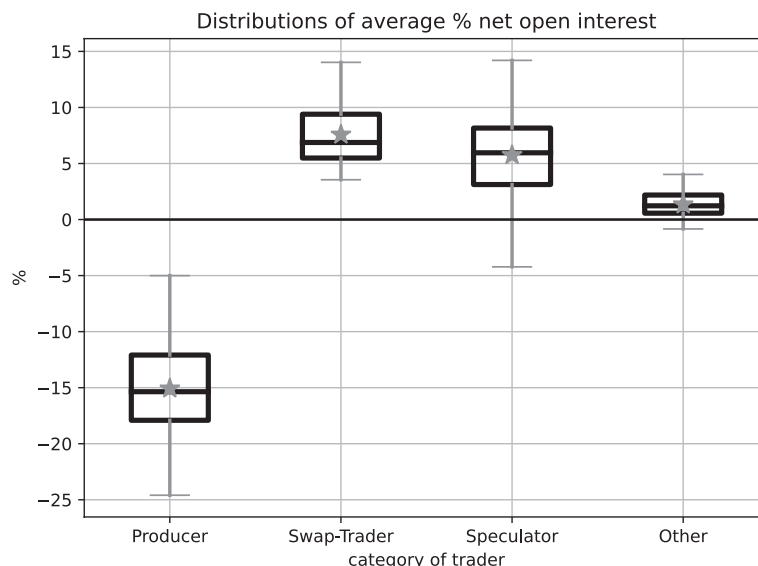


FIGURE 2 Average net positioning of traders by category. The figures shows ‘box-and-whiskers’ plots the distribution of the proportion of net open interest ($OI^{\%net,cat}$) for each category of traders $cat \in \{prod, swap, spec, other\}$. Each of the ‘boxes’ shows the median as well as the first and third quartiles. The ‘whiskers’ are defined by a distance of $1.5 \times$ the interquartile-range from the nearest quartile. Outliers, if any, were shown as individual dots outside the whiskers. The asterisks mark the means.

TABLE 3 The table shows the (cost-free) performance estimates for the categories as well as for a generic TSMOM strategy.

Sector	Statistic	Prod	Swap	Spec	Other	TSMOM
All	Returns (%)	0.11	0.41	-0.44	0.82	1.06
	Volatility (%)	4.37	3.54	3.50	2.97	3.58
	Sharpe ratio	0.02	0.12	-0.12	0.28	0.30
Agriculturals	Returns (%)	0.41	0.03	-0.95	1.15	0.90
	Volatility (%)	4.59	4.69	3.85	3.67	3.83
	Sharpe ratio	0.09	0.01	-0.25	0.31	0.24
Energies	Returns (%)	-0.31	0.22	1.80	0.50	1.74
	Volatility (%)	6.99	4.83	6.12	6.11	7.42
	Sharpe ratio	-0.04	0.05	0.29	0.08	0.23
Metals	Returns (%)	-0.80	1.84	-0.43	-0.02	1.06
	Volatility (%)	7.65	5.19	6.94	5.45	6.61
	Sharpe ratio	-0.10	0.35	-0.06	-0.00	0.16

Note: All markets are equally weighted and volatility scaled to an ex ante annualized volatility of 10%.

speculative OI, which would imply that the trade flows of speculators in commodity futures are (to some extent) predictable. This is a key feature of a trend-following system because TSMOM generates autocorrelated signals and positions by construction as it passes this feature on from the underlying market.⁷ Figure 3 shows the first order autocorrelations of the weekly changes in the net speculation OI for each market with 90%-confidence bands using the stationary bootstrap of Politis and Romano (1994). For all commodity markets, we find that the first order autocorrelation is statistically significantly positive. The average estimate is lowest for energies and highest for agricultural markets.

As a second step, we estimate the alignment coefficients in the regressions (5) and (6), which describe the magnitude to which the (changes in the) net speculative positions vary with the (changes in the) positions of a generic trend-following system as defined in section 2.2. Table 4 summarizes the results by market for both weekly changes and levels. The sector averages and an overall average are also shown at the bottom of the table. The estimated betas

