Momentum and Reversal on the Short-Term Horizon: Evidence from Commodity Markets

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ABSTRACT

This paper documents the coexistence of momentum and reversal on the short-term horizon. Utilizing unique investors' position data from commodity futures markets, we decompose returns into a flow component tied to speculators' net trading (Q) and an orthogonal residual component (R_nonQ). We find that R_nonQ can significantly and positively predict next-week return (short-term return-based momentum), while Q forecasts next-week return in a negative manner (short-term trading-based reversal). The short-term momentum effect applies to the ***entire*** cross-section of sample commodities and also to different subsamples of commodities with different characteristics. Further analysis suggests that this short-term momentum primarily reflects speculators' trend-chasing trading behavior, which strengthens when volatility/uncertainty is low and when the expected profitability of momentum strategy is high. We also show that short-term momentum signals (R_nonQ) can be aggregated to enhance the traditional intermediate-term momentum strategy and substantially improve its performance. By combining our empirical findings with a parsimonious model, we synthesize the microstructure-based liquidity-provision and behavioral trend-following mechanisms. Moreover, with the help of more granular investors' position data, we find that the liquidity-based short-term reversal should be characterized as a reversal strategy based on past speculators' trading rather than past commodity returns. Overall, our study demonstrates that momentum and reversal ***coexist*** on the same short-term horizon in commodity markets, overturns the previous canonical "reversal-at-short-horizon, momentum-at-intermediate-horizon" segmented perception, and therefore deepens our understanding about the overall return predictability in financial markets.

JEL Classification: G12, G13, G14.

Keywords: Momentum; Reversal; Trend-chasing; Liquidity provision; Commodity futures markets; Short-term horizon.

1 Introduction

Return momentum and reversal are two key anomalies in the asset pricing literature. Momentum typically manifests as return continuation over intermediate horizons of approximately three to twelve months (e.g., Jegadeesh and Titman (1993); Rouwenhorst (1998)). By contrast, at weekly to monthly horizon, returns tend to reverse (e.g., Lehmann (1990); Jegadeesh (1990)), and previous studies in the equity market (e.g., Avramov et al. (2006); Kaniel et al. (2008); Nagel (2012)) link such short-horizon return predictability to trading imbalances and liquidity provision. This well-documented pattern of short-term reversal and intermediate-term momentum is synthesized by Jegadeesh et al. (2025), and widely covered in asset-pricing textbooks (e.g., Ilmanen (2011); Ang (2014); Bali et al. (2016)).

Recent studies in the equity market refine the short-horizon "reversal-only" view by demonstrating that short-term momentum can arise for some specific types of stocks. In particular, Medhat and Schmeling (2022) observe a short-term momentum pattern for stocks with high turnover rate, and their finding becomes stronger for larger and more liquid stocks. Chen et al. (2023) find that at the monthly horizon, stocks with low (high) deviation salience measure exhibit significant short-term return continuation (reversal). Taken together, these findings indicate that short-term return predictability is not necessarily a uniform reversal effect – rather, it can manifest as either momentum or reversal depending on stock-specific characteristics. Thus, while the earlier literature typically treats momentum and reversal as distinct phenomena operating over different time horizons, these recent empirical evidence implies that their underlying mechanisms need not be mutually exclusive and may, in fact, occur simultaneously.

This raises a natural research question: can momentum and reversal *coexist* at the same short-term horizon? More specifically, is it possible to separately identify the forces that generate short-term momentum and those that generate short-term reversal for the

same security over the same time interval (e.g., over the weekly horizon)? Also, if there is indeed a short-term momentum effect, can it apply to the *entire* cross-section of sample commodities, instead of a subset of them? Answers to these questions can enhance our understanding about the return predictability on financial markets substantially.

Addressing these questions requires disentangling trading-induced price pressure from return components driven by other economic mechanisms, such as feedback trading or fundamental information. Without such separation, momentum and reversal effects may be conflated at the weekly horizon altogether, obscuring the empirical characterization of short-term return predictability. To enable this separation, we turn to commodity futures markets, which offer a unique advantage: weekly traders' position reports from the Commodity Futures Trading Commission (CFTC). This data granularity allows us to test whether a trading-pressure component and an orthogonal component can jointly generate both momentum and reversal, and such empirical tests can be conducted comprehensively across the entire cross-section of commodities.

Conceptually, our empirical analysis is well grounded in theory. Short-term reversal is widely attributed to liquidity provision: when risk-averse market makers absorb transitory order imbalances, prices move temporarily and subsequently revert as inventories are unloaded (e.g., Grossman and Miller (1988); Campell et al. (1993); Nagel (2012)). By contrast, momentum has been linked to mechanisms such as trend-chasing trading behavior and/or gradual information diffusion, where return continuation reflects either reinforcing trading or the gradual incorporation of news (e.g., Hong and Stein (1999); Barberis et al. (1998); Daniel et al. (1998)). Yet empirically, the momentum effect is difficult to detect on the short-term horizon when multiple forces—liquidity provision, trend-chasing, and information channels—operate concurrently in a tug-of-war manner (e.g., Jegadeesh et al. (2025)). By leveraging the CFTC weekly traders' position data,

we can observe trading pressure more directly and therefore partial out the liquidity-provision channel. This allows us to isolate non–trading-pressure return component and examine whether momentum exists on the short horizon more precisely.

We start our analysis by constructing a weekly net trading measure, $Q_{i,t}$, for non-commercial speculators in commodity i during week t, using the CFTC Commitments of Traders (COT) report. Kang et al. (2020) show that non-commercial speculators tend to consume liquidity in commodity futures markets and that such liquidity-consuming flows are followed by price reversals over subsequent weeks.[1] Controlling for this trading-based reversal effect allows us to assess the short-horizon return predictability in a more precise manner. More specifically, we run a cross-sectional projection regression of return for commodity i in week t ($R_{i,t}$) on the contemporaneous weekly net trading measure ($Q_{i,t}$), and define $R_nonQ_{i,t}$ as the residual component of the weekly return that is not explained by $Q_{i,t}$ in this regression. By construction, $R_nonQ_{i,t}$ is orthogonal to the speculators' trading pressure, and this allows us to examine short-term momentum in commodity markets in a cleaner manner.

Using the orthogonalized return measure $R_nonQ_{i,t}$, we document pronounced weekly short-horizon momentum in commodity markets. Our regression analysis shows that higher $R_nonQ_{i,t}$ leads to significantly higher returns in week t+1. A one–standard-deviation increase in $R_nonQ_{i,t}$ is associated with a 11.6 basis-point rise in next-week returns, which translates into 6.2% in annualized returns, higher than the commodity market average return of 4.7% per year. Further analysis suggests that this short-term momentum patten of R_nonQ holds regardless of whether speculators are net buyers or net sellers in week t, and it is robust across different types of commodities with different characteristics that include volume/turnover, open interest, hedging pressure, etc.

[1]The non-commercial speculators' net trading, $Q_{i,t}$, can be viewed as institutional trading demand in commodity markets. The resulting liquidity-driven short-term price reversal documented by Kang et al. (2020) is analogous to patterns emphasized in the equity market (e.g., Kaniel et al. (2008)).

To shed more light on the mechanism underlying the short-term momentum effect, we examine how this week's return signal maps into next-week trading and return components. Specifically, we track the impact of $R_nonQ_{i,t}$ into the two components of next week's return—$Q_{i,t+1}$ and $R_nonQ_{i,t+1}$. We find that weekly return continuation is mainly driven by the positive predictability of $R_nonQ_{i,t}$ on $Q_{i,t+1}$. That is, there exists a pronounced trend-chasing trading behavior in which non-commercial speculators scale up positions in recent winners and scale down in recent losers. This trading behavior accords with previous studies that find institutional investors chase winners and avoid losers (e.g., Grinblatt et al. (1995); Wermers (1999); Chae and Lewellen (2004)), and aligns well with the "momentum trader" setup adopted in the Hong and Stein (1999) model. In brief, our empirical finding here suggests that the primary driver for the short-term momentum observed in commodity markets is the speculator's trend-chasing trading behavior, instead of other possible reasons (e.g., gradual information diffusion), on the weekly frequency.

A further advantage for our study is that the CFTC position data allow a more granular examination on which factors drive speculators' trend-chasing behavior in commodity markets. Based on the prediction of Hong and Stein (1999), the intensity of trend-following should decline with return variance and rise with the perceived covariance between past and future momentum returns (i.e., the expected profitability of momentum strategy). Guided by this framework, we test the following two channels. First, for the variance channel, we find that speculators are significantly less likely to chase a commodity's recent performance when its return volatility is high. Second, to proxy the covariance (profitability) channel, we measure a commodity's crowding status, which is defined as the deviation of non-commercials' net long position in week t from its past 52-week moving average, scaled by open interest. For a momentum winner that has already been heavily accumulated by speculators (high crowding), the momentum trading is more likely in a later stage and thus offers lower expected profitability. Accordingly,

we observe a lower propensity for the speculators to chase the recent price trend. Taken together, these analyses use the granularity of CFTC position data to shed light on the determinants of institutional trend-chasing behavior in commodity markets.

We then examine the return predictability of $R_nonQ_{i,t}$ beyond the weekly horizon. Our analysis suggests that $R_nonQ_{i,t}$ can positively predict subsequent trading flow up to week t+3, which suggests that the speculative trend-chasing behavior lasts for several weeks and then unwinds subsequently. Moreover, we also find that $R_nonQ_{i,t}$ forecasts future trading-pressure-orthogonalized return components over the intermediate time window ranged from post one to twelve months, which could be related to the gradual information diffusion rationale. Taking these two factors together, we find that $R_nonQ_{i,t}$ can predict subsequent commodity futures returns up to the annual horizon, but its underlying economic mechanism switches from the trend-chasing trading behavior at the short-term horizon to the information diffusion rationale in the intermediate-term horizon. Therefore, it is not surprising that the short-term momentum effect is closely linked to the traditional intermediate-term momentum strategy. Probit analysis indicates that classifying a commodity as a short-term winner (loser) significantly increases the probability for it to be a winner (loser) over longer horizons (e.g., 3–12 months). Based on this connection, we use the alternative measure R_nonQ as the sorting variable for the traditional intermediate-term momentum strategy, and find that this adjustment can substantially improve its performance. For example, for the six-month (26-week) portfolio formation window, the annualized momentum return rises from 5.2% when sorting on the raw return (R) to 9.9% when sorting on R_nonQ, with an improvement of 4.7% per annum that is both statistically significant and economically important.

Beyond momentum, we also re-examine the short-term reversal effect in more detail by using the unique CFTC position data in commodity markets. The classical liquidity-

provision model represented by Grossman and Miller (1988) argues that risk-averse market makers require price concessions to absorb order imbalances. Therefore, the performance of short-term reversal strategy should be determined by the magnitude of the liquidity-demanding net trading flow.[2] However, in the existing literature, most studies focus on the equity market and proxy the liquidity demand with past one-week or one-month returns. Although this approach is a necessary compromise given the absence of traders' position data on the short-term horizon in equity markets, we should bear in mind that such past-return proxy is indirect and less precise, and therefore create a potential gap between the theoretical model and empirical analysis. In contrast, in commodity markets, we can construct a direct measure of liquidity-demanding net trading flow (Q), which allows us to examine whether the short-term reversal is driven by past trading or past returns in a more precise manner. Our analysis shows that the weekly reversal pattern in commodity markets is primarily driven by the past-week trading measure (Q), with little incremental role for past returns once the Q-measure is included. Moreover, the predictive power of Q on next-week return is stronger in high-volatility scenarios, which is consistent with the implications from classical microstructure models that the market makers demand higher compensation for their liquidity-provision service when markets are more volatile.

Our study contributes to the asset-pricing literature along several dimensions. First, we document the *coexistence* of momentum and reversal at the weekly horizon in commodity markets. We find that after controlling for the trading-based short-term reversal channel, there is a strong and pervasive short-term momentum effect across the *entire* cross-section of sample commodities. By showing that the trading-driven reversal and trend-following momentum operate *simultaneously* at the same weekly horizon,

[2]More specifically, Grossman and Miller (1988) suggests that the profitability of liquidity-based short-term reversal is driven by the size of liquidity-demanding trades, as well as the risk-averseness of market makers and the liquidity in the financial markets. This implies that larger net trading flows necessitates larger temporary price concessions to clear the market, and subsequent stronger reversal.

our empirical analysis overturns the canonical "reversal-at-short-horizon, momentum-at-intermediate-horizon" segmented perception, and hence sharpening our understanding of the overall return predictability in financial markets,

Second, we show that short-term momentum in commodity markets stems from speculators' trend-chasing trading behavior, and such trading behavior becomes stronger when volatility is low and the expected profitability of momentum is high. Our findings here contribute to to the literature about institutional investors' trading behavior pattern. Previous studies usually find the institutional investors (e.g., mutual fund managers) chase past winners over longer time horizon (i.e., quarterly frequency). Leveraging the unique weekly CFTC traders' position data allows us to examine the trading behavior of non-commercial speculators, which can be interpreted as the proxy for institutional investors on commodity markets, on a higher time frequency (i.e., weekly horizon). Our analysis provides direct empirical evidence that the speculators do chase past returns on the weekly horizon, and such trading behavior is the primary driver of the short-term momentum effect observed in commodity markets.

Third, we connect short-term and intermediate-term momentum by showing that the weekly R_nonQ signal can be effectively aggregated into the construction of the traditional 3-12 month momentum strategy. Specifically, short-term momentum winners identified by R_nonQ are more likely to be intermediate-term winners also, and implementing intermediate-term momentum strategy based on the sorting of cumulative R_nonQ returns yields materially higher profitability. Our finding here suggests that a better understanding about the momentum effect on the short-term horizon can help to improve the performance of the classical intermediate-term momentum strategy substantially.

At last but not least, for the short-term reversal literature, we show that when granular position data are available, the speculators' trading measure Q maps to the original

liquidity-provision mechanism of Grossman and Miller (1988) in a cleaner and more direct manner, and therefore is a more precise predictor of subsequent price reversals than return-based indirect proxies used in prior empirical work. In this sense, the "liquidity-based reversal" effect is better characterized as a short-term *trading*-based reversal rather than a short-term *return*-based reversal.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 documents the coexistence of short-term momentum and reversal in commodity markets and examines the underlying economic mechanism with an emphasis on short-term momentum. Section 4 links short-term momentum to its intermediate-term counterpart. Section 5 revisits the short-term reversal strategy through the lens of more granular position and trading data. Section 6 presents a concise theoretical framework that rationalizes the empirical findings. Section 7 concludes the paper.

2 Data and Methodology

2.1 Data

We employ commodity futures prices and trader position data covering 26 commodities on North American futures exchanges between January 1993 to September 2025. Daily price data are obtained from Commodity System Inc. Weekly returns (Tuesday-to-Tuesday) for commodity i in week t are constructed using the front-month contract as follows:[3]

$$R_{i,t} = \frac{F_i(t,T) - F_i(t-1,T)}{F_i(t-1,T)}$$

[3]The definition of front-month contract follows Kang et al. (2020). To be specific, for the Tuesday of the week t falling before the seventh calendar day of the month, the front-month contract is defined as the closest-to-maturity contract available including contracts that expire in the current calendar month. However, for the Tuesday of the week t on or after the seventh calendar day, the front-month contract is the contract that expires subsequent to the current calendar month.

where $F_i(t, T)$ is the futures price at the end of week t for a futures contract maturing on date T.

The Commodity Futures Trading Commission (CFTC) collects and aggregates the long and short positions of different types of market participants on commodity futures markets as of each Tuesday, and publicly disseminates this data through the Commitment of Traders (COT) report. In the COT report, traders are classified into three categories: commercial, non-commercial, and nonreportable. Referring to CFTC regulation, commercial traders are those who use futures primarily for hedging purpose, and non-commercial traders are those who are above the CFTC reporting threshold but do not satisfy the commercial definition. Following Kang et al. (2020), commercial and non-commercial traders can be interpreted as hedgers and speculators in commodity markets.[4]

In this study, we first obtain the net long position of non-commercial traders for commodity i in week t ($NetLong_{i,t}$), which is defined as the difference between their aggregate long and aggregate short positions. We then compute the net trading metric, $Q_{i,t}$, as the change in $NetLong_{i,t}$ from week t-1 to week t, scaled by the open interest in week t-1 ($OI_{i,t-1}$) as follows:

$$Q_{i,t} = \frac{NetLong_{i,t} - NetLong_{i,t-1}}{OI_{i,t-1}}$$

We consider the following pricing characteristics in commodity markets from related literature as the control variables: basis ($Basis_{i,t}$), basis momentum ($BasisMomentum_{i,t}$),

[4]More specifically, CFTC categorizes traders in commodity futures markets into the following three types in the COT data: (i) Commercial Traders: Hedgers (e.g., commodity producers and merchants) who need to manage the commodity price risk. (ii) Non-Commercial Traders: Speculators (e.g., CTA/hedge fund managers) who bet on commodity price movements. (iii) Nonreportable Positions: Smaller traders below the CFTC reporting thresholds. The non-commercial speculators' position data can be interpreted as a proxy for the trading activity of institutional investors on commodity markets, as suggested by recent studies.

and smoothed hedging pressure ($SHP_{i,t}$). For the basis, we follow Szymanowska et al. (2014) and define $Basis_{i,t}$ as the difference between $\ln(F_i(t,T_1))$ and $\ln(F_i(t,T_2))$, scaled by (T_2-T_1) in an annualized number, where $F_i(t,T_1)$ is the first-nearby and $F_i(t,T_2)$ is the second-nearby futures contracts for commodity i in week t. Following Boons and Porras Prado (2019), $BasisMomentum_{i,t}$ is defined as the difference between past 52-week price-momentum based on the first-nearby contract returns and that based on the second-nearby futures returns. For the construction of $SHP_{i,t}$, we follow Kang et al. (2020) and first compute the hedging pressure ($HP_{i,t}$) as the number of futures contract that the commercial traders short minus the number of contracts that they are long for commodity i in week t. We then estimate the smoothed hedging pressure ($SHP_{i,t}$) as its past 52-weeks' rolling moving average scaled by the total open interest ($OI_{i,t}$). In addition, we construct the realized volatility ($Volat_{i,t}$) and the crowding measure ($Crowding_{i,t}$) for our empirical analysis. $Volat_{i,t}$ is defined as the rolling standard deviation of returns over the preceding 52 weeks for commodity i in week t. $Crowding_{i,t}$ is computed as the difference between non-commercial traders' net long position (scaled by the open interest) and its past 52-week moving average for commodity i in week t, following Kang et al. (2025).

Table A1 provides the summary statistics for variables mentioned above across our sample commodities. In our sample period, the average weekly commodity futures return is 0.082%, which is equal to 4.26% per annum. We further notice that the weekly return standard deviation is 4.0%, which indicates large fluctuations in commodity futures prices. The average Q is 0.027%, and Q is positive in approximately 73% of the sample weeks. It implies that non-commercial speculators typically take long positions in commodity futures markets to accommodate the short hedging demand of commercial hedgers. This observation is consistent with classical Keynes's view on commodity markets.

2.2 Methodology

To separate the sources of weekly return predictability, we decompose each commodity's return $R_{i,t}$ into two orthogonal components. The first component, $Q_{i,t}$, is the speculators' (i.e., non-commercial traders) net trading activity, and the other component is the one that is orthogonal to Q, labeled as $R_nonQ_{i,t}$. This decomposition is motivated by Kang et al. (2020), who provide robust empirical evidence that commodities bought (sold) by speculators experience significant price decline (rise) in the week following the trade, and corroborate microstructure theory that impatient traders (i.e., non-commercials) demand liquidity and therefore offer a price concession to compensate risk-averse market makers for providing liquidity. More specifically, in each week t, we conduct the following cross-sectional regression across all sample commodities:

$$R_{i,t} = b_{0,t} + b_{1,t} \cdot Q_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the weekly commodity futures return for commodity i in week t; $Q_{i,t}$ is non-commercial traders' net long position change for commodity i in week t, which can be interpreted as the net trading activity for speculators; $\varepsilon_{i,t}$ is the residual item. The time-series average of the slope coefficient b_1 from the Fama-MacBeth cross-sectional regression in equation (1) is 0.41, with a t-statistic of 46.83. This highly significant coefficient estimate implies a strong positive relationship between the speculators' trading flow (Q) and contemporaneous commodity futures return (R), that is, the commodity futures price tends to increase (decrease) when there is a net buying (selling) pressure from speculators on commodity markets.

We then define the orthogonalized return component based on the equation (1) as below:

$$R_nonQ_{i,t} = b_{0,t} + \varepsilon_{i,t}.$$

The mean and standard deviation of the orthogonalized return component ($R_nonQ_{i,t}$) are 0.07% and 3.5%, respectively.

Moreover, we explore the distinct economic nature of these two components in Appendix Table A2. The orthogonalized return component ($R_nonQ_{i,t}$) is related to macro-level fundamental variables (e.g., inflation, business cycle, and freight rates), while $Q_{i,t}$ is not. This observation suggests that our decomposition does separate the gross return ($R_{i,t}$) into (i) a trading-flow component, $Q_{i,t}$, which captures non-commercial traders' liquidity demand that moves prices transiently and (ii) an orthogonal component, $R_nonQ_{i,t}$, which is related to the traders' belief and macroeconomic information.

3 Short-Term Momentum

3.1 Momentum on the Weekly Horizon: Regression and Portfolio Sorting Analysis

We start our analysis by conducting following regression to examine the return predictability in commodity markets over the weekly horizon:

$$R_{i,t+1} \;=\; c_0 + c_1\, R_{i,t} + \mathit{Controls} + u_{i,t+1}, \tag{2}$$

where control variables include the basis, basis-momentum, smoothed hedging pressure as described in Section 2.1. The first column in Table 1, Panel A shows a positive coefficient of $R_{i,t}$ on the next-week return $R_{i,t+1}$ in the univariate Fama-MacBeth regression. However, the next column suggests that this coefficient becomes insignificant after including the commonly-used control variables mentioned above. Furthermore, when we switch to the panel regression, the coefficient of $R_{i,t}$ becomes even more negligible. These findings suggest we can not assess whether there is any momentum effect on the short-term weekly

horizon in commodity markets by using the raw return ($R_{i,t}$) alone.

To obtain a better understanding of the return predictability on the short horizon, we replace $R_{i,t}$ with the two decomposed return components, $R_nonQ_{i,t}$ and $Q_{i,t}$, which are constructed as described in Section 2.2. More specifically, we estimate the following regression:

$$R_{i,t+1} = c_0 + c_1 R_nonQ_{i,t} + c_2 Q_{i,t} + Controls + u_{i,t+1}. \quad (3)$$

The coefficient estimates for the regression in equation (3) are reported in Table 1, Panel B. We find that $Q_{i,t}$ can significantly predict $R_{i,t+1}$ in a negative manner, which suggests that commodities that are heavily sold (bought) by speculators tend to have higher (lower) returns in the next week. This observation is consistent with the liquidity-based short-term reversal pattern documented in the related literature.

More importantly, after controlling for the $Q_{i,t}$-based short-term reversal effect, we find a positive return predictability based on $R_nonQ_{i,t}$ for the next-week return ($R_{i,t+1}$), that is, commodities with higher (lower) $R_nonQ_{i,t}$ tend to outperform (underperform) in the following week. The coefficient of $R_nonQ_{i,t}$ is statistically significant and economically important – a one-standard deviation increase in $R_nonQ_{i,t}$ is associated with a 11.6 basis points rise in next-week returns (i.e., 6.2% per annum). This observation indicates that there exists a strong and significant short-term momentum effect on the weekly horizon in commodity markets once the liquidity-based short-term reversal is controlled.

Table 1 here

Next, we examine whether the short-term momentum documented above is robust to different types of commodities by adopting a two-way dependent portfolio sorting analysis. In Table 2, we first partition the sample commodities into two sub-samples based on

a specific $Characteristic_{i,t}$ (Low vs. High) in week t, and then within each subsample, we further sort commodities into two portfolios based on $R_nonQ_{i,t}$ and observe their next-week returns. We consider a broad set of commodity characteristics, including volume, turnover, open interest, smoothed hedging pressure, past one-year momentum measure, past three-year value metric, etc. The two-way portfolio sorting analysis shows that the high-minus-low $R_nonQ_{i,t}$ portfolio consistently earns significant positive returns across different types of commodities, For instance, within both low and high dollar trading volume groups, the High-minus-Low $R_nonQ_{i,t}$ return spread remains to be significant at 0.24% and 0.19% per week, respectively.

Table 2 here

What's more, we also conduct Fama-Macbeth cross-sectional regressions of $R_{i,t+1}$ on $R_nonQ_{i,t}$ and its interactions with aforementioned characteristic-based dummy variables, as well as $Q_{i,t}$ and other control variables. As shown in Appendix Table A3, the coefficients of the interactive variables of $R_nonQ_{i,t}$ times either the high or low characteristic dummy variables are significant across all the regression specifications. This observation is consistent with our portfolio sorting analysis and highlights the robustness of the short-term momentum effect documented in this section.

To better illustrate the coexistence of momentum and reversal on the short-term horizon, we employ another double portfolio sorting analysis as shown in Table 3. In each week t, we independently double-sort on the sample commodities based on $Q_{i,t}$ and $R_nonQ_{i,t}$ to form four equal-weight portfolios, and then compute next-week portfolio returns and their differences across the 2×2 cells. This decomposition isolates the contribution of Q- and R_nonQ- driven signals to portfolio returns. Panel A reports the average portfolio return (gross return minus the commodity market return) in week

t+1 and difference-in-mean tests for each corresponding pair of portfolios. In Panel B, we calculate portfolio's expected return attributed to Q, defined as the product of c_2 in equation (3) and the cross-sectionally demeaned value of $Q_{p,t}$, that is, $Q_{p,t}$-$\bar{Q}_t$, where $\bar{Q}_t$ denotes the market-wide average of Q in week t. We find that longing past High-Q commodity futures and shorting Low-Q ones generates significantly negative return, with Q-related long-short spread of -0.25% (t-statistic: -8.30) and -0.26% (t-statistic: -8.49) in the Low and High R_nonQ groups, respectively. Similarly, in Panel C, we compute the R_nonQ-attributable component as the product of c_1 and demeaned $R_nonQ_{p,t}$. We find that this strategy longing High-R_nonQ commodity futures and shorting Low-R_nonQ generates significantly positive return, with R_nonQ-related long-short spread of 0.14% (t-statistic: 3.19) and 0.15% (t-statistic: 3.63) in the Low and High Q groups, respectively. Panel D is the sum of expected return from Panel B and C. The results indicate that commodities with Low $Q_{i,t}$ and High $R_nonQ_{i,t}$ exhibit the highest subsequent 1-week return (with weekly return of 0.21%), while commodities with High $Q_{i,t}$ and Low $R_nonQ_{i,t}$ generate the lowest (with weekly return of -0.21%). All these observations are consistent with our findings from the regression analysis above, and suggest that the $R_nonQ_{i,t}$-based short-term momentum and $Q_{i,t}$-based short-term reversal effects operate in a way that is independent to each other in commodity markets.

Table 3 here

In summary, our analysis here documents a strong and pervasive short-term momentum effect based on $R_nonQ_{i,t}$ in commodity markets. More specifically, the R_nonQ-based momentum strategy generates significant positive returns over the weekly horizon, and this short-term momentum strategy remains profitable across different types of commodities with different conditioning characteristics. What's more, we also find that the R_nonQ-based short-term momentum strategy operates independently alongside the Q-

based short-term reversal effect. All these findings imply a dual return predictability pattern in commodity markets: both the momentum and reversal effects can *coexist* for the same commodity at the same short-term weekly horizon.

3.2 Mechanism of Short-Term Momentum

To better understand the mechanism for the short-term return predictability described above, we conduct more depth analysis. First, we decompose $R_{i,t+1}$ into $Q_{i,t+1}$ and $R_nonQ_{i,t+1}$ in a similar way as in equation (1), and then we run the predicting regression for $Q_{i,t+1}$ and $R_nonQ_{i,t+1}$ seperately as follows:

$$Q_{i,t+1} = d_0 + d_1\, R_nonQ_{i,t} + d_2\, Q_{i,t} + Controls + \varepsilon^{Q}_{i,t+1}, \tag{4}$$

$$R_nonQ_{i,t+1} = e_0 + e_1\, R_nonQ_{i,t} + e_2\, Q_{i,t} + Controls + \varepsilon^{R_nonQ}_{i,t+1}. \tag{5}$$

Table 4 provides more in-depth intuition for the short-term momentum mechanism. In the first two columns of Fama-Macbeth regressions, the coefficient of $R_nonQ_{i,t}$ on $Q_{i,t+1}$ is 0.207 (t-statistics=21.70) without controls and 0.235 (t-statistics.=20.31) with controls. This observation suggests that the speculators interpret past return, particularly the orthogonal component R_nonQ as an important price signal. When prices increases (decreases) in week t, these speculators tend to buy (sell) their positions in t+1, and their buying (selling) activity will further push up (down) the commodity price in the next week. This empirical finding implies that trend-chasing trading behavior as an important driver for the momentum effect on short horizon. The order flow also exhibits a significant positive auto-correlation: the coefficient of $Q_{i,t}$ on $Q_{i,t+1}$ is 0.207 (t-statistics=29.84) without controls and 0.241 (t-statistics=29.25) with controls.

In contrast, the next two columns from Fama-Macbeth regressions validate the trading behavior of market makers according to microstructure theory, that is, liquidity provision

and quote smoothing. The coefficient of $Q_{i,t}$ on $R_nonQ_{i,t+1}$ is significantly negative with and without controls, indicating that speculators' liquidity demand can exert downward pressure on the next-week return component. What's more, the coefficient of $R_nonQ_{i,t}$ on $R_nonQ_{i,t+1}$ is also modestly negative. This observation can be explained by the quote smoothing effect as described in our parsimonious model in Section 6: market makers may perceive price moves orthogonal to order flow as transient and adjust subsequent quotes to reverse these fluctuations.

Table 4 here

To better illustrate the predictability of $R_nonQ_{i,t}$ and $Q_{i,t}$ on $R_nonQ_{i,t+1}$ and $Q_{i,t+1}$ mentioned above drive the short-term momentum and reversal effects observed in commodity markets, we plug equations (4) and (5) into the decomposing equation (1) as follows:

$$R_{i,t+1} = c_0 + (b_1 \cdot d_1 + e_1) \cdot R_nonQ_{i,t} + (b_1 \cdot d_2 + e_2) \cdot Q_{i,t} + \sigma_{i,t+1}. \tag{6}$$

Empirically, we show that the observed short-term momentum and reversal patterns on the commodity future return, $R_{i,t+1}$, are the net effects of all these detailed return and trading components' predictability, that is, $b_1 \cdot d_1 + e_1 > 0$ leads to momentum, while $b_1 \cdot d_2 + e_2 < 0$ leads to reversal. More specifically, according to the coefficient estimates of the Fama-Macbeth regressions presented in Table 1, Panel B, we have:

$$R_{i,t+1} = c_0 + 0.036 \cdot R_nonQ_{i,t} - 0.048 \cdot Q_{i,t} + \sigma_{i,t+1}. \tag{7}$$

The "reversal" from $Q_{i,t}$ and "momentum" from $R_nonQ_{i,t}$ can be traced from the esti-

mates presented in Table 4:

$$Q_{i,t+1} = d_0 + 0.235 \cdot R_nonQ_{i,t} + 0.241 \cdot Q_{i,t} + \epsilon_{i,t}, \tag{8}$$

and

$$R_nonQ_{i,t+1} = e_0 - 0.053 \cdot R_nonQ_{i,t} - 0.132 \cdot Q_{i,t} + u_{i,t}. \tag{9}$$

Given the estimated coefficient b_1 in the decomposing equation (1) is 0.41, it can be shown that

$$\begin{aligned} R_{i,t+1} &= (0.095 - 0.053) \cdot R_nonQ_{i,t} + (0.098 - 0.132) \cdot Q_{i,t} \\ &= 0.042 * R_nonQ_{i,t} - 0.034 * Q_{i,t} \end{aligned} \tag{10}$$

the coefficients computed in equation (10) are largely in line with the estimated coefficients in equation (7), as described in the following diagram.

$$Q_{i,t} \nearrow \; b_1 \cdot Q_{i,t+1}, \quad (0.098) \qquad R_nonQ_{\mathbf{i,t}}, \quad (\mathbf{-0.132}) \searrow \; R_{i,t+1} \quad (\mathbf{-0.034} \quad \textbf{Reversal})$$

$$R_nonQ_{i,t} \nearrow \; \mathbf{b_1 \cdot Q_{i,t+1}}, \; (\mathbf{0.095}) \qquad R_nonQ_{i,t}, \quad (-0.053) \searrow \; R_{i,t+1} \quad (\mathbf{+0.042} \quad \textbf{Momentum})$$

Our estimations here suggest that the positive predictive power of $R_nonQ_{i,t}$ on $R_{i,t+1}$ is mainly driven by the positive relationship between $R_nonQ_{i,t}$ and $Q_{i,t+1}$ (trend following, momentum), which dominates $R_nonQ_{i,t}$'s slightly reversal pattern on its own (liquidity provision, reversal). While the negative predictive power of $Q_{i,t}$ on $R_{i,t+1}$ is mainly driven by the negative relationship between $Q_{i,t}$ and $R_nonQ_{i,t+1}$ (liquidity provision, reversal), which dominates the effect of $Q_{i,t}$'s positive persistency on its own (trend following, momentum).

3.3 From Signal to Flow: The Trend-Chasing Trading Behavior

In this section, we first delve deeper into the economic intuition behind the short-term momentum in R_nonQ. Drawing on the framework of Hong and Stein (1999), we posit that the trend-chasing trading behavior of non-commercial speculators is governed by the trade-off between perceived risk and the expected profitability of momentum strategies. Specifically, trend-chasing trading demand attenuates when risk (e.g., return variance) is higher but strengthens when signals offer greater predictive power (e.g., higher covariance between order flow and next-week return). These channels form the economic foundation of our weekly framework as shown in later Section 6. Empirically, to test these hypotheses, we interact $R_nonQ_{i,t}$ with proxy variables for variance and covariance channels, that is, volatility, crowding, and cross-sectional disagreement. Throughout, we condition on contemporaneous flow $Q_{i,t}$ and the controls mentioned above.

For the variance channel test, we construct the proxy variable via 52-week rolling standard deviation of returns with adjustment method of the exponentially weighted moving average, and form cross-sectional $HighVolatDm_{i,t}$ and $LowVolatDm_{i,t}$ dummies each week. $HighVolatDm_{i,t}$ is a dummy variable that is set to 1 if the 52-week rolling return volatility for commodity i in week t is above the cross-sectional median of volatility in that week; otherwise it is 0. $LowVolatDm_{i,t}$ is the complementary indicator, equal to 1 when a commodity's volatility is at or below the median and 0 otherwise. The volatility-interaction Fama-Macbeth regression specification is:

$$\begin{aligned} Q_{i,t+1}\ (or\ R_{i,t+1}) = g_0 + g_1\, R_nonQ_{i,t} \cdot HighVolatDm_{i,t} \\ + g_2\, R_nonQ_{i,t} \cdot LowVolatDm_{i,t} + g_3\, Q_{i,t} + Controls + \varepsilon_{i,t+1}. \end{aligned} \quad (11)$$

Table 5, Panel A provides robust evidence that the momentum effect is significantly more pronounced in the low-volatility scenarios. When $Q_{i,t+1}$ is the dependent variable, in

the second column, the coefficient on the interaction term $R_nonQ_{i,t} \times LowVolat_Dm_{i,t}$ is 0.354, which is more than twice compared to the coefficient of $R_nonQ_{i,t} \times HighVolat_Dm_{i,t}$ (0.193). The difference between these two coefficients is statistically significant, with the related coefficient being 0.161, with t-statistics of 7.33. This observation suggests that the speculators' trend-chasing trading behavior is significantly stronger when the return variance is lower. When using $R_{i,t+1}$ as the dependent variable, the difference coefficient shown in the last column is 0.035 (t-statistics: 2.03), indicating that commotions with lower return variance have stronger predictive power of $R_nonQ_{i,t}$ for $R_{i,t+1}$. In brief, the speculators' trend-chasing trading behavior and the short-term momentum effect are stronger when the return volatility is lower, which is consistent with the Hong and Stein (1999) model implied.