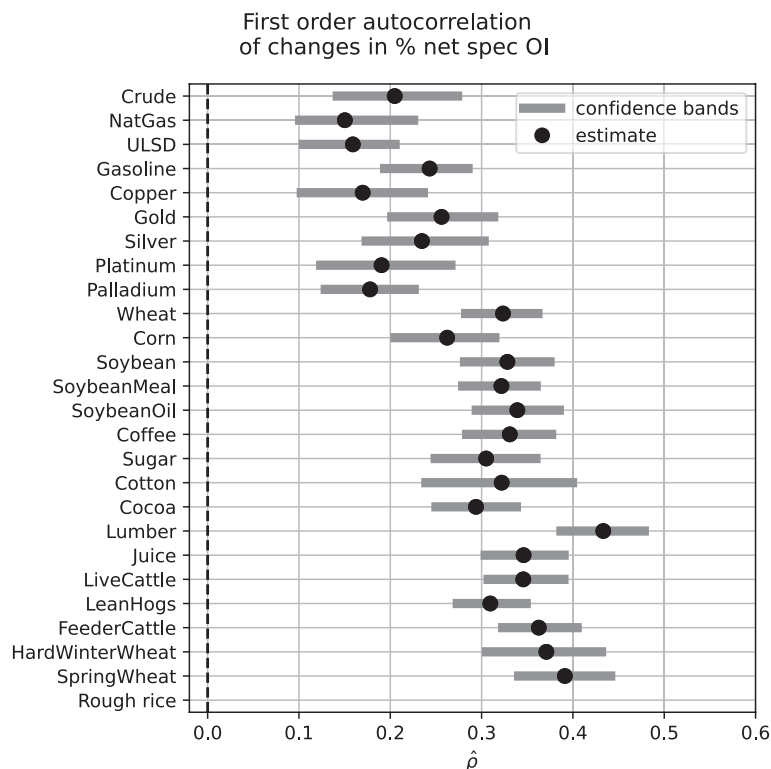


FIGURE 3 Autocorrelation of changes in % net speculative OI. Estimated first order autocorrelation of weekly changes in net speculative OI, i.e. for each market $i = 1, \dots, n$ we estimate $\hat{\rho}(\Delta \tilde{OI}_{i,t-1}^{\% \text{net, spec}}, \Delta \tilde{OI}_{it}^{\% \text{net, spec}})$. Confidence bands are computed as the 5% and 95% percentiles of the bootstrap samples.

from the levels regression tend to be higher than the estimated betas of the regression of the differences. The highest betas are found for agricultural markets followed by metals and energies, which is in line with the results from the analysis above. For example, for wheat and silver the estimated alignment betas for the regression in differences $\hat{\beta}_1^\Delta$ are 0.52 and 0.48, respectively, so that a standard deviation change in the generic TSMOM position corresponds on average to almost half a standard deviation change in the net speculative OI. The associated R_{OS}^2 are 0.27 and 0.24, respectively, which are highly statistically significantly greater than zero. In other words, the mean squared prediction error using the changes in the generic TSMOM position is about one quarter smaller than the mean squared prediction error of the mean. We also find that for the levels regression the vast majority of markets have statistically significantly positive intercepts $\hat{\beta}_0$ which suggests that speculators include some long-biased funds. This is most visible in energies, e.g. crude oil and gasoline, but also in metals, especially in gold and silver, and in agriculturals, e.g. in live cattle. Virtually all slope estimates for both regressions, $\hat{\beta}_1^\Delta$ and $\hat{\beta}_1$, are statistically significantly positive which supports the original hypothesis that the speculative OI is predominantly driven by trend-followers. This has been recently also discussed by Boos and Grob (2023). With the exception of lumber all out-of-sample R^2 s are statistically significantly positive. The R_{OS}^2 is higher for the levels regression. The lowest slope coefficient estimates and lowest out-of-sample R^2 are generally found for energy markets. This result suggests that in energy markets there are more fundamentally driven traders than for instance in agricultural markets where the empirical evidence of trend-following speculators is virtually irrefutable.

4.2 | Speculative alignment and momentum performance

A potential consequence of speculative crowding is the improvement or deterioration of the predominant investment strategy's performance (e.g. Baltas, 2019; Bollen et al., 2021). Using the alignment betas we have estimated in previous section, we now test the hypothesis that a higher degree of alignment leads to a degeneration of the trend-following

TABLE 4 The table shows the estimation results for the regressions (5) in the leftmost three columns and (6) in the rightmost three columns for the 26 commodity markets for the full sample period.