For the covariance channel, we proxy expected momentum profitability with $Crowding_{i,t}$. The definition of crowding follows Kang et al. (2025), which could capture unusual concentrations of speculative length relative to a commodity's typical level. We then construct crowding dummies ($HighCrowdingDm_{i,t}$ and $LowCrowdingDm_{i,t}$). In each week t, we first split commodities by the sign of the orthogonalized return measure $R_nonQ_{i,t}$ (positive v.s. negative). Within each sign group, we sort by $Crowding_{i,t}$ into high and low subgroups using a median split (cross-sectional within the group). We then define:

$$\begin{aligned} HighCrowdingDm_{i,t} = \mathbf{1}\Big\{ R_nonQ_{i,t} > 0 \ \wedge \ Crowding_{i,t} \geq \mathrm{med}_t^{(+)}(Crowding) \Big\} \\ + \mathbf{1}\Big\{ R_nonQ_{i,t} < 0 \ \wedge \ Crowding_{i,t} < \mathrm{med}_t^{(-)}(Crowding) \Big\}, \end{aligned}$$

i.e., $HighCrowdingDm_{i,t} = 1$ when the position of speculators is already heavily aligned with the recent $R_nonQ_{i,t}$ signal (speculators holding more long positions for the past winners and more short positions for the past losers), and 0 otherwise. The complementary dummy is $LowCrowdingDm_{i,t} = 1 - HighCrowdingDm_{i,t}$, which captures states where

positioning is *not* aligned with the recent $R_nonQ_{i,t}$ signal. The regression interaction specification is:

$$Q_{i,t+1} \text{ (or } R_{i,t+1}) = f_0 + f_1\, R_nonQ_{i,t} \cdot HighCrowdingDm_{i,t} + f_2\, R_nonQ_{i,t} \cdot LowCrowdingDm_{i,t} + f_3\, Q_{i,t} + Controls + \varepsilon_{i,t+1}. \tag{12}$$

Table 5, Panel B shows that the predictive power of R_nonQ is stronger when speculators' position is less crowded (i.e., the momentum is still in its early stage) and it significantly diminishes when becomes more crowded (i.e., the momentum is in its late stage). Specifically, in the regression with $Q_{i,t+1}$ as the dependent variable, the interaction term for the low-crowding regime ($R_nonQ_{i,t} \cdot LowCrowding_Dm_{i,t}$) exhibits significantly positive coefficient of 0.360, where for the high-crowding regime ($R_nonQ_{i,t} \cdot HighCrowding_Dm_{i,t}$) drops to 0.126 . The difference between these two coefficients is statistically significant at 0.234 (t-statistics=12.30). This observation suggests that speculators' next-week trend-chasing trading flow is statistically stronger when the trade is not crowded.

In addition, a similar pattern emerges with $R_{i,t+1}$ as the dependent variable. In the low-crowding subsample, R_nonQ strongly predicts positive future returns with a significant coefficient of 0.062. However, in the high-crowding subsample, the predictive power essentially vanishes, with an insignificant coefficient of 0.009. The difference of the coefficient estimates between the two regimes is 0.053 (t-statistics=3.28), indicating that the short-term return momentum occurs mainly for the commodities with low crowding status.

Table 5 here

For the dispersion channel, we proxy belief heterogeneity and signal noisiness at the market-week level by cross-sectional return dispersion (CSD). When dispersion is high, realized returns become more dispersed across commodities, indicating that idiosyncratic shocks dominate the cross-section and the common component is weaker. In such environments, the perceived covariance between last week's signal and next-week returns, $b_{i,t}$, is lower, so the trend-following intensity declines and the R_nonQ momentum effect weakens. This mechanism is consistent with the variance–predictability trade-off highlighted in Hong and Stein (1999) and with the broader disagreement literature that interprets dispersion as differences of opinion and noisier signals (e.g., Diether et al. (2002); Boehme et al. (2006)). Related work also links aggregate idiosyncratic variation/dispersion to weaker common dynamics at the market level Verousis and Voukelatos (2017).

Empirically, we construct the weekly CSD measure as either the interquartile range (IQR) or the cross-sectional standard deviation of commodity returns ($R_{i,t}$). We then define a dummy variable, $LowDispersion_Dm$, which equals one for weeks falling in the bottom 50% of the CSD distribution (i.e., low dispersion regimes) and zero otherwise. We expect the momentum effect driven by R_nonQ to be significantly stronger in these low-dispersion periods, where signals are cleaner and belief heterogeneity is lower. Panel regressions with commodity fixed effects estimate:

$$\begin{aligned} Q_{i,t+1}\ (or\ R_{i,t+1}) = h_0 + h_1\, R_nonQ_{i,t} + h_2\, R_nonQ_{i,t} \cdot LowDispersionDm_t \\ + h_3\, Q_{i,t} + Controls + \varepsilon_{i,t+1}. \end{aligned} \tag{13}$$

Table 6 provides strong support for the hypothesis that the trend-following behavior of speculators and the resulting return predictability are significantly concentrated in low-dispersion regimes. Regarding $Q_{i,t+1}$ as the dependent variable, it reveals that the intensity of speculative trend-chasing is more pronounced during periods of low

cross-sectional dispersion. In the first two columns, the interaction term ($R_nonQ_{i,t} \cdot LowDispersion_Dm_t$) is significantly positive, with 0.064 (t-statistics=3.13) and 0.128 (t-statistics=7.81), respectively. This suggests that when CDS is low, speculators tend to aggressively adjust their positions to chase the trend. Similarly, with $R_{i,t+1}$ as the dependent variable, it reveals that in low-dispersion weeks, the predictive power of R_nonQ becomes highly significant. These findings confirm that the predictability of the R_nonQ is conditional on the information environment, that is, return continuation is stronger when cross-sectional dispersion is lower. [5]

Table 6 here

Next, we examine the duration of the speculators' trend-chasing trading behavior. Previous analyses suggest that the speculators' trend-chasing behavior is a primary driver of the short-term momentum pattern in commodity markets. We now examine the persistence of this behavior by regressing subsequent 1-6 weeks' Q and R on $R_nonQ_{i,t}$, $Q_{i,t}$, and control variables. As documented in the Table 7, $R_nonQ_{i,t}$ exerts a significantly positive effect on subsequent position changes ($Q_{i,t+n}$) for the first three weeks, though the magnitude of the coefficient diminishes over time. By week t+4, the effect becomes statistically insignificant and near zero. In weeks t+5 and t+6, the relationship turns negative. These results suggest that the trend-chasing behavior lasts for around three weeks, and then it fades and eventually reverses. The return predictability based on $R_nonQ_{i,t}$ exhibits a similar pattern: it is significantly positive for the first three weeks, and becomes insignificant in week t+4, t+5 and t+6. [6]

[5] We present robustness tests to examine the variance and covariance channels underlying the short-term momentum pattern of R (see Appendix Table A4). The results indicate that momentum pattern of R is significantly stronger among commodities characterized by low volatility and low crowding. Moreover, in Appendix Table A5, we investigate the dispersion channel. The interaction terms between $R_nonQ_{i,t}$ (as well as $R_{i,t}$) and market-level dispersion ($Dispersion_t$) are significantly negative, suggesting that the momentum effects for both $R_nonQ_{i,t}$ and $R_{i,t}$ are statistically stronger when market noise is lower.

[6] Notably, this negative reversal in total returns (R) is much weaker than the pronounced reversal

All these results elucidate the dynamic of the short-term momentum effect of $R_nonQ_{i,t}$. The weekly short-term predictability of $R_nonQ_{i,t}$ is driven by trend-chasing, not information diffusion, as shown by its negative autocorrelation. While speculators' trend-chasing pattern dissipates in week t+4 and even reverses later, total returns do not collapse, which may arise from the gradual information diffusion.

Table 7 here

In addition, we are also interested to examine whether the trend-chasing trading behavior can be affected by the past performance of peer commodities, other than the performance of the commodity itself, that is, the stylish momentum effect suggested by Wang and Yu (2025). We then construct trading signal based on the commodity's peer return. Specifically, in each week t, we first sort all sample commodities by their $R_{i,t}$, and divide them into two sub-groups to calculate the average $R_{j,t}$ ($j \neq i$, j and i in the same sub-group), denoted as $StyMomSig_Raw_{i,t}$. Then, in each week t, we conduct cross sectional regression of $StyMomSig_Raw_{i,t}$ on $R_nonQ_{i,t}$ and $Q_{i,t}$, with constant a_t and coefficients $b_R_nonQ_t$ and b_Q_t. Consequently, $StyMomSig_Resid_{i,t}$ is computed as follows:

$$StyMomSig_Resid_{i,t} = StyMomSig_Raw_{i,t} - a_t - b_{R_nonQ,t} \cdot R_nonQ_{i,t} - b_{Q,t} \cdot Q_{i,t} \quad (14)$$

Panel A shows the results of subsequent one-week's $Q/R/R_nonQ$ on the style-related variables, orthogonalized return component ($R_nonQ_{i,t}$), speculators' net long position change ($Q_{i,t}$), and controls variables. In the last column with $Q_{i,t+1}$ as the dependent variable, the coefficient of $R_nonQ_{i,t}$ is 0.233 (t-statistic: 20.09), larger than that of $StyMomSig_Resid_{i,t}$ with coefficient 0.057 (t-statistic: 4.22). We find that the effect of

observed in speculators' position changes (Q). This discrepancy arises because $R_nonQ_{i,t}$ itself exhibits a slightly positive (though insignificant) predictability in weeks t+5 and t+6 (see Appendix Table A6).

$StyMomSig_Resid_{i,t}$ on $R_{i,t+1}$ becomes insignificant, with coefficient and corresponding t-statistics both nearly zero. This attributes to another force: as shown in Appendix Table A7, when including control variables, $StyMomSig_Resid_{i,t}$ negatively predicts $R_nonQ_{i,t+1}$, with coefficient of -0.023 (t-statistic: -2.19) in the univariate regression and -0.016 (t-statistic: -1.49) in the multivariate regression. Panel B presents the result during the subsequent 2-3 weeks' horizon. The trend-chasing behavior exhibited by $R_nonQ_{i,t}$ and $StyMomSig_Resid_{i,t}$ is notable, exerting a significantly positive effect on the $Q_{i,t+2-t+3}$. Meanwhile, $StyMomSig_Resid_{i,t}$ no longer shows negative impact on $R_nonQ_{i,t+2-t+3}$. Consequently, it total effect on $R_{i,t+2-t+3}$ becomes marginally significant in a positive manner. In brief, our finding suggests that speculators' trend-chasing trading behavior not only exists in characteristic (R_nonQ) itself, but also in the style-investing induced component ($StyMomSig_Resid$).

Table 8 here

Overall, in this section, we document the co-existence of short-term momentum (based on $R_nonQ_{i,t}$) and short-term reversal (based on $Q_{i,t}$), and demonstrate that the short-term momentum effect is robust across different types of commodities with different characteristics. We then show that the short-term momentum is primarily driven by the speculators' trend-chasing trading behavior, and such behavior becomes stronger for commodities with low volatility or low crowding status. We also provide additional empirical evidence that the trend-chasing trading behavior occurs not only for the individual commodity itself, but also at its peers level, that is, speculators chase both commodity i's own return and the returns of its momentum peers. It is worthy to note that the trend-chasing behavior persists only for about three weeks, then vanishing and unwinding itself afterwards.

4 Connection Between Short-Term and Intermediate-Term Momentum

In this section, We explore the relationship between the new short-term momentum documented in our study and the traditional intermediate-term momentum strategy.

4.1 The Return Predictive Power of *R_nonQ* on Longer Time Horizon

We examine how the weekly return signal $R_nonQ_{i,t}$ can forecast future commodity returns over longer horizon. In each week t, sample commodities are sorted by $R_nonQ_{i,t}$ into tercile portfolios (High, Median, and Low), and Table 9 presents subsequent cumulative returns over the 1–3, 4–13, 14–26, and 27–52 weeks time interval in Panel A, together with their decomposition into *Q-related* and *Q-orthogonal* components in Panels B and C, respectively.

Table 9 here

Panel A in Table 9 shows that the High–Low spread in cumulative returns is positive over 1–3 weeks and remains economically meaningful over the subsequent 4–13, 14–26, and 27–52 weeks, implying that $R_nonQ_{i,t}$ positively forecasts future returns up to one year.[7] To examine how the momentum effect propagates beyond the weekly horizon, we track the evolution of the speculators' net trading (Q), and the trading-orthogonalized return component (R_nonQ) over the time window up to annual horizon as follows.

[7]In Appendix Table A8, we also provide results from Fama-Macbeth cross-sectional regressions of subsequent 1–3, 4–13, 14–26, and 27–52 weeks' total returns, Q-related components and Q-orthogonal components on an intercept, $R_nonQ_{i,t}$, $Q_{i,t}$, and control variables. The results indicate that $Q_{i,t}$ exerts a significantly negative effect on cumulative returns over the subsequent 1–3 weeks, though this effect dissipates over longer horizons. In contrast, $R_nonQ_{i,t}$ exhibits short-term momentum over the 1–3 week horizon, and a similar momentum pattern persists even at the 27–52 week horizon, consistent with our findings above.

First, our analysis suggests a distinct "ramp-up in short-term, unwind in intermediate-term" trading flow pattern. As shown in Panel B, during the subsequent 1-3 week horizon, the High–Low spread in trading-related return components stands at 0.71% (t-statistics=15.01), indicating a significant positive ramp-up trading trends. However, this trading flow tend to reverse over longer horizons. In the 4-13 week interval, this spread turns negative at -0.59% (t-statistics=-8.60), and it further diminishes in the 14-26 and 27-52 week time intervals. These observations imply a hump-shaped trading flow pattern: the initial amplification turns negative in longer term – producing short-term momentum and an intermediate-term reversal in the trading-related return component. A possible reason for this pattern is that short-horizon trend-chasing can overshoot, followed by a subsequent correction that reverses part of the earlier trading flow (e.g., De Bondt and Thaler (1985), Daniel et al. (1998)).

Second, we identify a more persistent longer-horizon gradual diffusion pattern for the trading-orthogonalized return component (R_nonQ). As shown in Panel C, High-Low spread in R_nonQ is -0.16 over the initial 1-3 week horizon, indicating a mild short-term reversion, which could be possibly caused by transient price pressure and liquidity drag as suggested in our model presented in later Section 6. However, and also more importantly, the High-Low spread in the trading-orthogonalized return component (R_nonQ) turns to be significantly positive over longer horizons. For example, the spread is 0.90% for weeks 4-13, 0.89% for weeks 14-26, and 1.43% for weeks 27-52, with all these three trading-orthogonalized return component spreads being statistically significant and economically meaningful. Our empirical observation here implies a gradual information diffusion mechanism embedded in the R_nonQ component as suggested by Hong and Stein (1999) and Jegadeesh et al. (2025).

The net effect of $R_nonQ_{i,t}$ on subsequent weeks' cumulative commodity returns re-

flects the combination of the trading-flow pattern and gradual information diffusion pattern mentioned above. As the flow component exhibits a short-term ramp-up followed by reversal, and the orthogonalized return component shows initial reversion before substantial strengthening in later weeks, the aggregate High-Low return spread remains consistently positive across the 1-52 week horizon. That is, sorting on $R_nonQ_{i,t}$ not only captures return continuation at the weekly horizon but also aligns positions with signals that continue to pay off in longer time horizon.

Figure 1 plots the cumulative High–minus–Low portfolio returns over the subsequent 1–52 weeks for (i) the trading-flow component R_Q, (ii) the trading-orthogonalized component R_nonQ, and (iii) the total return (R), with portfolios formed each week by sorting commodities on $R_nonQ_{i,t}$.

Figure 1 here

The figure reveals a clear transition between channels across horizons. In the short horizon (weeks 1–3), the R_Q curve rises sharply while $R_nonQ_{i,t}$ exhibits mild self-reversion, producing a net increase in total R; this reflects a trend-chasing ramp-up in positions that amplifies near-term continuation. Moving into intermediate horizons (weeks 4–13), the flow path flattens and turns down as prior flow pressure is unwound, whereas in the orthogonalized-return-component path, $R_nonQ_{i,t}$ turns positive and accumulates, so the total R curve continues to climb. Over longer intervals (weeks 14–26 and 27–52), $R_nonQ_{i,t}$ remains the dominant contributor to cumulative gains while the R_Q path is flat to negative, leaving the total R curve on a steadily rising trajectory.

Taken together, the figure visualizes the mechanism documented in Table 9: short-term continuation is driven by a trading-flow component ramp-up that subsequently mean reverts, while the orthogonal (fundamentals-linked) component strengthens over months,

yielding persistent intermediate-term momentum in total returns.

4.2 The Relationship Between Short-Term and Intermediate-Term Momentum Strategies

The empirical asset-pricing literature predominantly implements momentum by sorting on intermediate-term cumulative returns, and then buying past winners and shorting past losers. Our tests bridge this canon with short-term, week-by-week return signals, showing how weekly "wins" and "losses" can aggregate into intermediate-term winner/loser classifications.

In each week t, we classify intermediate-term winners/losers using cumulative returns over $H \in \{4, 13, 26, 39, 52\}$ weeks into tercile portfolios, and $I_AW_{i,t}$ ($I_AL_{i,t}$) equals one if commodity i is in the top (bottom) tercile, and 0 otherwise. In parallel, we count weekly short-term wins/losses over the past weeks, building $Count_Winner_{i,t}$ and $Count_Loser_{i,t}$. We then estimate probit models of $I_AW_{i,t}$ on $Count_Winner_{i,t}$ and of $I_AL_{i,t}$ on $Count_Loser_{i,t}$.

Table 10 reports that short-term signals strongly and monotonically map into intermediate-term classifications. For winners, one additional weekly win raises the probability of being an intermediate-term winner by 30.1% at $H = 4$ weeks, 10.0% at 26 weeks, and 6.3% at 52 weeks (all $z \geq 40.5$).

Short-term wins/losses aggregate: the more frequent the weekly wins (losses), the higher the probability of being classified as a multi-week winner (loser). The effect size declines as the horizon expands—consistent with dilution—yet statistical significance remains very strong across all H [8].

[8] In Appendix Table A9, the profits of short-term and intermediate-term momentum strategies exhibit a strong positive association, with correlation coefficients ranging from 0.81 to 0.83 across all sample periods, underscoring a robust co-movement between short- and intermediate-term momentum profits.

Table 10 here

4.3 An Improved Intermediate-Term Momentum Strategy Based on R_nonQ

Since we have already established close connection between short-term and intermediate-term momentum, it is natural to expect that using R_nonQ, instead of the raw return (R) as the sorting variable can improve intermediate-term momentum performance.

At the end of week $t-1$, we compute the cumulative R_nonQ over an intermediate-term formation window $H \in \{13, 26, 39, 52\}$ and sort sample commodities into terciles. The *Improved Intermediate-Term Momentum* strategy takes long positions in the High–R_nonQ tercile and short positions in the Low–R_nonQ tercile in week t (equal-weighted, rebalanced weekly). For comparison, we implement the identical procedure using cumulative R.

Table 11 shows that sorting based on R_nonQ consistently delivers larger weekly High-minus-Low profits than sorting on the raw return (R) across all intermediate horizons. For instance, at $H = 26$ weeks, it earns 0.19% (9.88% per annum) vs. 0.10% (5.20% per annum), with an improvement of 0.09% (4.68%). The edge persists at longer windows: 0.24% (12.48% per annum) vs. 0.17% (8.84% per annum) at $H = 52$, with the significant increase of 0.06% (3.63% per annum).

Table 11 here

Figure 2, which plots cumulative momentum profits from 1994–2024, shows the R_nonQ curves remains to be substantially and systematically above the raw-return-based curves for all the intermediate-term windows, visually corroborating the tabulated gains presented in Table 11.

Figure 2 here

Because R_nonQ distills the return component orthogonal to contemporaneous Q, it provides a cleaner and more effective momentum signal that translates from short-term strength into stronger intermediate-term profits. The empirical tests in Table 11 and the cumulative returns in Figure 2 support adopting R_nonQ as the alternative sorting variable for an enhanced intermediate-term momentum strategy.

Moreover, we consider the application of machine learning method for the performance of intermediate-term momentum strategy. Gu et al. (2020) indicate that momentum consistently emerges as a dominant predictive signal across all machine-learning models. Particularly, our goal is to illustrate how machine learning can help uncover the dynamic structure of momentum across different time horizons and enable more informed and adaptive weighting of historical returns in momentum portfolio construction. Figure 3 illustrates that based on the orthogonalized momentum signal (R_nonQ), machine learning enhanced momentum strategies (e.g., XGBoost and RandomForest) outperform. Importantly, the selected machine-learning models leverage the same R_nonQ historical data as the benchmark, merely processed through non-linear algorithms rather than simple cumulative summation. These findings reveal a two-tiered enhancement in signal processing: first, the transition from raw returns (R) to orthogonalized return components (R_nonQ) effectively purges liquidity-based reversal, establishing a robust baseline; second, applying machine learning to these identical inputs (R_nonQ) unlocks substantial increments that linear accumulation misses. The divergence is visually striking in the later sample period. All together, our analysis here underscores that machine-learning-based optimization serves as a powerful mechanism to future refine intermediate momentum strategies.

Figure 3 here

5 Short-Term Reversal Revisited in More Detail

Short-term return reversal is well established in the literature and is often explained by liquidity provision—market makers absorb temporary order-flow imbalances and later re-balance inventory, inducing price reversion. We present additional empirical evidence to better illustrate the mechanism of this liquidity channel by utilizing the speculators' net-trading measure (Q).[9]

We conduct Fama-Macbeth regressions of next week's return $R_{i,t+1}$ on non-commercial speculators' net trading ($Q_{i,t}$), interact $Q_{i,t}$ with the magnitude and sign of $R_nonQ_{i,t}$, and with volatility dummies, controlling for standard covariates ($\text{Basis}_{i,t}$, $\text{Basis-Momentum}_{i,t}$, and $\text{SHP}_{i,t}$. The goal is to test whether the $Q_{i,t}$–driven reversal is (i) robust to the information content in R_nonQ and (ii) stronger when volatility is high.

Table 12 shows the following empirical findings. First, $Q_{i,t}$ negatively predicts $R_{i,t+1}$ across all specifications, confirming the liquidity-based reversal effect on the short-term horizon. Second, this return predictability is independent of the magnitude or the sign of $R_nonQ_{i,t}$: interactions with high/low $R_nonQ_{i,t}$ and with $R_nonQ_{i,t}$'s sign are small and statistically insignificant, leaving the core $Q_{i,t}$-based liquidity reversal effect intact. Third, the liquidity-based reversal is amplified in high volatility scenario: the $Q_{i,t}$ coefficient is more negative under *VolatHigh* than under *VolatLow* (e.g., about -0.095 vs. -0.023), consistent with the implication from market microstructure models that higher volatility raises inventory risk and the cost of providing immediacy, leading to stronger subsequent price reversion.

[9] As for the empirical tests, classical literature utilizes past several weeks or months returns as the sorting variables to construct reversal strategies via portfolio sorting approach. For instance, Lehmann (1990) sorts stocks based on their returns in week t–1 and takes long (short) positions in the bottom (top) half of the cross–section.

Table 12 here

These patterns align well with the liquidity-provision mechanism: when the net trading measure ($Q_{i,t}$) indicates the liquidity-demanding speculators' trading flow, prices first move to accommodate such demand of immediacy, and then partially reverse as liquidity providers unwind risk—especially in high-volatility scenarios where inventory costs are elevated (Grossman and Miller, 1988). The robustness to the variation of R_nonQ's magnitude and sign suggests the short-term reversal effect primarily operate through the liquidity channel represented by $Q_{i,t}$.

Therefore, our analysis in this section shed more light on the liquidity-based nature of the short-term reversal effect. We find that $Q_{i,t}$ is a more precise predictor of $R_{i,t+1}$. And this return predictability becomes more pronounced in high volatility scenarios. In contrast, the trading-orthogonalized return component $R_nonQ_{i,t}$ has little influence on the liquidity-based short-term reversal. Therefore, the "liquidity-based reversal" effect is better characterized as a short-term trading-based reversal rather than a return-based reversal.[10]

6 Theoretical Explanation

In this section, we develop a theoretical framework that explains the key findings of our empirical analysis. We propose a reduced-form model that accounts for the coexistence of short-term momentum and reversal, and discuss the mechanism through which short-term return dynamics transition into intermediate-term momentum.

[10]In Appendix Table A10, we conduct panel regressions of the subsequent week's return ($R_{i,t+1}$) on an intercept, non-commercial speculators' net long position change ($Q_{i,t}$), its interaction with dummy variables related to the joint sign patterns of $Q_{i,t}$ and $R_nonQ_{i,t}$, and control variables. Empirical results indicate that the coefficients of $Q_{i,t}$ are significantly negative across all specifications, while the interaction terms are insignificant. This suggests that the reversal effect is not conditional on the alignment of the sign of Q and R_nonQ, supporting the liquidity-based reversal hypothesis.

6.1 Non-Commercials: Signal, Beliefs, Flow (Week t)

We adopt the standard microstructure price–order-flow decomposition, consistent with linear price impact and the supply of immediacy (e.g., Kyle (1985); Grossman and Miller (1988)) and widely used in empirical work (e.g., Hasbrouck (2007); de Jong and Rindi (2009)), and treat $(Q_{i,t},\ R_{i,t}^{\text{nonQ}})$ as the model's state variables.

At the end of week t, Non-commercials take the orthogonal component as a simple price signal Hong and Stein (1999) and set

$$E_t[R_{i,t+1}] \ = \ b_{i,t}\,\text{R_nonQ}_{i,t}, \qquad \text{Var}_t(R_{i,t+1}) \ = \ \sigma_{i,t}^2,$$

then implement $q_{i,t} = \alpha_{i,t}\text{R_nonQ}_{i,t}$.[11]

Trend-chaser objective (mean–variance). At the end of week t, the intensity $\alpha_{i,t}$ solves

$$\max_{\alpha_{i,t}} \Big\{ E_t[q_{i,t}R_{i,t+1}] - \tfrac{\gamma}{2}\ \text{Var}_t(q_{i,t}R_{i,t+1}) \Big\},$$

which yields (see details in Appendix 1)

$$\alpha_{i,t}^{*} \ = \ \frac{b_{i,t}}{\gamma\,\sigma_{i,t}^2}. \tag{3}$$

Order flow persistence implies next-week flow

$$Q_{i,t+1} \ = \ \psi_Q\,Q_{i,t} \ + \ \alpha_{i,t}\,\text{R_nonQ}_{i,t} \ + \ \nu_{i,t+1}, \qquad \psi_Q > 0. \tag{2}$$

combines *order flow persistence* and the *new trade* induced by the signal. The coefficient

[11] Trend-followers choose the end-of-week trade increment $q_{i,t} = \alpha_{i,t}R_nonQ_{i,t}$, where $R_nonQ_{i,t}$ is the most recently observed (week-t) Q-orthogonal return. The trade is executed at the close of week t and therefore shows up in next week's flow $Q_{i,t+1}$.

$\psi_Q > 0$ captures how existing order flows carry over into next week;[12] The loading $\alpha_{i,t}$ is the end-of-week *trend intensity* chosen by non-commercials, inherits the sign of perceived predictability $b_{i,t}$ and, in our trend-chasing setting, is *typically positive*. This specification is consistent with signal-driven position updates (trend chasing) and persistent order flow in microstructure models (e.g., Hong and Stein (1999); Hasbrouck (2007)).

6.2 Commercials: Liquidity Provision with Objective (Week t+1)

Immediacy suppliers (market makers/hedgers) absorb order flow and then rebalance inventories; empirically, this generates short-run mean reversion and a compensation for absorbing flow (e.g., Grossman and Miller (1988); Nagel (2012)). Denote the transient price concession (orthogonal component) by $m_{i,t} \equiv \text{R_nonQ}_{i,t}$ and inventory by $I_{i,t} = Q_{i,t}$. Outside demand is linear in next week's concession, so inventory evolves as

$$I_{i,t+1} = I_{i,t} + \kappa\, m_{i,t+1} - \varepsilon_{i,t+1}, \qquad \kappa > 0.$$

Market maker objective (convex loss). The market maker chooses $m_{i,t+1}$ to minimize

$$\mathcal{L}(m_{i,t+1}) = \tfrac{a}{2}\, m_{i,t+1}^2 + \tfrac{\phi}{2}\,(m_{i,t+1} - \rho_m m_{i,t})^2 + \tfrac{b}{2}\,\big(I_{i,t} + \kappa m_{i,t+1} - \varepsilon_{i,t+1}\big)^2,$$

where: (i) $a > 0$ penalizes immediacy concessions (temporary impact), (ii) $\phi > 0$, $\rho_m < 0$ capture quote resilience/self-reversion, and (iii) $b > 0$ penalizes inventory risk.[13] Solving (FOC) yields the reduced-form orthogonal-component dynamics (See details in Ap-

[12] Signed order flow is empirically persistent at short horizons. The main drivers are (i) order splitting/optimal execution, (ii) correlated demands/herding by institutions, and (iii) gradual inventory/book-resilience adjustments.

[13] The three components of $\mathcal{L}$—(i) a convex price concession/temporary impact term, (ii) a resilience (quote-smoothing) penalty, and (iii) a quadratic inventory-risk term—are standard in market-making and microstructure objectives, consistent with optimal execution and market maker pricing models (e.g., Almgren and Chriss (2001); Hasbrouck (2007); Madhavan and Smidt (1993)) and the supply-of-immediacy framework that underpins short-run reversal (Grossman and Miller (1988); Nagel (2012)).

pendix 2.)

$$R_nonQ_{i,t+1} \;=\; \chi_R\, R_nonQ_{i,t} \;+\; \chi_Q\, Q_{i,t} \;+\; \varepsilon_{i,t+1}, \qquad \chi_R < 0,\ \chi_Q < 0, \tag{4}$$

i.e., mild self-reversion ($\chi_R < 0$) and compensation for absorbing flow ($\chi_Q < 0$), consistent with inventory/immediacy channels (e.g., Grossman and Miller (1988); Nagel (2012)) and market maker inventory evidence (e.g., Madhavan and Smidt (1993); Hasbrouck (2007)).

6.3 Prediction and Coexistence (Same Horizon)

Combining the week-t decomposition, end-of-week decision, order flow persistence, and next-week orthogonal-component dynamics gives

$$R_{i,t+1} \;=\; (b_1\psi_Q + \chi_Q)\, Q_{i,t} \;+\; (b_1\alpha^*_{i,t} + \chi_R)\, R_nonQ_{i,t} \;+\; \text{shock}. \tag{5}$$

Two effects coexist:

$$\underbrace{c_Q}_{\text{reversal}} \;=\; b_1\psi_Q + \chi_Q \;<\; 0, \qquad \underbrace{c_{\text{nonQ}}}_{\text{momentum}} \;=\; b_1\alpha^*_{i,t} + \chi_R \;>\; 0.$$

Reversal is the liquidity channel (market makers lean against flow $\chi_Q < 0$ overwhelms mild order flow persistence $b_1\psi_Q > 0$), while momentum is endogenous trend-chasing (positive $b_1\alpha^*_{i,t}$ overwhelms mild self-reversion $\chi_R < 0$), consistent with behavioral trend-chasing (e.g., Hong and Stein (1999)) and weekly/time-series momentum across futures, FX, and bonds (e.g., Moskowitz et al. (2012)).

Comparative statics and empirical mapping. From the model above, we have (i) c_{nonQ} rises with $b_{i,t}$ and falls with $\sigma^2_{i,t}$; (ii) $|c_Q|$ strengthens when liquidity strains intensify

(more negative χ_Q or ψ_Q). We estimate

$$R_{i,t+1} = c_0 + c_{\text{nonQ}}\, R_nonQ_{i,t} + c_Q\, Q_{i,t} + Controls + u_{i,t+1},$$

expecting $c_{\text{nonQ}} > 0$ and $c_Q < 0$; auxiliary one-step tests map the dynamics: $R_nonQ_{i,t} \to Q_{i,t+1} > 0$ (trend-chasing ramp-up) and $Q_{i,t} \to R_nonQ_{i,t+1} < 0$ (market makers' leaning).

6.4 Discussion: Transition from Short-Term to Intermediate-Term Momentum

Iterating the weekly dynamics of $Q_{i,t}$ (flow component) and $\text{R_nonQ}_{i,t}$ (orthogonal component) implies a hump-shaped *flow component* impulse (trend-chasing ramp-up then inventory-driven unwind) alongside a one-week *orthogonal component* resilience drag; the observed intermediate-term build-up in the orthogonal component can be attributed to gradual information diffusion, consistent with Hong and Stein (1999) and the documented reversal-to-momentum transition in Jegadeesh et al. (2025).

1. **Flow path ($\text{R_nonQ}_{i,t} \Rightarrow Q_{i,t+h}$): ramp-up $\Rightarrow$ unwind.** When $\text{R_nonQ}_{i,t} \uparrow$, trend-chasing makes $Q_{i,t+1} \uparrow$, so the flow contribution to returns is initially positive. As positions accumulate, inventory/risk budgets bind and immediacy suppliers lean against imbalances; with transient (decaying) impact and $\chi_Q < 0$, the *cumulative* flow contribution turns *negative* over longer term (unwind/mean reversion).[14]

   A complementary behavioral channel is that momentum traders can *overshoot* in the ramp-up phase and subsequently take profits, so speculative flow itself reverses

[14] Let $S_t = (Q_t, \text{R_nonQ}_t)'$ with $S_{t+1} = AS_t + u_{t+1}$, $A = \begin{pmatrix} \psi_Q & \alpha \\ \chi_Q & \chi_R \end{pmatrix}$, $\psi_Q, \alpha > 0$, $\chi_Q, \chi_R < 0$. Iteration gives $S_{t+h} = A^h S_t + \sum_{j=1}^{h} A^{j-1} u_{t+h-j+1}$ and $R_{t+h} = b_1 Q_{t+h} + \text{R_nonQ}_{t+h}$. Thus $\text{R_nonQ}_t \uparrow \Rightarrow Q_{t+1} \uparrow$ (ramp-up via $\alpha > 0$), while the feedback $Q \to \text{R_nonQ}$ ($\chi_Q < 0$) and resilience ($\chi_R < 0$) make the *cumulative* flow contribution mean-revert (unwind) over multi-week horizons.

after the initial amplification—reinforcing the intermediate-term unwind;

2. **Orthogonal path ($\mathbf{R_nonQ}_{i,t} \Rightarrow \mathbf{R_nonQ}_{i,t+h}$): resilience blip $\Rightarrow$ diffusion.** The orthogonal path exhibits a small one-week drag from *quote resilience/quote-smoothing* ($\chi_R < 0$). Beyond short horizon, *gradual information diffusion* lifts the orthogonal component; the *cumulative* orthogonal contribution becomes *positive* and grows over intermediate term, consistent with diffusion-based momentum (Hong and Stein, 1999; Jegadeesh et al., 2025).

These transitions—flow ramp-up then unwind (inventory/leaning), and orthogonal resilience blip then diffusion—match the leg-by-leg sign changes in our multi-horizon decompositions (Table 6; Figure 1).

Because the flow path flips from positive (ramp-up) to negative (unwind) while the orthogonal path flips from a brief resilience-induced drag to sustained gains (diffusion), total returns remain *positive* at intermediate horizons. The short-run block (trend-chasing and quote resilience) is consistent with the reduced-form mapping in our model, and it nests the *slow-diffusion* mechanism of Hong and Stein (1999) and the reversal-to-momentum transition emphasized by Jegadeesh et al. (2025).

7 Conclusion

We show that short-term momentum and reversal *coexist* in commodity markets. Using CFTC weekly traders' position data, we decompose commodity futures returns into (i) a flow component (Q) that represents non-commercial speculators' net trading activity, and (ii) an orthogonalized return component (R_nonQ) that captures price movements not spanned by contemporaneous speculators' trading flow. This decomposition clearly identifies two distinct return predictability on the short-term horizon: R_nonQ positively

predicts next-week returns (return-based momentum), while Q forecasts subsequent commodity returns in a negative manner (trading-based reversal).

Analysis of the joint evolution dynamics of Q and R_nonQ reveals mechanism in which non-commercial speculators chase past price trends: they scale up (down) positions in recent winners (losers). Such trend-chasing trading behavior and the associated return continuation become stronger when the volatility/dispersion is low and the expected profitability of momentum is high. We also find that short-term return signals connect naturally to the traditional intermediate-horizon momentum strategy: short-term momentum winners are more likely to be intermediate-term winners also, and sorting on cumulative R_nonQ rather than raw returns delivers substantially stronger performance for the intermediate-term momentum strategies.

Taken together, our analysis reconciles return-based momentum with liquidity-based reversal at the short-term horizon. While our empirical laboratory is in commodity futures markets, the approach is portable: in markets with comparable traders' position or flow data, decomposing returns into trading-related and orthogonal components provides the possible venue to separate return continuation from liquidity-based reversal. This enables a better assessment for the short-term return predictability in financial markets, which can enhance our understanding about the market efficiency in asset pricing research.

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Figure 1: High-Low Portfolio's Cumulative R_Q, R_nonQ, and R in the Subsequent 1–52 Weeks, Sorted by R_nonQ

This figure plots the High-minus-Low portfolio's cumulative Q-related returns (R_Q, defined as R - R_nonQ), Q-orthogonal returns (R_nonQ), and total returns (R) in the subsequent 1∼52 weeks. In each week t, we sort all sample commodities by their $R_nonQ_{i,t}$, and form three portfolios (High, Median, and Low). Then, we calculate the subsequent 1∼52 weeks' cumulative return difference between High and Low portfolios. The black solid line, gray dots, and blue dashed line denote R, R_Q, and R_nonQ, respectively.