	$\hat{\beta}_0^\Delta$	$\hat{\beta}_1^\Delta$	R^2_{OS}	$\hat{\beta}_0$	$\hat{\beta}_1$	$R^2_{OS,\Delta}$
Crude	.00	.37***	.15***	2.34***	.32***	.10*
NatGas	-.01	.36***	.13***	-.05	.48***	.26***
HeatingOil / ULSD	.01	.33***	.08***	.61***	.64***	.44***
Gasoline	.01	.32***	.09***	2.14***	.51***	.31***
Copper	.01	.46***	.22***	.20***	.70***	.51***
Gold	.00	.47***	.24***	1.44***	.68***	.48***
Silver	-.00	.48***	.24***	1.24***	.67***	.45***
Platinum	-.00	.38***	.14***	1.09***	.46***	.18**
Palladium	-.02	.32***	.10***	.72**	.65***	.43***
Wheat	-.00	.52***	.27***	-.17	.66***	.43***
Corn	-.01	.48***	.24***	.65***	.72***	.54***
Soybean	-.01	.45***	.22***	.78***	.72***	.55***
SoybeanMeal	.00	.45***	.18***	.80***	.76***	.60***
SoybeanOil	-.01	.40***	.19***	.57***	.74***	.57***
Coffee	.00	.46***	.21***	.35***	.83***	.71***
Sugar	-.00	.38***	.14***	.78***	.76***	.57***
Cotton	-.00	.33***	.10***	1.01***	.72***	.48***
Cocoa	-.01	.33***	.11***	.57***	.70***	.48***
Lumber	-.00	.03***	-.06	-.02	.34***	-.05
Juice	-.00	.35***	.12***	.21***	.86***	.76***
LiveCattle	-.01	.24***	.06***	1.75***	.70***	.49***
LeanHogs	-.00	.31***	.10***	1.16***	.70***	.54***
FeederCattle	-.00	.23***	.06***	.81***	.53***	.26***
HardWinterWheat	-.02	.38***	.17***	.87***	.57***	.35***
SpringWheat	-.03	.29***	.08***	.44***	.53***	.27***
Rough rice	.00	.23***	.05***	.15*	.59***	.36***
All	-.00	.36	.14	.79	.64	.43
Ags	-.01	.34	.13	.63	.67	.47
Energies	.00	.35	.11	1.26	.49	.28
Metals	-.00	.42	.19	.94	.63	.41

Note: In addition to the coefficient estimates also OOS- R^2 are reported. At the bottom sector and overall averages are shown (without significance test). At market level statistical significance is test for using the stationary bootstrap and is denoted by ‘*’ for p -values < 10%, ‘**’ for p -values < 5% and ‘***’ for p -values < 1%. There are no p -values for the averaged values at the bottom of the table.

performance. Consequently, we now regress the realized Sharpe ratios for the generic TSMOM strategy each commodity market on the corresponding estimated alignment betas, i.e.

$$\text{TSMOM-Sharp ratio}_i = \alpha_0^\Delta + \alpha_1^\Delta \hat{\beta}_{1,i}^\Delta + \eta_i^\Delta \quad (8)$$

and equivalently for the estimated coefficient of from the levels regression, $\hat{\beta}_1$. In this second stage test, we face an errors-in-variables problem as the alignment betas are measured with ‘measurement error’. The resulting attenuation bias of the coefficient estimates in (8) causes the subsequent inference to be more conservative because the estimates will be closer to zero and p -values will be (slightly) overstated. Consequently, if a significant relationship was found, the attenuation bias will cause this relationship to be understated and the ‘true’ relationship will in tendency be even stronger.

TABLE 5 Estimated slope coefficients for the simple regression (8) and the panel regressions (9) and (10) of profitability on alignment betas.

Model/Sector	All	Agriculturals	Energies	Metals
Panel A: For Δ-alignment betas				
Simple regression full sample	−7.99***	N/A	N/A	N/A
Simple regression annual sub-samples	−1.37***	−0.66***	−0.06	−0.25**
Fixed effects regression annual sub-samples	−1.76***	−1.48***	−1.58***	−2.88***
Fixed and time effects regression annual sub-samples	−1.76***	−1.39***	−0.51*	−2.41***
Panel B: For level-alignment betas				
Simple regression full sample	−0.18	N/A	N/A	N/A
Simple regression annual sub-samples	−0.47***	−0.66***	−0.06	−0.25
Fixed effects regression annual sub-samples	−0.43***	−0.66***	−0.03	−0.17
Fixed and time effects regression annual sub-samples	−0.43***	−0.56***	0.01	0.31

Note: Only the slope coefficient estimates are reported. In Panel A the results for the Δ -alignment betas from regression (5) are reported and in Panel B the results for the levels alignment betas from (6) are reported. Statistical significance is denoted by ** for p -values < 10%, *** for p -values < 5% and **** for p -values < 1%.

If we use the full sample estimates, we have only 26 observations to estimate the simple model (8). In order to increase the sample size we sub-sample the data for each calendar year so that we have 52 observations to compute each combination of estimated alignment beta and realized TSMOM Sharpe ratio. Thus, in this case we have approximately 400 observations (16 years \times 26 markets). With these annual sub-samples the data has a panel structure which we estimate with fixed effects to allow for potential differences in the average realized TSMOM Sharpe ratios between different commodity markets, i.e.

$$\text{TSMOM-Sharpe ratio}_{i,t} = \gamma_{0,i}^{\Delta} + \gamma_1^{\Delta} \hat{\beta}_{1,it}^{\Delta} + \eta_{it}^{\Delta} \quad (9)$$

and analogously for the levels alignment betas. We can further extend the specification (9) to include time effects to allow for differences in years when the TSMOM strategy may have been generally more or less profitable, so that we also estimate the model

$$\text{TSMOM-Sharpe ratio}_{i,t} = \delta_{0,i}^{\Delta} + \delta_{1,t}^{\Delta} + \delta_2^{\Delta} \hat{\beta}_{1,it}^{\Delta} + \eta_{it}^{\Delta} \quad (10)$$

and again analogously for the levels alignment betas.

The empirical results for the simple model (8) for both full sample estimates and for the annual sub-samples as well as the results for the panel models (9) and (10) for the annual sub-samples are shown in Table 5. Panel A contains the results for the Δ -alignment betas and Panel B for corresponding results for the levels alignment betas. Due to the small number of observations if we use the full sample alignment betas, we do not estimate (8) for each sector separately whilst we also provide sector-specific estimates for all cases where we use the annual sub-samples.

We find that overall across all markets and also just in the agricultural sector the estimated slope coefficients are statistically significantly negative for all regressions. This supports the main hypothesis that a greater degree of alignment is negatively related to the contemporaneous risk-adjusted performance of a generic TSMOM strategy. For the Δ -alignment betas the estimated slope coefficients for energies and metals are also statistically significantly negative (with the exception of the results for the specification (8) for energies if the annual sub-samples are used). For the levels alignment betas the results are similar. Overall and for the agriculturals sector the slope coefficients are statistically significantly negative whilst the results for energies and metals are not statistically significant. In case of specification (10) for the energies and the metals sectors, the slope coefficient estimates are not statistically significantly different from zero. Especially for energies, this result appears to be in line with the results from the first stage alignment regressions, where we found that for the levels regression the average estimated alignment beta was the lowest for this sector. As in energies there is the least evidence for TSMOM traders to be the predominant traders among the speculators, it is not surprising that we do not find a statistically significant relationship between alignment and trend-following performance. Also, in energies the average correlation between the aggregate trading activity between producers and speculators is absolutely the lowest

among the commodity sectors and the correlation between the aggregate trading activity between speculators and other traders is the highest among the commodity sectors, which suggests that the dynamics in energies are somewhat different to the other commodity sectors.

These results suggest that for commodity futures markets, especially in agriculturals, there is some tendency that if speculators on aggregate behave more similarly to a generic trend-follower the strategy the performance for that market tends to be weaker. However, this does not imply that trend-following does not work on more crowded commodity markets but merely that the expected risk-adjusted trend-following return is in tendency lower than for less crowded markets. Moreover, the strong relationship in agriculturals markets may be explained by the greater internal diversification of that sector because the markets there are more heterogenous.

Next, we test the robustness of the results above with respect to their sensitivity to the specification of the generic trend-following positions.

5 | ROBUSTNESS

The main design choices we have made in the analyses above concern the definition of the trend-following positions. Throughout the main text, we use the simple signal as defined in (3) and scale the positions inversely proportional to a forecast of the market volatility as in (4). For the former we can add a forecast function, see Levine and Pedersen (2016), which (nonlinearly) maps the basic TSMOM signal to a forecast. Changing the look-back for the basic signal is also a possibility. For instance, Kwon et al. (2020) document momentum in commodity markets also at shorter horizons. We found, however, that the alignment betas are maximized for a look-back of 260 business days,⁸ which suggests that most CTAs indeed trend-follow using this look-back period. For the latter we can change the half-life in the RiskMetrics forecast used in the volatility scaling, where we have so far used the standard RiskMetrics (1996) parameters. As the 11.2-day half-life tends to be fairly quick,⁹ we also use a slower 260-day half-life.¹⁰