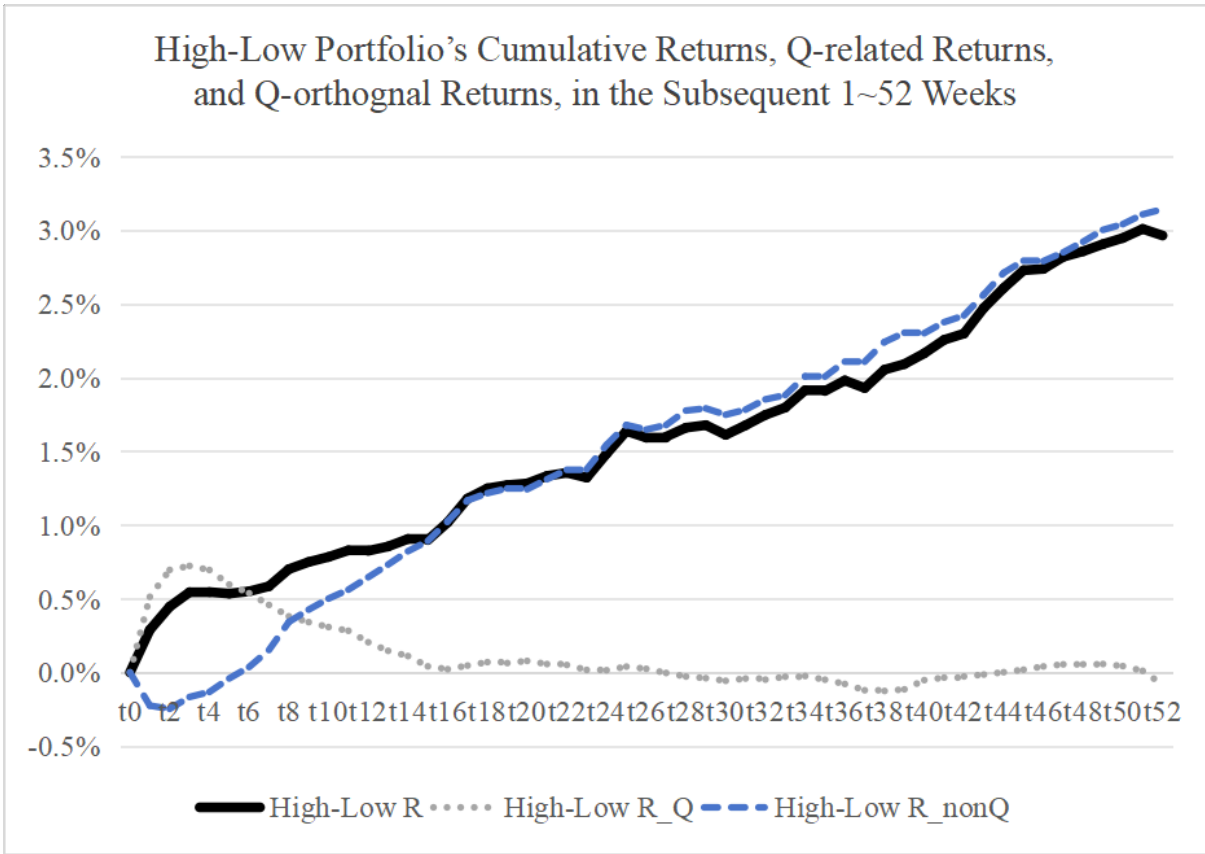
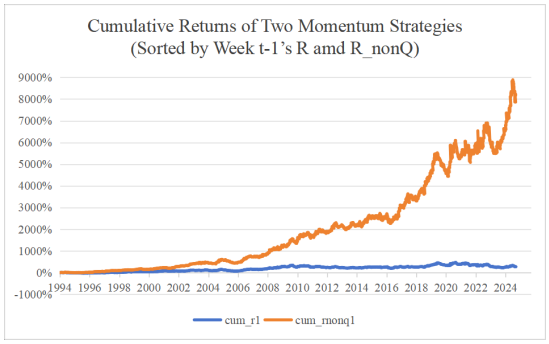
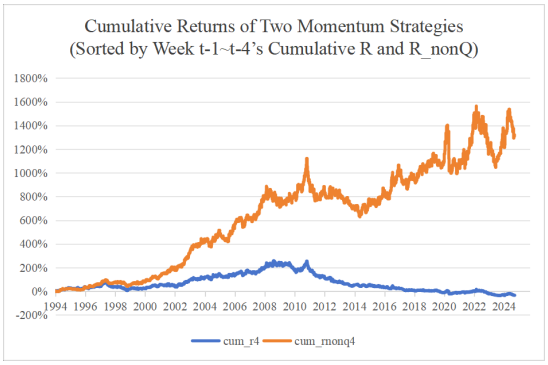


Figure 2: Profits of R- and R_nonQ-based Momentum Strategies

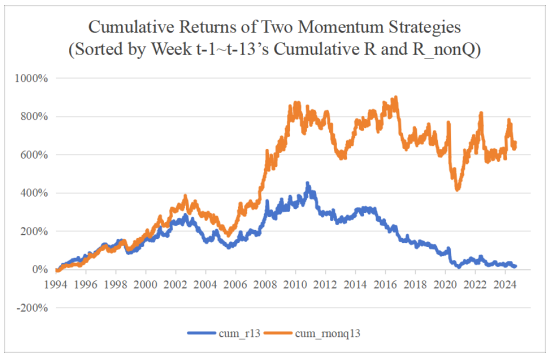
This figure presents the profits of R- and R_nonQ-based momentum strategies from 1994 to 2024. In each week t, we sort all sample commodities into three groups by their past 1-, 4-, 13-, 26-, 39-, and 52-weeks' cumulative R or R_nonQ, respectively, and calculate the subsequent one-week's return difference between High and Low portfolios. Then, we plot the cumulative return difference of each momentum strategy from 1994 to 2024. Blue solid line is the profit of R-based momentum strategies, and orange for R_nonQ-based momentum strategies.



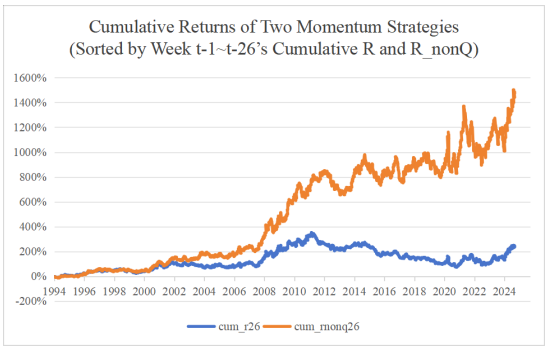
(a) by week t-1 R and R_nonQ



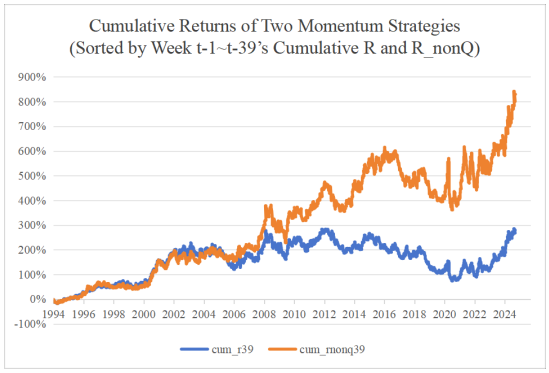
(b) by week t-1~t-4 R and R_nonQ



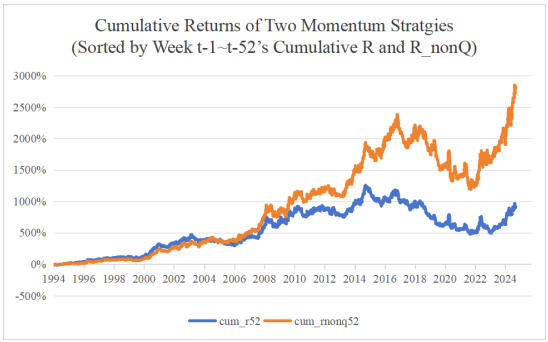
(c) by week t-1~t-13 R and R_nonQ



(d) by week t-1~t-26 R and R_nonQ



(e) by week t-1~t-39 R and R_nonQ



(f) by week t-1~t-52 R and R_nonQ

Figure 3: Profits of Intermediate-Term Momentum Strategy Based on the Machine Learning Approach

This figure illustrates the cumulative returns of four intermediate-term momentum strategies. The first two strategies utilize machine learning algorithms, XGBoost (blue line) and Random Forest (orange line), to predict momentum signals. Specifically, above two models are trained on a rolling 15-year window, using historical weekly orthogonalized return component (R_nonQ) from t-1 to t-52 as input, where these 52 lagged returns are aggregated into four distinct features representing quarterly averages (e.g., Feature 1 represents the average return of weeks t-1 to t-13, and so forth). The remaining two strategies serve as benchmarks: one constructed based on the past 52-week cumulative R_nonQ (yellow line), and the other based on the non-quarterly adjusted cumulative R (green line). In each week t, all sample commodities are sorted weekly into terciles (High, Median, Low) based on their respective signals. The plotted curves represent the cumulative performance of a long-short portfolio, calculated as the difference in average weekly returns between the High and Low terciles.

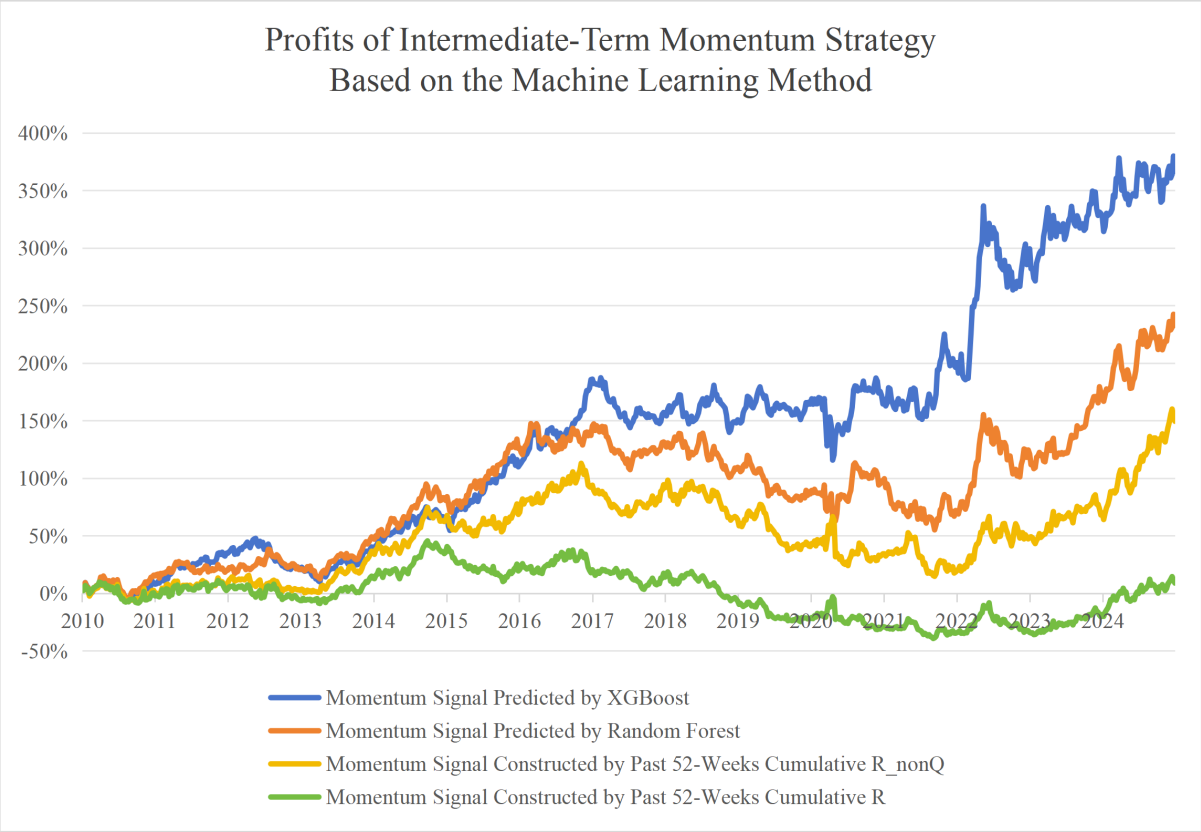


Table 1: The Predictability of R, R_nonQ, and Q

The table presents the coefficients and t-statistics from Fama-Macbeth cross-sectional regressions and panel regressions of commodity futures return in week t+1 ($R_{i,t+1}$) on an intercept, commodity futures return in week t ($R_{i,t}$), non-commercial traders' net long position change from week t-1 to week t, scaled by the open interest in week t-1 ($Q_{i,t}$), the orthogonalized return component ($R_nonQ_{i,t}$), and controls. The control variables are $Basis_{i,t}$, $BasisMomentum_{i,t}$ and smoothed hedging pressure ($SHP_{i,t}$). $Basis_{i,t}$ is the difference between commodity i's log price of first- and second-nearby contracts, scaled by the time gap between two contracts. $BasisMomentum_{i,t}$ is the difference between the past 52-weeks' price momentum based on the first- and the second-nearby contract returns. $SHP_{i,t}$ is smoothed hedging pressure, which is the 52-week moving average of the net short positions of commercial traders from week t-51 to week t, scaled by open interest in week t. Panel A reports the return predictability of $R_{i,t}$, and Panel B is for the predictability of two orthogonal components, R_nonQ and Q. In Fama-Macbeth regressions, t-statistics are adjusted using Newey-West method with six lags. Panel regressions include commodity- and weekly-level fixed effects, with standard errors clustered at the commodity level.

Panel A: The Return Predictability of $R_{i,t}$

	Fama-Macbeth		Panel	
$R_{i,t}$	0.016	0.010	-0.001	0.000
	(*2.16*)	(*1.25*)	(*-0.16*)	(*0.05*)
Controls	No	Yes	No	Yes
Adj R^2	4.4%	12.3%	14.9%	15.0%

Panel B: The Predictability of $R_nonQ_{i,t}$ and $Q_{i,t}$

	Fama-Macbeth		Panel	
$R_nonQ_{i,t}$	0.046	0.036	0.024	0.026
	(*5.42*)	(*3.98*)	(*2.44*)	(*2.68*)
$Q_{i,t}$	-0.052	-0.048	-0.042	-0.039
	(*-8.40*)	(*-7.63*)	(*-5.51*)	(*-5.48*)
Controls	No	Yes	No	Yes
Adj R^2	5.6%	13.5%	15.1%	15.2%

Table 2: Short-Term Momentum Pattern of R_nonQ Across All Characteristics

This table reports the portfolio's subsequent one-week return and t-statistics. In each week t, we first sort all sample commodities by their $characteristic_{i,t}$ into two sub-samples (High and Low), and then in each sub-sample, we rank commodities by their $R_nonQ_{i,t}$ (High $R_nonQ_{i,t}$ and Low $R_nonQ_{i,t}$), and then calculate portfolio's average return in week t+1. Characteristics include the dollar and number of trading volume and open interest of first-nearby contract; turnover ratio, computed as trading volume divided by open interest; smoothed hedging pressure; price momentum, measured as the cumulative return from week t-52 to t-1; past value ratio, defined as the price at week t-156 divided by the price at week t; and basis momentum. t-statistics are adjusted using Newey-West method, with 6 lags.

$R_{i,t+1}$	$Volume_{i,t}^{dollar}$		$Volume_{i,t}^{number}$		$Turnover_{i,t}$	
	Low	High	Low	High	Low	High
Low $R_nonQ_{i,t}$	-0.01%	-0.02%	-0.01%	-0.02%	-0.04%	0.03%
High $R_nonQ_{i,t}$	0.23%	0.17%	0.24%	0.14%	0.19%	0.18%
High-Low	0.24%	0.19%	0.25%	0.16%	0.22%	0.16%
(t-statistics)	(*4.23*)	(*3.52*)	(*4.38*)	(*2.92*)	(*4.10*)	(*2.83*)
$R_{i,t+1}$	$OI_{i,t}^{dollar}$		$OI_{i,t}^{volume}$		$SHP_{i,t}$	
	Low	High	Low	High	Low	High
Low $R_nonQ_{i,t}$	-0.01%	-0.03%	-0.05%	0.02%	-0.05%	0.06%
High $R_nonQ_{i,t}$	0.26%	0.14%	0.25%	0.14%	0.08%	0.28%
High-Low	0.26%	0.16%	0.31%	0.12%	0.13%	0.22%
(t-statistics)	(*4.70*)	(*3.17*)	(*5.26*)	(*2.06*)	(*2.42*)	(*3.94*)
$R_{i,t+1}$	$Past-Momentum_{i,t}$		$Past-Value_{i,t}$		$Basis-Momentum_{i,t}$	
	Low	High	Low	High	Low	High
Low $R_nonQ_{i,t}$	-0.06%	0.04%	-0.05%	0.02%	-0.08%	0.07%
High $R_nonQ_{i,t}$	0.10%	0.27%	0.19%	0.20%	0.10%	0.26%
High-Low	0.16%	0.23%	0.24%	0.18%	0.18%	0.19%
(t-statistics)	(*2.78*)	(*4.03*)	(*4.29*)	(*2.98*)	(*3.39*)	(*3.51*)

Table 3: Two-Way Portfolio Sorting Based on the Q and R_nonQ

This table studies the dynamic interaction between non-commercial traders' net long position change (Q) and the orthogonalized return component (R_nonQ). In each week t, sample commodities are independently double-sorted by $Q_{i,t}$ and $R_nonQ_{i,t}$, forming four portfolios. Conducting cross-sectional regressions of $R_{i,t+1}$ on $Q_{i,t}$, $R_nonQ_{i,t}$, $Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$, we obtain the coefficients b_Q_t and $b_R_nonQ_t$ on a weekly basis. Panel A reports average excess returns (v.s.market) in week t+1. Panels B and C show expected returns attributable to Q and R_nonQ, computed as b_Q_t*$Q_{p,t}$ and $b_R_nonQ_t$*$R_nonQ_{p,t}$, where $Q_{p,t}$ and $R_nonQ_{p,t}$ denote the net portfolio p's average Q and R_nonQ deviated from their respective cross-section means. Panel D presents the sum expected return of two signals. t-statistics shown in the parentheses for the return difference are adjusted using the Newey-West method with six lags.

Panel A: Excess Return of the Four Portfolios in Week t+1

	Low $R_nonQ_{i,t}$	High $R_nonQ_{i,t}$	Diff	t-statistics
Low $Q_{i,t}$	0.02%	0.24%	0.22%	(*4.03*)
High $Q_{i,t}$	-0.22%	-0.03%	0.19%	(*3.36*)
Diff	-0.24%	-0.27%		
t-statistics	(*-4.28*)	(*-4.72*)		

Panel B: Expected Returns Attributed to Q in Week t+1

	Low $R_nonQ_{i,t}$	High $R_nonQ_{i,t}$	Diff	t-statistics
Low $Q_{i,t}$	0.12%	0.13%	0.02%	(*1.85*)
High $Q_{i,t}$	-0.13%	-0.13%	0.00%	(*0.50*)
Diff	-0.25%	-0.26%		
t-statistics	(*-8.30*)	(*-8.49*)		

Panel C: Expected Returns Attributed to R_nonQ in Week t+1

	Low $R_nonQ_{i,t}$	High $R_nonQ_{i,t}$	Diff	t-statistics
Low $Q_{i,t}$	-0.06%	0.07%	0.14%	(*3.19*)
High $Q_{i,t}$	-0.08%	0.07%	0.15%	(*3.63*)
Diff	-0.02%	0.00%		
t-statistics	(*-1.35*)	(*-0.16*)		

Panel D: Total Expected Returns from Q and R_nonQ in Week t+1

	Low $R_nonQ_{i,t}$	High $R_nonQ_{i,t}$	Diff	t-statistics
Low $Q_{i,t}$	0.05%	0.21%	0.16%	(*3.55*)
High $Q_{i,t}$	-0.21%	-0.05%	0.16%	(*3.65*)
Diff	-0.26%	-0.26%		
t-statistics	(*-7.97*)	(*-7.58*)		

Table 4: The Short-Term Predictability of Q and R_nonQ

The table presents the coefficients from Fama-Macbeth cross-sectional regressions or panel regressions of non-commercial traders' net long position change in week t+1 ($Q_{i,t+1}$) or the return component orthogonal to contemporaneous Q in week t+1 ($R_nonQ_{i,t+1}$) on an intercept, $Q_{i,t}$, $R_nonQ_{i,t}$, with and without controls. The control variables are $Basis_{i,t}$, $Basis_Momentum_{i,t}$ and $SHP_{i,t}$. In Fama-Macbeth regressions, t-statistics showed in parentheses are adjusted using the Newey-West method with six lags. Panel regressions include commodity- and weekly-level fixed effects, with standard errors clustered at the commodity level.