As forecast functions we use linear, i.e. the plain return, binary, i.e. the sign function applied to the underlying return (e.g. Moskowitz et al., 2012), and a function with a roll-over as used by Lim et al. (2019), i.e. $f(s) = s \exp(-s^2/4)/0.89$. Consequently, we repeat the main two tests with these six parameter constellations. The results for the regressions in (5) and (6) are summarized in Table 6. For each setup, the regressions are estimated again for each market and the average results are shown in that table. It can be seen that in all cases the average alignment beta estimates are positive and of similar magnitude as in the original test.

Using the same set of constellations for TSMOM position generation as above, the results for the second stage regressions between the alignment betas and the contemporaneous Sharpe ratio of the corresponding TSMOM strategy can be found in Table 7 analogous to Table 5 but for the different specifications of the generic TSMOM positions. Panel A of that table shows the results for the regressions (8–10) using the betas from the Δ -alignment regression (5) and Panel B shows the corresponding results for the levels alignment betas from (6). The first case in each of the two panels is identical to the results in Table 5. For both the Δ -alignment and for the levels alignment betas the main results appear robust to the different TSMOM strategy specifications: Overall and for agricultural markets all estimates slope coefficients are statistically significantly negative. The results for energies and metals the TSMOM models with the ‘roll-over’ are also statistically significantly negative (for the Δ -alignment). However, across all different TSMOM strategy setups only the results for agriculturals and for all commodity markets are consistently statistically significant, which supports the key findings above.

Overall, we find that the key findings of the analysis above are insensitive to the exact definition of the generic TSMOM positions.

6 | INVESTMENT EXERCISE

The empirical evidence that we found in section 4.2 raises the question whether the effect can be exploited profitably in a dynamic investment strategy. For instance, we could overweight the allocation to the TSMOM strategy on those markets with the lowest alignment betas and underweight those with higher alignment betas. Consequently, we run an investment exercise based on the annual alignment betas. We form two portfolios, each consisting of half of the available markets, one which trades TSMOM on the lowest alignment beta markets and one that trades TSMOM on the highest alignment beta markets. We repeat the same backtesting methodology for all market together and then also by sector to avoid sector-biases.

TABLE 6 Robustness test: Estimated coefficients for alignment regressions (5) and (6) averaged across markets within each sector for the various robustness setups for the generic TSMOM positions.

Forecast function	Volatility scaling half-life	Sector	$\hat{\beta}_0^\Delta$	$\hat{\beta}_1^\Delta$	$R^2_{OS,\Delta}$	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2_{OS}
Linear	11.2 days	All	−.00	.36	.14	.79	.64	.43
		Agriculturals	−.01	.34	.13	.63	.67	.47
		Energies	.00	.35	.11	1.26	.49	.28
		Metals	−.00	.42	.19	.94	.63	.41
Linear	260 days	All	−.00	.38	.16	.78	.64	.44
		Agriculturals	−.01	.37	.15	.61	.69	.49
		Energies	.00	.35	.12	1.30	.48	.28
		Metals	−.00	.45	.21	.95	.62	.38
Binary	11.2 days	All	−.00	.16	.02	.82	.58	.35
		Agriculturals	−.01	.15	.02	.66	.62	.40
		Energies	.00	.14	.01	1.25	.45	.23
		Metals	−.00	.20	.04	1.00	.55	.31
Binary	260 days	All	−.00	.15	.02	.81	.61	.39
		Agriculturals	−.01	.14	.02	.64	.65	.44
		Energies	.00	.14	.02	1.29	.49	.27
		Metals	−.00	.19	.04	1.01	.56	.32
Roll over	11.2 days	All	−.00	.29	.09	.82	.64	.43
		Agriculturals	−.01	.28	.09	.67	.68	.47
		Energies	.00	.27	.07	1.24	.51	.30
		Metals	−.00	.37	.14	1.00	.61	.38
Roll over	260 days	All	−.00	.30	.10	.82	.66	.47
		Agriculturals	−.01	.29	.09	.65	.71	.52
		Energies	.00	.26	.07	1.30	.53	.33
		Metals	−.00	.36	.14	1.01	.61	.38

First, in a full look-ahead exercise we use the estimated alignment betas of the same period to which we apply it. This does not constitute a tradeable setup but is intended to provide a valuable insight into the potential maximum benefit that one could hope to harvested from exploiting the effect, i.e. if the estimated alignment betas were known a priori. Second, we run a full out-of-sample analysis, where the alignment beta is estimated using data of the previous year and the TSMOM performance of the corresponding markets is calculated over the next year. This constitutes a tradable setup which could be implemented e.g. by a CTA.

The empirical results of these two backtests are shown in Table 8. The table shows the Sharpe ratios for each sector for both the low alignment beta and the high alignment beta portfolios over the full sample period. The upper part of the table contains the results for the look-ahead analysis and the bottom part of the out-of-sample analysis. The reported p-values are for the null hypothesis that the portfolio with high alignment betas has a Sharpe ratio at least as high as the portfolio with low alignment betas. The left-most three columns are for the betas estimated in the differences regression (5) and the rightmost three columns for the betas from the levels regression (6).

The look-ahead analysis mirrors the results from section 4.2. Overall and for agriculturals the differences in the performances are statistically significant for both alignment betas. For metals there is an outperformance but not statistically significant. Analogous to the statistical tests, for the energies sector the performances are statistically insignificantly different. As expected, the out-of-sample (OOS) analysis shows weaker results whilst in the OOS analysis we find differences between the two types of alignment betas. Only for the Δ -alignment betas we find some evidence that the effect can be exploited whilst there is no such evidence for the levels regression betas. In particular, overall and for agriculturals the effect is statistically significantly present using the Δ -alignment betas. For the other two sectors, the differences in

TABLE 7 Robustness test: Estimated slope coefficients for the simple regression (8) as well as for the panel regressions (9) and (10) of the profitability of the TSMOM strategy on the corresponding alignment betas for different definitions of the generic momentum signals.

Setup and model/sector	All	Agriculturals	Energies	Metals
Panel A: For Δ-alignment betas				
<i>Forecast: linear, volatility scaling half-life: 11.2 days</i>				
Simple regression full sample	−7.99***	N/A	N/A	N/A
Simple regression annual sub-samples	−1.37***	−0.66***	−0.06	−0.25**
Fixed effects regression annual sub-samples	−1.76***	−1.48***	−1.58***	−2.88***
Fixed and time effects regression annual sub-samples	−1.76***	−1.39***	−0.51*	−2.41***
<i>Forecast: linear, volatility scaling half-life: 260 days</i>				
Simple regression full sample	−4.17**	N/A	N/A	N/A
Simple regression annual sub-samples	−1.34***	−0.73***	−0.24*	−0.59**
Fixed effects regression annual sub-samples	−1.74***	−1.35***	−2.50***	−2.57***
Fixed and time effects regression annual sub-samples	−1.74***	−1.16***	−1.84***	−1.90***
<i>Forecast: binary, volatility scaling half-life: 11.2 days</i>				
Simple regression full sample	−7.44***	N/A	N/A	N/A
Simple regression annual sub-samples	−1.38***	−0.70***	−0.39	−0.63**
Fixed effects regression annual sub-samples	−1.44***	−1.27***	−1.76***	−1.88*
Fixed and time effects regression annual sub-samples	−1.44***	−1.30***	−0.90**	−1.74**
<i>Forecast: binary, volatility scaling half-life: 260 days</i>				
Simple regression full sample	−5.14***	N/A	N/A	N/A
Simple regression annual sub-samples	−0.89***	−0.61**	−0.29	−0.75
Fixed effects regression annual sub-samples	−0.95***	−0.86***	−1.31**	−1.03
Fixed and time effects regression annual sub-samples	−0.95***	−0.80**	−1.24*	−1.29
<i>Forecast: roll over, volatility scaling half-life: 11.2 days</i>				
Simple regression full sample	−8.04***	N/A	N/A	N/A
Simple regression annual sub-samples	−2.19***	−0.88***	−0.59**	−0.98***
Fixed effects regression annual sub-samples	−2.44***	−2.19***	−1.96***	−3.93***
Fixed and time effects regression annual sub-samples	−2.44***	−2.44***	−1.87***	−3.57***
<i>Forecast: roll over, volatility scaling half-life: 260 days</i>				
Simple regression full sample	−4.94**	N/A	N/A	N/A
Simple regression annual sub-samples	−1.97***	−0.86***	−0.62***	−0.98***
Fixed effects regression annual sub-samples	−2.05***	−1.97***	−1.58***	−2.60***
Fixed and time effects regression annual sub-samples	−2.05***	−2.09***	−1.98***	−2.19***
Panel B: For levels alignment betas				
<i>Forecast: linear, volatility scaling half-life: 11.2 days</i>				
Simple regression full sample	−0.18	N/A	N/A	N/A
Simple regression annual sub-samples	−0.47***	−0.66***	−0.06	−0.25
Fixed effects regression annual sub-samples	−0.43***	−0.66***	−0.03	−0.17
Fixed and time effects regression annual sub-samples	−0.43***	−0.56***	0.01	0.31
<i>Forecast: linear, volatility scaling half-life: 260 days</i>				
Simple regression full sample	−0.18	N/A	N/A	N/A
Simple regression annual sub-samples	−0.60***	−0.73***	−0.24*	−0.59**
Fixed effects regression annual sub-samples	−0.58***	−0.77***	−0.19	−0.53
Fixed and time effects regression annual sub-samples	−0.58***	−0.68***	−0.18	−0.10
<i>Forecast: binary, volatility scaling half-life: 11.2 days</i>				