	Fama-Macbeth Regression				Panel Regression			
	$Q_{i,t+1}$		$R_nonQ_{i,t+1}$		$Q_{i,t+1}$		$R_nonQ_{i,t+1}$	
$R_nonQ_{i,t}$	0.207	0.235	-0.035	-0.053	0.164	0.17	-0.039	-0.040
	(*21.70*)	(*20.31*)	(*-4.40*)	(*-6.31*)	(*6.42*)	(*6.58*)	(*-4.28*)	(*-4.33*)
$Q_{i,t}$	0.24	0.241	-0.134	-0.132	0.226	0.223	-0.112	-0.110
	(*29.84*)	(*29.25*)	(*-23.21*)	(*-22.54*)	(*21.02*)	(*21.14*)	(*-13.19*)	(*-13.32*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj R^2	11.3%	14.5%	7.9%	16.1%	11.5%	11.7%	16.3%	16.5%

Table 5: Volatility, Crowding and Short-Term Momentum Pattern of R_nonQ

This table presents the coefficients from Fama-Macbeth regressions of either non-commercial traders' net long position change in week t+1 ($Q_{i,t+1}$) or commodity futures return in week t+1 ($R_{i,t+1}$) on the intercept, orthogonalized return component ($R_nonQ_{i,t}$), its intersections with volatility- or crowding- related dummies, $Q_{i,t}$ and control variables ($Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$). Specifically, $Volatility_{i,t}$ is defined as the past 52-week rolling standard deviation of each commodity's returns; $Crowding_{i,t}$ is defined as the difference between $NetLong_{i,t}$ (the non-commercial traders net long position in week t), minus the 52 weeks' moving average of $NetLong$ from week t-1 to week t-52, scaled by commodity i's open interest in week t. In Panel A, the dummy variable $HighVolat_Dm_{i,t}$ ($LowVolat_Dm_{i,t}$) equals 1 if the commodity i's volatility is above (below) the cross-sectional median in week t, and 0 otherwise. In Panel B, all sample commodities are first grouped by the sign of $R_nonQ_{i,t}$ (positive v.s. negative), and within each group sorted by $crowding_{i,t}$ into high and low subgroups. The dummy variable $HighCrowding_Dm_{i,t}$ equals 1 if a commodity belongs to positive-R_nonQ / high-$crowding$, or negative-R_nonQ / low-$crowding$, and 0 otherwise. The dummy variable $LowCrowding_Dm_{i,t}$=1-$HighCrowding_Dm_{i,t}$. t-statistics shown in the parenthesis are adjusted using the Newey-West method with six lags.

Panel A: Volatility and Short-Term Momentum

	$Q_{i,t+1}$			$R_{i,t+1}$		
$R_nonQ_{i,t}$	0.235		0.193	0.036		0.027
	(*20.31*)		(*13.44*)	(*3.98*)		(*2.36*)
$R_nonQ_{i,t}$*$HighVolat_Dm_{i,t}$		0.193			0.027	
		(*13.44*)			(*2.36*)	
$R_nonQ_{i,t}$*$LowVolat_Dm_{i,t}$		0.354	0.161		0.062	0.035
		(*19.05*)	(*7.33*)		(*4.60*)	(*2.03*)
$Q_{i,t}$	0.241	0.249	0.249	-0.047	-0.046	-0.046
	(*29.25*)	(*29.14*)	(*29.14*)	(*-7.63*)	(*-6.60*)	(*-6.60*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	14.5%	14.9%	14.9%	13.6%	14.8%	14.8%

Panel B: Crowding and Short-Term Momentum

	$Q_{i,t+1}$			$R_{i,t+1}$		
$R_nonQ_{i,t}$	0.235		0.126	0.036		0.009
	(20.31)		*(9.50)*	*(3.98)*		*(0.73)*
$R_nonQ_{i,t}$*$HighCrowding_Dm_{i,t}$		0.126			0.009	
		(9.50)			*(0.73)*	
$R_nonQ_{i,t}$*$LowCrowding_Dm_{i,t}$		0.36	0.234		0.062	0.053
		(21.73)	*(12.30)*		*(4.93)*	*(3.28)*
$Q_{i,t}$	0.241	0.255	0.255	-0.048	-0.039	-0.039
	(29.25)	*(30.01)*	*(30.01)*	*(-7.63)*	*(-5.72)*	*(-5.72)*
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	14.5%	15.1%	15.1%	13.6%	15.6%	15.6%

Table 6: Return Dispersion and Short-Term Momentum Pattern of R_nonQ

This table presents the coefficients from panel regressions of non-commercial traders' net long position change in week t+1 ($Q_{i,t+1}$) or return ($R_{i,t+1}$) on an intercept, orthogonalized return component ($R_nonQ_{i,t}$), its intersections with dispersion- related dummy, $Q_{i,t}$ and control variables ($Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$). Weekly return dispersion is measured by the interquartile return range (Ret_Spread) and the standard deviation of cross-sectional commodity futures return ($Ret_Std.Dev.$) in week t. The dummy variable $LowDispersion_Dm_t$ equals 1 if the dispersion measure falls in the bottom 50th percentile across all sample weeks, and 0 otherwise. Panel regressions include commodity-level fixed effects, with standard errors clustered at the commodity level.

	$Q_{i,t+1}$		$R_{i,t+1}$	
	Ret Spread	*Ret Std.Dev.*	*Ret Spread*	*Ret Std.Dev.*
$R_nonQ_{i,t}$	0.143	0.130	0.003	0.000
	(*6.49*)	(*6.02*)	(*0.30*)	(*0.00*)
$R_nonQ_{i,t}$*$LowDispersion_Dm_t$	0.064	0.128	0.045	0.068
	(*3.13*)	(*7.81*)	(*3.37*)	(*4.03*)
$Q_{i,t}$	0.225	0.225	-0.039	-0.040
	(*22.00*)	(*22.03*)	(*-5.44*)	(*-5.48*)
Controls	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
Adj R^2	7.6%	7.8%	0.4%	0.4%

Table 7: Duration of Trend-chasing Trading Behavior

This table present the average slope and t-statistics from Fama-MacBeth regressions of speculators' net long position changes (Q) or returns (R) over subsequent 1- to 6-week horizons (single and cumulative) on the week t's orthogonal return component (R_nonQ) and Q, and controls. Control variables are $Basis_{i,t}$, $SHP_{i,t}$, and $Basis - Momentum_{i,t}$. t-statistics are adjusted with Newey-West method, with 6 lags.

Dependent Variable: Subsequent 1-6 Weeks' Q									
	$Q_{i,t+1}$	$Q_{i,t+2}$	$Q_{i,t+3}$	$Q_{i,t+4}$	$Q_{i,t+5}$	$Q_{i,t+6}$	$Q_{i,t+1}$	$Q_{i,t+2-t+3}$	$Q_{i,t+4-t+6}$
$R_nonQ_{i,t}$	0.234	0.086	0.020	-0.004	-0.035	-0.020	0.234	0.106	-0.058
	(*20.28*)	(*8.94*)	(*2.38*)	(*-0.40*)	(*-4.07*)	(*-2.47*)	(*20.28*)	(*7.44*)	(*-3.52*)
$Q_{i,t}$	0.241	0.015	-0.048	-0.076	-0.064	-0.036	0.241	-0.033	-0.176
	(*29.33*)	(*1.91*)	(*-5.53*)	(*-8.37*)	(*-7.24*)	(*-3.82*)	(*29.33*)	(*-2.40*)	(*-9.14*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	14.5%	6.8%	6.3%	7.3%	6.7%	6.9%	14.5%	7.0%	8.3%
Dependent Variable: Subsequent 1-6 Weeks' R									
	$R_{i,t+1}$	$R_{i,t+2}$	$R_{i,t+3}$	$R_{i,t+4}$	$R_{i,t+5}$	$R_{i,t+6}$	$R_{i,t+1}$	$R_{i,t+2-t+3}$	$R_{i,t+4-t+6}$
$R_nonQ_{i,t}$	0.036	0.021	0.021	-0.003	-0.002	0.002	0.036	0.041	-0.003
	(*3.98*)	(*2.23*)	(*2.23*)	(*-0.32*)	(*-0.16*)	(*0.20*)	(*3.98*)	(*3.15*)	*(-0.18)*
$Q_{i,t}$	-0.047	-0.035	-0.015	-0.016	0.001	0.004	-0.047	-0.05	-0.010
	(*-7.37*)	(*-5.32*)	(*-2.32*)	(*-2.38*)	(*-0.23*)	(*-0.68*)	(*-7.37*)	(*-5.02*)	(*-0.75*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	13.6%	13.0%	12.6%	12.9%	12.1%	11.9%	13.6%	13.0%	12.3%

Table 8: Individual-Level and Peer-Level Trend-Chasing Trading Behavior

This table shows the average slope and t-statistics from Fama-Macbeth cross-section regression of subsequent 1-week's or subsequent 2-3 weeks' cumulative speculators' net long position change (Q) or commodity futures return (R) on the style-based residual signal that is orthogonal to R_nonQ and Q ($StyleMomSignal_{i,t}$), orthogonalized return component ($R_nonQ_{i,t}$), speculators' net long position change ($Q_{i,t}$), and controls ($Basis_{i,t}$, $BasisMomentum_{i,t}$, and $SHP_{i,t}$). To simplify the notation, we replace $StyMomSig_Resid_{i,t}$ with $StyMomSignal_{i,t}$ in the following table. t-statistics are adjusted using Newey-West method, with 6 lags.

	Over the 1-Week Horizon				Over the 2–3 Weeks Horizon				Over the 4–6 Weeks Horizon			
	$Q_{i,t+1}$		$R_{i,t+1}$		$Q_{i,t+2-t+3}$		$R_{i,t+2-t+3}$		$Q_{i,t+4-t+6}$		$R_{i,t+4-t+6}$	
$StyMomSignal_{i,t}$	0.071	0.057	-0.001	0.001	0.062	0.062	0.036	0.035	-0.028	-0.028	0.026	0.031
	(*5.19*)	(*4.22*)	(*-0.09*)	(*0.10*)	(*2.99*)	(*2.99*)	(*2.25*)	(*2.14*)	(*-1.07*)	(*-1.09*)	(*1.39*)	(*1.60*)
$R_nonQ_{i,t}$		0.233		0.037		0.103		0.040		-0.057		-0.004
		(*20.09*)		(*3.96*)		(*7.23*)		(*3.16*)		(*-3.45*)		(*-0.27*)
$Q_{i,t}$		0.240		-0.049		-0.034		-0.049		-0.179		-0.010
		(*29.24*)		(*-7.67*)		(*-2.49*)		(*-4.97*)		(*-9.40*)		(*-0.74*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	3.1%	14.9%	8.7%	14.3%	3.9%	7.8%	8.9%	13.7%	4.0%	8.7%	8.5%	12.8%

Table 9: Portfolio Sorting Approach by R_nonQ

This table reports subsequent weeks' average portfolio returns sorted by the orthogonalized return component ($R_nonQ_{i,t}$). In each week t, sample commodities are formed into three portfolios by the tercile of $R_nonQ_{i,t}$. Panel A reports the cumulative returns over subsequent 1 to 52 weeks' holding periods. These total return are decomposed into two components, Q-related returns and Q-orthogonal returns. In detail, Panel B and Panel C report the time-series averages of return components. The values reported in the table are in percent. t-statistics for the return difference between High and Low portfolios are adjusted using Newey-West method with 6 lags.

Panel A: Portfolio Subsequent Weeks' Returns

	R (p,t+1∼t+3)	R (p,t+4∼t+13)	R (p,t+14∼t+26)	R (p,t+27∼t+52)
Low $R_nonQ_{i,t}$	0.02	0.69	0.70	1.73
Median $R_nonQ_{i,t}$	0.17	0.86	1.24	2.45
High $R_nonQ_{i,t}$	0.56	1.00	1.43	2.95
High-Low	0.54	0.31	0.73	1.22
t-statistics	(*6.25*)	(*1.74*)	(*3.59*)	(*3.94*)

Panel B: Portfolio Subsequent Weeks' Q-related Returns

	R_Q (p,t+1∼t+3)	R_Q (p,t+4∼t+13)	R_Q (p,t+14∼t+26)	R_Q (p,t+27∼t+52)
Low $R_nonQ_{i,t}$	-0.35	0.32	0.14	0.34
Median $R_nonQ_{i,t}$	0.04	0.13	0.17	0.44
High $R_nonQ_{i,t}$	0.37	-0.26	-0.02	0.24
High-Low	0.71	-0.59	-0.16	-0.10
t-statistics	(*15.01*)	(*-8.60*)	(*-1.99*)	(*-1.08*)

Panel C: Portfolio Subsequent Weeks' Q-orthogonal Returns

	R_nonQ (p,t+1∼t+3)	R_nonQ (p,t+4∼t+13)	R_nonQ (p,t+14∼t+26)	R_nonQ (p,t+27∼t+52)
Low $R_nonQ_{i,t}$	0.36	0.35	0.54	1.27
Median $R_nonQ_{i,t}$	0.12	0.72	1.07	1.95
High $R_nonQ_{i,t}$	0.20	1.26	1.43	2.70
High-Low	-0.16	0.90	0.89	1.43
t-statistics	(*-1.91*)	(*5.73*)	(*4.90*)	(*5.01*)

Table 10: Persistence of Winners and Losers by Past Return(s)

The table reports the average discrete increase in the predicted probability of the commodity in the top tercile ($I_AW_{i,t}$=1) or bottom tercile ($I_AL_{i,t}$=1) when the count of historical wins (losses) increases by 1 unit. In each week t, we sort all sample commodities by their past 13-, 39-, or 52 weeks' cumulative returns, and $I_AW_{i,t}$ equals 1 ($I_AL_{i,t}$ equals 1) if commodity i is in top (bottom) tercile, and 0 otherwise. The independent variable is the count of weeks in the preceding corresponding 13-, 26-, 39-, or 52-week window during which the commodity's weekly return was in the top (bottom) tercile. Predicted probabilities are derived from the probit regressions:

$$\Pr(I_AW_{i,t} = 1 \mid Win_Count) = \Phi(\beta_0 + \beta_1 \cdot Win_Count)$$
$$\Pr(I_AL_{i,t} = 1 \mid Loss_Count) = \Phi(\beta_0 + \beta_1 \cdot Loss_Count)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF).

	Winner		Loser	
	margins	z-statistics	margins	z-statistics
13 weeks	15.61%	(*92.80*)	15.59%	(*122.60*)
26 weeks	10.01%	(*64.38*)	9.95%	(*67.89*)
39 weeks	7.37%	(*48.99*)	7.55%	(*54.77*)
52 weeks	6.26%	(*40.46*)	6.20%	(*42.59*)

Table 11: The Profits of Short- and Intermediate-Term Momentum Strategies

This table reports the momentum profits derived from sorting commodities based on their cumulative past returns (R) and orthogonalized return component (R_nonQ) over the formation windows of 1, 4, 13, 26, 39, and 52 weeks ending in week t-1. Commodities are sorted into three portfolios according to cumulative R or R_nonQ for each formation period. The return difference between the high and low portfolios in week t is calculated as the momentum profit. For instance, [1-week sorted by R] represents the momentum profit when sorting by the most recent week's total return, and [1-week sorted by R_nonQ] uses the orthogonal component return. The [1-week Diff] indicates the return difference in momentum profits between these two strategies, with similar comparisons made for the 4-, 13-, 26-, 39-, and 52-week formation intervals. t-statistics shown in the parentheses for the return and return difference are adjusted using the Newey-West method with six lags.

Formation Period	sorted by R	sorted by R_nonQ	Diff
1-week	0.09%	0.29%	0.20%
	(*1.66*)	(*5.75*)	(*6.75*)
4-week	0.00%	0.18%	0.18%
	(*-0.08*)	(*3.33*)	(*5.44*)
13-week	0.04%	0.15%	0.11%
	(*0.68*)	(*2.70*)	(*3.16*)
26-week	0.10%	0.19%	0.09%
	(*1.77*)	(*3.41*)	(*3.11*)
39-week	0.11%	0.17%	0.06%
	(*1.92*)	(*3.01*)	(*2.24*)
52-week	0.17%	0.24%	0.06%
	(*3.05*)	(*4.20*)	(*2.31*)

Table 12: Liquidity-based Return Reversal

This table reports the results from the Fama-Macbeth cross-sectional regressions of commodity futures return in week t+1 ($R_{i,t+1}$) on the non-commercials' net long position change ($Q_{i,t}$), its intersections with return- and volatility- related dummy variables, $R_nonQ_{i,t}$ and controls ($Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$). Specifically, in each week t, we sort all sample commodities by their $R_nonQ_{i,t}$, and dummy variable $RnonQHigh_Dm_{i,t}$ ($RnonQLow_Dm_{i,t}$) equals one if $R_nonQ_{i,t}$ in the top (bottom) 50th percentile, and 0 otherwise. In each week t, if $R_nonQ_{i,t}$ is positive (negative), then $RnonQPos_Dm_{i,t}$=1 ($RnonQNeg_Dm_{i,t}$=1), and 0 otherwise. In each week t, we sort all sample commodities by their $Volatility_{i,t}$, which is calculated by the rolling 52-week return standard deviation; the dummy variable $VolatHigh_Dm_{i,t}$=1 ($VolatLow_Dm_{i,t}$=1) if $Volatility_{i,t}$ in the top (bottom) 50th percentile cross-sectionally, and 0 otherwise. t-statistics shown in the parentheses are adjusted using Newey-West method with six lags.