TABLE 7 (Continued)

Setup and model/sector	All	Agriculturals	Energies	Metals
Simple regression full sample	−0.10	N/A	N/A	N/A
Simple regression annual sub-samples	−0.63***	−0.70***	−0.39***	−0.63*
Fixed effects regression annual sub-samples	−0.63***	−0.70***	−0.34	−0.66
Fixed and time effects regression annual sub-samples	−0.63***	−0.70***	−0.23	−0.14
<i>Forecast: binary, volatility scaling half-life: 260 days</i>				
Simple regression full sample	0.15	N/A	N/A	N/A
Simple regression annual sub-samples	−0.57***	−0.61***	−0.29***	−0.75***
Fixed effects regression annual sub-samples	−0.59***	−0.65***	−0.32	−0.74*
Fixed and time effects regression annual sub-samples	−0.59***	−0.63***	−0.43	0.08
<i>Forecast: roll over, volatility scaling half-life: 11.2 days</i>				
Simple regression full sample	−0.07	N/A	N/A	N/A
Simple regression annual sub-samples	−0.84***	−0.88***	−0.59***	−0.98***
Fixed effects regression annual sub-samples	−0.89***	−0.93***	−0.52	−1.13**
Fixed and time effects regression annual sub-samples	−0.89***	−0.94***	−0.39	−0.65
<i>Forecast: roll over, volatility scaling half-life: 260 days</i>				
Simple regression full sample	0.13	N/A	N/A	N/A
Simple regression annual sub-samples	−0.84***	−0.86***	−0.62***	−0.98***
Fixed effects regression annual sub-samples	−0.87***	−0.91***	−0.57**	−1.04***
Fixed and time effects regression annual sub-samples	−0.87***	−0.91***	−0.73*	−0.56*

Note: In Panel A the results for the Δ -alignment betas are reported and in Panel B the results for the levels alignment betas are reported. Only the slope coefficient estimates are reported. Statistical significance is denoted by '*' for p -values < 10%, '**' for p -values < 5% and '***' for p -values < 1%.

TABLE 8 Backtest results: We report the Sharpe ratios for an equally weighted TSMOM strategy using only high and only low alignment beta markets.

	TSMOM-sharpe Low Δ -alignment beta	TSMOM-sharpe High Δ -alignment beta	p -Value	TSMOM-sharpe Low levels- alignment beta	TSMOM-sharpe High levels- alignment beta	p -Value
Look-ahead						
All	.55	−.13	.00	.47	−.01	.01
Ags	.48	−.14	.00	.48	−.17	.00
Energies	.23	.24	.51	.16	.24	.64
Metals	.17	.03	.31	.26	.17	.38
Out-of-sample						
All	.32	.02	.07	.15	.29	.73
Ags	.32	−.12	.05	−.00	.26	.83
Energies	.20	.11	.38	.02	.29	.90
Metals	.22	−.05	.21	−.09	.23	.86

Note: The top rows contain the results for a look-ahead analysis where the betas are estimated over the same period over which the portfolio is formed. The bottom rows contain the results for the out-of-sample analysis where the alignment betas are estimated over the previous year and the portfolio is formed over the next year. The leftmost three columns use the alignment betas from the regression in differences whilst the rightmost three columns use the alignment betas from the levels regression. The p -values are computed for the null hypothesis that the high alignment beta portfolio has a Sharpe ratio at least as high as the portfolio with the low alignment betas.

performance also exist but are not statistically significant. For the betas from the levels regression, there is no evidence to suggest that the effect can be profitably exploited.