	Dep. Var.=$R_{i,t+1}$					
$Q_{i,t}$	-0.052		-0.058		-0.023	
	(*-5.65*)		(*-5.19*)		(*-3.03*)	
$Q_{i,t}$*$RnonQHigh_Dm_{i,t}$	0.009	-0.043				
	(*0.66*)	(*-4.18*)				
$Q_{i,t}$*$RnonQLow_Dm_{i,t}$		-0.052				
		(*-5.65*)				
$Q_{i,t}$*$RnonQPos_Dm_{i,t}$			-0.001	-0.059		
			(*-0.04*)	(*-4.56*)		
$Q_{i,t}$*$RnonQNeg_Dm_{i,t}$				-0.058		
				(*-5.19*)		
$Q_{i,t}$*$VolatHigh_Dm_{i,t}$					-0.072	-0.095
					(*-4.54*)	(*-6.71*)
$Q_{i,t}$*$VolatLow_Dm_{i,t}$						-0.023
						(*-3.03*)
$R_nonQ_{i,t}$	0.038	0.038	0.037	0.037	0.039	0.039
	(*3.96*)	(*3.96*)	(*3.85*)	(*3.85*)	(*4.11*)	(*4.11*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	13.9%	13.9%	14.0%	14.0%	14.4%	14.4%

Appendix A: Tables

This appendix presents robustness tests corresponding to the tables in the main paper. Table A1 reports summary statistics for the primary variables used in our analysis. Table A2 investigates the distinct sources of the two orthogonal variables, Q and R_nonQ. In Table A3, utilizing the characteristics defined above, we conduct Fama-MacBeth regressions of $R_{i,t+1}$ on $R_nonQ_{i,t}$ and its interaction with $Characteristic_{i,t}$, to confirm the pervasiveness of short-term momentum pattern in R_nonQ. Table A4 and Table A5 examine the variance, covariance, and disagreement channels associated with the gross commodity futures return ($R_{i,t}$). Table A6 assesses the predictive power of $R_nonQ_{i,t}$ and $Q_{i,t}$ for subsequent R_nonQ over horizons ranging from one to six weeks. Similarly, Table A7 investigates the predictability of peer return ($StyMomSignal_{i,t}$) and individual return ($R_nonQ_{i,t}$) on the following R_nonQ across the same 1-to-6-week horizons. Table A8 employs Fama-MacBeth regressions to analyze the predictability of R_nonQ and Q for subsequent gross returns (R), Q-related returns (R_Q), and Q-orthogonal returns (R_nonQ) over 1-to-52-week horizons. Table A9 documents the time-series correlation between intermediate-term momentum returns and aggregated short-term momentum returns. In Table A10, we explore the trading-based reversals conditioned on the joint signs of Q and R_nonQ, concluding that the reversal effect is driven by trading behavior (Q) rather than past returns.

Table A1: Summary Statistics

This table presents the mean and standard deviation of key variables for each commodity over the period from January 1993 to September 2025. $R_{i,t}$ is the weekly return of commodity i in week t, defined as $[F_{i,t,T}$ - $F_{i,t-1,T}$ $/F_{i,t-1,T}]$, where $F_{i,t,T}$ is the futures price at the end of week t for a contract maturing on date T. $Q_{i,t}$ is defined as the non-commercial traders' net purchase of futures contracts, calculated as the change in non-commercial traders' net long position of commodity i between weeks t-1 and t, scaled by the open interest in week t-1, that is, $Q_{i,t} = [Net_Long_Position_{i,t}$- $Net_Long_Position_{i,t-1}]/Open_Interest_{i,t-1}$. $R_nonQ_{i,t}$ is the Q-orthogonal return component. We define the log futures basis ($Basis_{i,t}$) as $[ln(F_{i,t,T2})$-$ln(F_{i,t,T1})]/(T_2$-$T_1)$, where $F_{i,t,T1}$ and $F_{i,t,T2}$ are the prices of the first-nearby and second-nearby futures contracts for commodity i in week t. The basis momentum ($Basis_Momentum_{i,t}$) is defined as the difference between the past 52-week price momentum based on the first-nearby futures contract returns and that based on the second-nearby futures returns. For the construction of Smoothed Hedging Pressure ($SHP_{i,t}$), we calculate the hedging pressure as the number of futures contracts that the commercial traders are short minus the number of contracts that they are long, and then estimate the smoothed hedging pressure ($SHP_{i,t}$) as its rolling past 52-weeks' moving average, scaled by the total open interest, for commodity i in week t. $Crowding_{i,t}$ is defined as the non-commercial traders net long position of commodity i in week t, minus its 52 weeks' moving average from week t-1 to week t-52, scaled by commodity i's open interest in week t. $Volatility_{i,t}$ is defined as the past 52-week rolling standard deviation of each commodity's returns. All values are reported in percent.

	R		Q		Basis		Basis-Mom		SHP		Crowding		Volatility	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Wheat	-0.112	4.159	-0.006	3.572	-10.9	12.0	-1.9	5.1	-0.1	10.8	-0.4	9.6	3.6	1.0
KansasWheat	-0.005	3.981	-0.001	3.196	-6.2	13.1	1.6	5.0	7.6	9.6	-0.2	10.5	3.4	0.9
MinnWheat	0.074	3.580	-0.009	3.378	-2.3	15.5	4.0	10.3	6.7	12.1	-0.5	10.9	3.0	1.0
Corn	-0.009	3.560	0.027	3.000	-7.8	19.4	1.9	6.2	3.4	9.9	-0.2	10.9	3.0	0.9
Oat	0.209	4.744	0.042	4.806	-1.3	26.4	6.3	15.0	31.7	13.5	0.7	11.4	4.1	1.0
Soybean	0.137	3.109	0.003	3.307	3.6	24.0	1.6	4.7	9.1	12.1	-0.5	12.2	2.7	0.7
SoybeanOil	0.047	3.420	0.013	3.834	-2.5	12.1	1.6	4.4	12.5	11.0	-0.1	11.4	2.9	0.9
SoybeanMeal	0.259	3.651	0.017	3.549	9.1	27.5	4.2	8.8	19.1	9.4	0.0	11.0	3.2	0.8
RoughRice	-0.084	3.451	0.051	4.655	-8.2	25.2	-1.7	5.6	10.7	19.2	0.2	14.4	3.0	0.9
Oil	0.213	5.561	0.021	1.841	-1.5	28.3	-1.2	8.2	9.5	9.2	0.2	4.7	4.4	2.4
HeatingOil	0.195	4.621	0.007	2.305	-0.5	22.0	0.2	6.3	8.9	5.4	0.0	5.3	3.9	1.3
NaturalGas	-0.258	6.673	-0.012	1.945	-22.7	58.9	-6.3	13.1	-1.6	9.4	-0.1	5.9	5.7	1.5
Cotton	0.012	3.971	0.032	5.188	-4.6	17.7	0.2	8.3	11.5	15.8	0.0	17.8	3.4	1.1
OrangeJuice	0.196	4.561	0.025	5.489	-3.9	15.9	5.8	10.6	22.0	19.1	0.4	17.8	4.0	0.9
Lumber	-0.034	5.006	-0.055	7.178	-8.0	29.0	1.1	30.8	9.1	13.9	-0.5	18.2	4.2	1.5
Cocoa	0.224	4.226	0.010	3.287	-2.5	12.4	3.4	7.4	13.6	13.2	0.1	10.2	3.6	1.0
Sugar	0.140	4.273	0.035	3.752	2.6	20.1	1.0	10.2	15.8	11.5	0.0	12.7	3.7	1.0
Coffee	0.128	5.133	0.000	4.771	-6.7	14.3	2.7	9.9	11.6	11.3	0.3	13.3	4.4	1.2
Platinum	0.106	3.267	0.112	7.509	0.0	3.4	0.5	2.0	46.0	16.6	-0.3	17.3	2.7	1.0
Palladium	0.236	5.028	0.059	5.461	-0.7	5.2	0.6	4.9	31.5	34.5	-1.1	15.8	4.2	1.5
Silver	0.132	3.995	0.063	4.872	-3.0	2.0	0.0	0.7	37.0	12.7	0.1	12.1	3.4	1.2
Copper	0.163	3.287	0.011	4.402	0.3	6.3	-0.8	2.8	6.9	15.5	0.2	13.2	2.8	0.8
Gold	0.094	2.210	0.090	5.462	-2.7	1.9	0.2	0.4	27.9	22.2	0.5	12.8	1.9	0.7
LeanHogs	-0.016	3.928	0.044	3.542	-14.9	54.7	0.2	12.7	2.8	9.1	0.1	12.1	3.3	1.2
LiveCattle	0.052	2.170	0.060	2.838	-3.5	20.0	-0.2	5.3	7.9	9.3	0.3	9.8	1.9	0.6
FeedCattle	0.043	2.197	0.070	4.102	-2.7	13.3	0.4	4.2	-7.5	6.5	0.0	12.4	1.9	0.6
Average	0.082	3.991	0.027	4.125	-3.9	19.3	1.0	7.8	13.6	13.2	0.0	12.1	3.4	1.1

Table A2: The Determinants of Q and R_nonQ

This table presents the coefficients of non-commercial traders' net long change ($Q_{i,t}$ or the orthogonalized return component ($R_nonQ_{i,t}$) on the U.S. inflation rate ($Inflation_t$), the NBER Recession dummy ($Recession_t$), and the Baltic Dry Index (BDI_t). $Inflation_m$ is reported monthly, and thus we assign $Inflation_d$ as $Inflation_m$ for each day d in month m, and then define weekly $Inflation_t$ as the average of $Inflation_d$ when days d is in week t. $Recession_m$ is reported on the monthly basis, and thus we assign $Recession_d$ as $Recession_m$ for each day d in month m, and then define weekly $Recession_t$ as the average of $Recession_d$ when days d is in week t. Baltic Dry Index (BDI) is reported daily, and thus we define BDI_t as the average of BDI_d when days d is in week t. On the weekly basis, the mean, standard deviation, and median of $Inflation$ are 0.21%, 0.27%, and 0.21%, respectively, and corresponding statistics of BDI are 2,040, 1,724, and 1,464. Panel regressions include commodity-level fixed effect, and standard errors are clustered at the commodity and weekly levels.

	$Q_{i,t}$			$R_nonQ_{i,t}$		
$Inflation_t$	0.113			0.602		
	(*1.12*)			(*2.39*)		
$Recession_t$		-0.001			-0.005	
		(*-1.08*)			(*-1.76*)	
BDI_t			0.000			0.006
			(*-0.23*)			(*2.09*)
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	-0.1%	-0.1%	-0.1%	0.2%	0.2%	0.1%

Table A3: Short-Term Return Predictability of R_nonQ Across Various Characteristics

This table presents the average slope and t-statistics from Fama-Macbeth regressions of subsequent 1-week return ($R_{i,t+1}$) on the orthogonalized return component ($R_nonQ_{i,t}$), its interaction with characteristics-related dummies, speculators' net long position change ($Q_{i,t}$), and control variables. In Panel A, in each week t, we rank all sample commodities by their $Q_{i,t}$, and $HighQ_Dm_{i,t}$ ($LowQ_Dm_{i,t}$) equals to 1 if $Q_{i,t}$ is on the top (bottom) 50 percentile, and 0 otherwise; $PosQ_Dm_{i,t}$ ($NegQ_Dm_{i,t}$) equals to 1 if $Q_{i,t}$ is positive (negative), and 0 otherwise. In Panel B, C, and D, in each week t, we sort all sample commodities by their corresponding $Characteristics_{i,t}$, and $HighCharacteristic_Dm_{i,t}$ ($LowCharacteristic_Dm_{i,t}$) equals to if it is on the top (bottom) 50 percentile, and 0 otherwise. t-statistics shown in the parentheses are adjusted using Newey-West method, with 6 lags.

Panel A: (Un-)Conditional Return Predictability of $R_nonQ_{i,t}$ on the Q-Based characteristics

	Dep. Var. = $R_{i,t+1}$				
$R_nonQ_{i,t}$	0.036		0.024		0.039
	(*3.98*)		(*1.90*)		(*2.89*)
$R_nonQ_{i,t}$*$HighQ_Dm_{i,t}$		0.024			
		(*1.90*)			
$R_nonQ_{i,t}$*$LowQ_Dm_{i,t}$		0.045	0.021		
		(*3.72*)	(*1.27*)		
$R_nonQ_{i,t}$*$PosQ_Dm_{i,t}$				0.039	
				(*2.89*)	
$R_nonQ_{i,t}$*$NegQ_Dm_{i,t}$				0.054	0.013
				(*4.23*)	(*0.78*)
$Q_{i,t}$	-0.048	-0.046	-0.046	-0.046	-0.046
	(*-7.63*)	(*-6.53*)	(*-6.53*)	(*-6.91*)	(*-6.91*)
Controls	Yes	Yes	Yes	Yes	Yes
Adj R^2	13.5%	14.8%	14.8%	15.3%	15.3%

Panel B: Conditional Return Predictability of $R_nonQ_{i,t}$ on the Volume- and Turnover-Based Characteristics

	Dep. Var.=$R_{i,t+1}$					
$R_nonQ_{i,t}$		0.036		0.033		0.030
		(*2.78*)		(*2.58*)		(*2.50*)
$R_nonQ_{i,t}$*$HighDollarVol_Dm_{i,t}$	0.036					
	2.78					
$R_nonQ_{i,t}$*$LowDollarVol_Dm_{i,t}$	0.043	0.007				
	(*3.40*)	(*0.42*)				
$R_nonQ_{i,t}$*$HighNumVol_Dm_{i,t}$			0.033			
			(*2.58*)			
$R_nonQ_{i,t}$*$LowNumVol_Dm_{i,t}$			0.048	0.014		
			(*3.70*)	(*0.82*)		
$R_nonQ_{i,t}$*$HighTurnover_Dm_{i,t}$					0.030	
					(*2.50*)	
$R_nonQ_{i,t}$*$LowTurnover_Dm_{i,t}$					0.052	0.022
					(*3.87*)	(*1.32*)
$Q_{i,t}$	-0.049	-0.049	-0.051	-0.051	-0.048	-0.048
	(*-7.55*)	(*-7.55*)	(*-7.75*)	(*-7.75*)	(*-7.14*)	(*-7.14*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	15.8%	15.8%	15.7%	15.7%	15.8%	15.8%

Panel C: Conditional Return Predictability of $R_nonQ_{i,t}$ on the Open Interest- and SHP-Based Characteristics

	Dep. Var.=$R_{i,t+1}$					
$R_nonQ_{i,t}$		0.030		0.026		0.053
		(*2.37*)		(*2.02*)		(*4.23*)
$R_nonQ_{i,t}$*$HighDollarOI_Dm_{i,t}$	0.030					
	(*2.37*)					
$R_nonQ_{i,t}$*$LowDollarOI_Dm_{i,t}$	0.050	0.020				
	(*4.06*)	(*1.17*)				
$R_nonQ_{i,t}$*$HighNumOI_Dm_{i,t}$			0.026			
			(*2.02*)			
$R_nonQ_{i,t}$*$LowNumOI_Dm_{i,t}$			0.054	0.029		
			(*4.37*)	(*1.70*)		
$R_nonQ_{i,t}$*$HighSHP_Dm_{i,t}$					0.053	
					(*4.23*)	
$R_nonQ_{i,t}$*$LowSHP_Dm_{i,t}$					0.025	-0.025
					(*2.06*)	(*-1.54*)
$Q_{i,t}$	-0.048	-0.048	-0.049	-0.049	-0.048	-0.048
	(*-7.49*)	(*-7.49*)	(*-7.58*)	(*-7.58*)	(*-7.32*)	(*-7.32*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	15.6%	15.6%	15.2%	15.2%	15.3%	15.3%

Panel D: Conditional Return Predictability of $R_nonQ_{i,t}$ on the Past-Momentum-, Past-Value- and Basis-Momentum -Based Characteristics

	Dep. Var.=$R_{i,t+1}$					
$R_nonQ_{i,t}$		0.049		0.032		0.047
		(*3.35*)		(*2.65*)		(*3.35*)
$R_nonQ_{i,t}$*$HighPastMom_Dm_{i,t}$	0.049					
	(*3.35*)					
$R_nonQ_{i,t}$*$LowPastMom_Dm_{i,t}$	0.037	-0.012				
	(*3.06*)	(*-0.62*)				
$R_nonQ_{i,t}$*$HighPastValue_Dm_{i,t}$			0.032			
			(*2.65*)			
$R_nonQ_{i,t}$*$LowPastValue_Dm_{i,t}$			0.042	0.010		
			(*3.09*)	(*0.58*)		
$R_nonQ_{i,t}$*$HighBasisMom_Dm_{i,t}$					0.047	
					(*3.35*)	
$R_nonQ_{i,t}$*$LowBasisMom_Dm_{i,t}$					0.029	-0.018
					(*2.29*)	(*-0.99*)
$Q_{i,t}$	-0.047	-0.047	-0.050	-0.050	-0.050	-0.050
	(*-6.85*)	(*-6.85*)	(*-7.34*)	(*-7.34*)	(*-7.50*)	(*-7.50*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	15.9%	15.9%	15.3%	15.3%	15.5%	15.5%

Table A4: Volatility, Crowding, and Short-Term Momentum Pattern of R

This table presents the average slope of coefficients from Fama-Macbeth regressions of non-commercial traders' net long position change in week t+1 ($Q_{i,t+1}$) and subsequent week's return ($R_{i,t+1}$) on $R_{i,t}$, its interaction with crowding-related dummies, and controls. The control variables are $Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$. In each week t, all sample commodities are first grouped by the sign of $R_{i,t}$ (positive vs. negative), and within each group sorted by $crowding_{i,t}$ into high- and low-crowding subgroups. The dummy $HighCrowding_Dm_{i,t}$ equals 1 if a commodity belongs to positive-R / high-*crowding*, or negative-R / low-*crowding*, and 0 otherwise. Similarly, the dummy $LowCrowding_Dm_{i,t}$ equals 1 if a commodity belongs to negative-R / high-*crowding*, or positive-R / low-*crowding*, and 0 otherwise. The dummy variable $HighVolat_Dm_{i,t}$ ($LowVolat_Dm_{i,t}$) equals 1 if a commodity's volatility is above (below) the cross-sectional median in week t, and 0 otherwise. t-statistics in the parentheses are adjusted using Newey-West method with 6 lags.

	$Q_{i,t+1}$					$R_{i,t+1}$				
$R_{i,t}$	0.314		0.236		0.262	0.010		-0.022		0.000
	(*28.25*)		(*19.75*)		(*20.50*)	(*1.25*)		(*-2.19*)		(*-0.05*)
$R_{i,t}$*$HighCrowding_Dm_{i,t}$		0.236					-0.022			
		(*19.75*)					(*-2.19*)			
$R_{i,t}$*$LowCrowding_Dm_{i,t}$		0.420	0.184				0.046	0.067		
		(*25.25*)	(*10.74*)				(*4.12*)	(*4.99*)		
$R_{i,t}$*$HighVolat_Dm_{i,t}$				0.253					0.003	
				(*19.90*)					(*0.26*)	
$R_{i,t}$*$LowVolat_Dm_{i,t}$				0.461	0.209				0.028	0.025
				(*26.14*)	(*11.01*)				(*2.52*)	(*1.81*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	10.0%	10.9%	10.9%	10.8%	10.8%	12.3%	14.4%	14.4%	13.5%	13.5%

Table A5: Dispersion and Short-Term Momentum Pattern

This table presents the coefficients from panel regressions of non-commercial traders' net long position change in week t+1 ($Q_{i,t+1}$) or return ($R_{i,t+1}$) on an intercept, the orthogonalized return component ($R_nonQ_{i,t}$) or return ($R_{i,t}$), its intersections with dispersion-related dummy, $Q_{i,t}$ and control variables ($Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$). Return dispersion in week t is measured by the interquartile range and the standard deviation of commodity futures return ($R_{i,t}$) across the cross-section. The dummy variable $LowDispersion_Dm_t$ equals 1 if the dispersion measure falls in the bottom 50th percentile across all sample weeks, and 0 otherwise. Panel regressions include commodity-level fixed effect, with standard errors clustered at the commodity level.