Consequently, the effect that the alignment beta negatively correlates with TSMOM performance is predominately a contemporaneous effect and has limited, if any, predictive power. agriculturals may be an exception though. Overall, we believe that the effect cannot be exploited in a dynamic investment strategy. However, the static nature of the effect could possibly be harvested statically by including predominately commodity futures markets in a TSMOM portfolio that are less commonly traded by other CTAs.

7 | CONCLUSIONS

In this paper, we investigate the relationship between the aggregate net positions of speculators and the positions of a generic momentum strategy across a broad range of commodity futures markets. We find that the time series of both types of positions are closely aligned across all investigated commodity markets. The evidence prevails for both the levels regression and in differences. The high alignment suggests some level of speculative, strategy-specific crowding in commodity futures markets. Using the estimated alignment coefficients, we also document a weak but statistically significant tendency of time series momentum performance to degenerate when the speculators in the underlying market are more aligned with momentum traders. Albeit the correlations are negative across all sectors, the evidence is strongest in agricultural commodities. In an investment exercise the statistical tests are validated in a historical backtest – both in-sample and out-of-sample. Although there is also some evidence to support the latter, the effect appears to be predominately contemporaneous and thus it may not be possible to benefit from this effect in a dynamic trading strategy. However, the negative impact on momentum performances suggests that ‘harder-to-access’ or less commonly trend-followed commodity futures markets may not only provide diversification benefits for a CTA program also be more profitable on a single-asset basis.

DATA AVAILABILITY STATEMENT

The data in this paper are downloaded from Bloomberg and are thus subject to licensing constraints.

ORCID

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Endnotes

¹Throughout this paper we use the terms ‘momentum’ and ‘trend-following’ interchangeably. Essentially, the term ‘momentum’ covers both cross-sectional momentum and time series momentum, which corresponds to trend-following. As we do not use the former, the latter is here also simply referred to as momentum.

²It should be noted that for cross-sectional equity momentum Barroso et al. (2022) find that crowding does not alone explain increased tail risk.

³Some minor limitations apply to the historical data, see CFTC (2022) for details.

⁴Contract value is defined as the quoted price times the corresponding contract multiplier.

⁵The actual target σ^{target} does not matter as we consider the aggregate speculators and not one specific CTA.

⁶The trend-following signals in (3) use total excess returns, which can be decomposed into a spot and a carry component (see Kojien et al., 2018). Thus, if there is no secular trend in the spot component, the negative carry of those commodity markets trading in contango will cause the trend-following signals to be short on average.

⁷To see this, we use a generalized definition of the TSMOM signal in (3) which is the weighted sum of risk adjusted returns, $s_t = \sum_s w_s R_{t-s}$, $R_t = r_t / \hat{\sigma}_t$ and $w_s \geq 0$. This definition coincides with the one in Harvey et al. (2021) if one assumes homoscedasticity and with the signal definition in (3) if one further assumes equal weights $w_s = 1 / S$. Now we re-write the changes in this momentum signal as $\Delta s_t = \sum_s w_s (R_{t-s} - R_{t-1-s})$. Using the baseline case of $w_s = 1 / S$ we get $\Delta s_t = (R_t - R_{t-S-1}) / S$. Assuming simple autocorrelation in returns, $\text{cov}(R_t, R_{t-s}) = \rho^s$, we get $\text{cov}(\Delta s_t, \Delta s_{t-1}) = (2\rho - \rho^S - \rho^{S+2}) / S^2 \approx 2\rho / S^2$ noting that $\rho \gg \rho^S$. With $\text{var}(R_t) = 1$ we have $\text{var}(\Delta s_t) = 2(1 - \rho^{S+1}) / S^2$ and thus $\text{corr}(\Delta s_t, \Delta s_{t-1}) \approx \rho$.

⁸These results are not reported here for brevity and are available upon request.

⁹The recommended smoothing coefficient for daily data is 0.94 which translates to a half-life of approximately 11.2023 days.

¹⁰In a volatility shock scenario a CTA will absolutely reduce its position in the respective market. The shorter the half-life of the volatility forecast, the more responsive the position scaling and the larger the trade size. Consequently, a CTA will limit its own capacity *ceteris paribus* if the volatility forecast is faster.

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