	$Q_{i,t+1}$				$R_{i,t+1}$			
	Ret_Spread		*Ret_Std.Dev.*		*Ret_Spread*		*Ret_Std.Dev.*	
$R_nonQ_{i,t}$	0.287		0.264		0.142		0.097	
	(*5.41*)		(*5.31*)		(*5.91*)		(*2.69*)	
$R_nonQ_{i,t}$*$Dispersion_t$	-2.549		-2.082		-2.591		-1.651	
	(*-4.11*)		(*-2.96*)		(*-6.00*)		(*-1.97*)	
$Q_{i,t}$	0.225		0.225		-0.04		-0.04	
	(*21.95*)		(*21.66*)		(*-5.41*)		(*-5.40*)	
$R_{i,t}$		0.373		0.376		0.099		0.061
		(*6.26*)		(*6.35*)		(*4.74*)		(*1.87*)
$R_{i,t}$*$Dispersion_t$		-2.715		-2.855		-2.142		-1.386
		(*-4.12*)		(*-3.40*)		(*-5.89*)		(*-1.76*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	7.7%	5.8%	7.8%	6.0%	0.5%	0.3%	0.5%	0.3%

Table A6: Duration of Trend-Chasing Trading Behavior

This table present the average slope and t-statistics from Fama-MacBeth regressions of orthogonal return component (R_nonQ) over subsequent 1- to 6-week horizons (single and cumulative) on the week t's R_nonQ, Q, and controls. Control variables are $Basis_{i,t}$, $SHP_{i,t}$, and $BasisMomentum_{i,t}$. t-statistics are adjusted with Newey-West method, with 6 lags.

Dependent Variable: Subsequent 1 6 Weeks' R_nonQ									
	R_nonQ (i,t+1)	R_nonQ (i,t+2)	R_nonQ (i,t+3)	R_nonQ (i,t+4)	R_nonQ (i,t+5)	R_nonQ (i,t+6)	R_nonQ (i,t+1)	R_nonQ (i,t+2–t+3)	R_nonQ (i,t+4–t+6)
$R_nonQ_{i,t}$	-0.053	-0.01	0.013	0.000	0.011	0.007	-0.053	0.002	0.019
	(*-6.29*)	(*-1.22*)	(*1.52*)	(*0.01*)	(*1.26*)	(*0.91*)	(*-6.29*)	(*0.18*)	(*1.40*)
$Q_{i,t}$	-0.133	-0.041	0.002	0.011	0.021	0.012	-0.133	-0.039	0.046
	(*-22.52*)	(*-7.09*)	(*-0.37*)	(*-1.71*)	(*-4.13*)	(*-2.12*)	(*-22.52*)	(*-4.69*)	(*4.07*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	16.1%	13.1%	13.0%	13.3%	12.4%	11.9%	16.1%	13.7%	12.8%

Table A7: Individual-Level and Peer-Level Trend-Chasing Trading Behavior

This table shows the average slope and t-statistics from Fama-Macbeth cross-section regression of subsequent 1-week's or subsequent 2-3 weeks' cumulative orthogonalized return component (R_nonQ) on the style-based residual signal that is orthogonal to R_nonQ and Q ($StyleMomSignal_{i,t}$), orthogonalized return component ($R_nonQ_{i,t}$), speculators' net long position change ($Q_{i,t}$), and controls ($Basis_{i,t}$, $BasisMomentum_{i,t}$, and $SHP_{i,t}$). t-statistics are adjusted using Newey-West method, with 6 lags.

	$R_nonQ_{i,t+1}$		$R_nonQ_{i,t+2-t+3}$		$R_nonQ_{i,t+4-t+6}$	
$StyMomSignal_{i,t}$	-0.023	-0.016	0.011	0.011	0.040	0.044
	(*-2.09*)	(*-1.49*)	(*0.82*)	(*0.81*)	(*2.43*)	(*2.65*)
$R_nonQ_{i,t}$		-0.053		0.005		0.018
		(*-6.20*)		(*0.38*)		(*1.31*)
$Q_{i,t}$		-0.134		-0.037		0.046
		(*-22.85*)		(*-4.48*)		(*4.07*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	8.7%	16.6%	9.4%	14.1%	9.0%	13.2%

Table A8: The Return Predictability of *R_nonQ* by Fama-Macbeth Approach

This table presents the average coefficients from Fama-Macbeth cross-sectional regressions of subsequent 1∼3, 4∼13, 14∼26, and 27∼52 weeks' cumulative total returns, *Q*-related returns, and *Q*-orthogonal returns on $R_nonQ_{i,t}$, $Q_{i,t}$ and control variables ($Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$). *t*-statistics shown in the parentheses are adjusted using Newey-West method, with 6 lags.

Panel A: When Dependent Variables are Subsequent Weeks' Total Returns

	R (i,t+1∼t+3)	*R* (i,t+4∼t+13)	*R* (i,t+14∼t+26)	*R* (i,t+27∼t+52)
$R_nonQ_{i,t}$	0.077	-0.015	0.026	0.141
	(*4.76*)	(*-0.52*)	(*0.76*)	(*2.96*)
$Q_{i,t}$	-0.098	-0.027	-0.033	0.071
	(*-8.08*)	(*-1.16*)	(*-1.26*)	(*1.55*)
Controls	Yes	Yes	Yes	Yes
Adj R^2	13.4%	12.2%	12.1%	10.8%

Panel B: When Dependent Variables are Subsequent Weeks' *Q*-related Returns

	R_Q (i,t+1∼t+3)	*R_Q* (i,t+4∼t+13)	*R_Q* (i,t+14∼t+26)	*R_Q* (i,t+27∼t+52)
$R_nonQ_{i,t}$	0.125	-0.074	-0.026	-0.017
	(*16.64*)	(*-7.06*)	(*-2.14*)	(*-1.10*)
$Q_{i,t}$	0.07	-0.146	-0.088	0.006
	(*8.90*)	(*-10.68*)	(*-5.57*)	(*0.32*)
Controls	Yes	Yes	Yes	Yes
Adj R^2	10.0%	8.9%	7.9%	7.8%

Panel C: When Dependent Variables are Subsequent Weeks' *Q*-orthogonal Returns

	R_nonQ (i,t+1∼t+3)	*R_nonQ* (i,t+4∼t+13)	*R_nonQ* (i,t+14∼t+26)	*R_nonQ* (i,t+27∼t+52)
$R_nonQ_{i,t}$	-0.049	0.062	0.052	0.161
	(*-3.26*)	(*2.31*)	(*1.68*)	(*3.63*)
$Q_{i,t}$	-0.167	0.117	0.059	0.054
	(*-16.50*)	(*5.99*)	(*2.67*)	(*1.39*)
Controls	Yes	Yes	Yes	Yes
Adj R^2	15.4%	13.7%	12.7%	10.4%

Table A9: Correlation of Short-Term and Intermediate-Term Momentum

This table presents the average return of short-term and intermediate-term momentum strategies. In each week t, we sort sample commodities by their t-1, t-2,...t-52 single week's $R_{i,t-k}$ or $R_nonQ_{i,t-k}$, and form three portfolios (High, Median, and Low), and then calculate return difference between High and Low portfolio in week t, denoted as short-term momentum profit(t-k), k=1, 2,...52. In particular, *13-Week Average Short-Term Profit Based on R* is the equal average profits of short-term momentum strategies with $R_{i,t-k}$ as the sorting variable, k=1, 2,...13. In each week t, we also sort all sample commodities by their cumulative R or R_nonQ during week t-1$\sim t$-13, t-1$\sim t$-26, t-1$\sim t$-39, and t-1$\sim t$-52, and form three portfolios (High, Median, and Low), respectively. Then calculate return difference between High and Low portfolio in week t, denoted as k-week intermediate-term profit, k=13, 26, 39, 52. Particularly, *13-Week Traditional Intermediate-Term Profit Based on R* is the profit from intermediate-term momentum strategy with $R_{i,t-1\sim t-13}$ as the sorting variable.

Period	Momentum Profit	Based on R	corr	R_nonQ	corr
13-Week	Average Short-Term	0.03%	0.83	0.06%	0.81
	Traditional Intermediate-Term	0.04%		0.15%	
26-Week	Average Short-Term	0.03%	0.81	0.05%	0.81
	Traditional Intermediate-Term	0.10%		0.19%	
39-Week	Average Shorrt-Term	0.03%	0.82	0.04%	0.81
	Traditional Intermediate-Term	0.11%		0.17%	
52-Week	Average Shorrt-Term	0.04%	0.83	0.05%	0.82
	Traditional Intermediate-Term	0.17%		0.24%	

Table A10: Revisit of Trading-Based Reversal with Joint Signs of Q and R_nonQ

This table presents the coefficients from the panel regressions of subsequent week's return ($R_{i,t+1}$) on an intercept, the non-commercials' net long position change ($Q_{i,t}$), its interaction with joint sign-related dummy variables, ($R_nonQ_{i,t}$), and control variables. The control variables are $Basis_{i,t}$, $Basis_Momentum_{i,t}$, and $SHP_{i,t}$. If $Q_{i,t}$ and $R_nonQ_{i,t}$ are positive, then $QPos_RnonQPos_Dm_{i,t}$ equals 1, and 0 otherwise. If $Q_{i,t}$ is positive and R_nonQ is negative, then $QPos_RnonQNeg_Dm_{i,t}$ equals 1, and 0 otherwise. If $Q_{i,t}$ is negative and R_nonQ is positive, then $QNeg_RnonQPos_Dm_{i,t}$ equals 1, and 0 otherwise. If $Q_{i,t}$ and $R_nonQ_{i,t}$ are negative, then $QNeg_RnonQNeg_Dm_{i,t}$ equals 1, and 0 otherwise. If $Q_{i,t}$ and $R_nonQ_{i,t}$ have the same (opposite) signs, $SameSign_Dm_{i,t}$ ($OppoSign_Dm_{i,t}$) equals 1, and 0 otherwise. Panel regressions include commodity and weekly fixed effects, and standard errors are clustered at the commodity level.

	$R_{i,t+1}$					
$Q_{i,t}$	-0.036	-0.041	-0.035	-0.038	-0.036	-0.039
	(*-5.08*)	(*-5.83*)	(*-4.98*)	(*-4.27*)	(*-3.79*)	(*-5.11*)
$Q_{i,t}$*$QPos_RnonQPos_Dm_{i,t}$	-0.008					
	(*-0.63*)					
$Q_{i,t}$*$QPos_RnonQNeg_Dm_{i,t}$		0.012				
		(*1.19*)				
$Q_{i,t}$*$QNeg_RnonQPos_Dm_{i,t}$			-0.009			
			(*-0.78*)			
$Q_{i,t}$*$QNeg_RnonQNeg_Dm_{i,t}$				0.003		
				(*0.22*)		
$Q_{i,t}$*$SameSign_Dm_{i,t}$					-0.003	
					(*-0.29*)	
$Q_{i,t}$*$OppoSign_Dm_{i,t}$						0.003
						(*0.29*)
$R_nonQ_{i,t}$	0.031	0.031	0.028	0.029	0.031	0.031
	(*2.86*)	(*2.85*)	(*2.65*)	(*2.61*)	(*2.65*)	(*2.65*)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	13.4%	13.4%	13.4%	13.4%	13.4%	13.4%

Appendix B: Theoretical Model

1 Trend-Chaser Objective: Solution and Mapping

Set-up. At the end of week t, non-commercials implement $q_{i,t} = \alpha_{i,t}\,\mathrm{R_nonQ}_{i,t}$ and hold beliefs

$$E_t[R_{i,t+1}] \;=\; b_{i,t}\,\mathrm{R_nonQ}_{i,t}, \qquad \mathrm{Var}_t(R_{i,t+1}) \;=\; \sigma^2_{i,t}.$$

They choose intensity $\alpha_{i,t}$ to solve the mean–variance problem

$$\max_{\alpha_{i,t}} \Big\{\; E_t[q_{i,t}R_{i,t+1}] - \tfrac{\gamma}{2}\;\mathrm{Var}_t(q_{i,t}R_{i,t+1})\Big\}.$$

Expand each term. Using $q_{i,t} = \alpha_{i,t}\,\mathrm{R_nonQ}_{i,t}$ and the beliefs above,

$$E_t[q_{i,t}R_{i,t+1}] = \alpha_{i,t}\,\mathrm{R_nonQ}_{i,t}\cdot b_{i,t}\,\mathrm{R_nonQ}_{i,t} = \alpha_{i,t}\,b_{i,t}\,\mathrm{R_nonQ}^2_{i,t},$$

$$\mathrm{Var}_t(q_{i,t}R_{i,t+1}) = \alpha^2_{i,t}\,\mathrm{R_nonQ}^2_{i,t}\;\mathrm{Var}_t(R_{i,t+1}) = \alpha^2_{i,t}\,\mathrm{R_nonQ}^2_{i,t}\,\sigma^2_{i,t},$$

Factor the known signal magnitude. Since $\mathrm{R_nonQ}_{i,t}$ is known at time t, the objective factors $\mathrm{R_nonQ}^2_{i,t}$ and reduces to a scalar problem:

$$\max_{\alpha_{i,t}}\; \alpha_{i,t}\,b_{i,t} - \frac{\gamma}{2}\,\alpha^2_{i,t}\,\sigma^2_{i,t}$$

First-order condition and solution. Differentiating w.r.t. $\alpha_{i,t}$ and setting to zero,

$$b_{i,t} - \gamma\,\sigma_{i,t}^2\,\alpha_{i,t} \;=\; 0 \quad\Longrightarrow\quad \boxed{\alpha_{i,t}^{*} \;=\; \frac{b_{i,t}}{\gamma\,\sigma_{i,t}^2}}. \tag{3}$$

Economic intuition. A stronger perceived predictability $b_{i,t}$ raises intensity; higher risk $\sigma_{i,t}^2$ lowers it.

Inventory persistence mapping. Given the end-of-week decision, next-week flow obeys

$$Q_{i,t+1} \;=\; \psi_Q\,Q_{i,t} \;+\; \alpha_{i,t}\,\mathrm{R_nonQ}_{i,t} \;+\; \nu_{i,t+1}, \qquad 0 < \psi_Q < 1, \tag{2}$$

combining *inventory carry-over* ($\psi_Q\,Q_{i,t}$) and the *new trade* induced by the signal ($\alpha_{i,t}\,\mathrm{R_nonQ}_{i,t}$).

Comparative statics.

$$\frac{\partial \alpha_{i,t}^{*}}{\partial b_{i,t}} > 0, \qquad \frac{\partial \alpha_{i,t}^{*}}{\partial \sigma_{i,t}^2} < 0,$$

Perceived covariance increases trend-chasing intensity while risk dampens it.

2 market maker Objective: Solution and Mapping to (χ_R, χ_Q)

Set-up. Let the orthogonal component be $m_{i,t} \equiv \mathrm{R_nonQ}_{i,t}$ and inventory be $I_{i,t} = Q_{i,t}$. Outside demand is linear in next-week concessions, so inventories evolve as

$$I_{i,t+1} \;=\; I_{i,t} \;+\; \kappa\,m_{i,t+1} \;-\; \varepsilon_{i,t+1}, \qquad \kappa > 0.$$

Objective and parameters. The market maker chooses $m_{i,t+1}$ to minimize the convex loss

$$\mathcal{L}(m_{i,t+1}) = \tfrac{a}{2}\, m_{i,t+1}^2 + \tfrac{\phi}{2}\,(m_{i,t+1} - \rho_m\, m_{i,t})^2 + \tfrac{b}{2}\,\big(I_{i,t} + \kappa\, m_{i,t+1} - \varepsilon_{i,t+1}\big)^2,$$

where: $a > 0$ penalizes concessions (temporary impact), $b > 0$ penalizes inventory risk, and $\phi > 0$, $\rho_m < 0$ capture quote resilience/self-reversion.

First-order condition. Differentiate w.r.t. $m_{i,t+1}$:

$$a\, m_{i,t+1} + \phi\,(m_{i,t+1} - \rho_m m_{i,t}) + b\,\kappa\,\big(I_{i,t} + \kappa m_{i,t+1} - \varepsilon_{i,t+1}\big) \;=\; 0.$$

Collect terms. Define $\mathcal{D} \equiv a + \phi + b\kappa^2$. Rearranging,

$$\mathcal{D}\, m_{i,t+1} - \phi\rho_m\, m_{i,t} + b\kappa\, I_{i,t} - b\kappa\, \varepsilon_{i,t+1} \;=\; 0 \quad\Longrightarrow\quad m_{i,t+1} = \frac{\phi\rho_m}{\mathcal{D}}\, m_{i,t} - \frac{b\kappa}{\mathcal{D}}\, I_{i,t} + \frac{b\kappa}{\mathcal{D}}\, \varepsilon_{i,t+1}.$$

Reduced-form for the orthogonal component. With $m_{i,t} = \mathrm{R_nonQ}_{i,t}$ and $I_{i,t} = Q_{i,t}$,

$$\boxed{R_{\mathrm{nonQ},i,t+1} \;=\; \chi_R\, \mathrm{R_nonQ}_{i,t} \;+\; \chi_Q\, Q_{i,t} \;+\; \tilde{\varepsilon}_{i,t+1}}, \qquad \chi_R \;=\; \frac{\phi\rho_m}{\mathcal{D}} \;<\; 0, \qquad \chi_Q \;=\; -\,\frac{b\kappa}{\mathcal{D}} \;<\; 0, \tag{4}$$

where $\tilde{\varepsilon}_{i,t+1} \equiv \frac{b\kappa}{\mathcal{D}}\, \varepsilon_{i,t+1}$. Quote resilience yields mild self-reversion ($\chi_R < 0$) and inventory costs imply compensation for absorbing flow ($\chi_Q < 0$).

Stronger inventory penalties or demand sensitivity magnify leaning against flow; stronger resilience speeds self-reversion.

3 Coexistence at the Same Weekly Horizon

Combine trader, persistence, and market maker dynamics. Start from the return decomposition,

$$R_{i,t} \;=\; b_0 + b_1\, Q_{i,t} + \varepsilon_{i,t}, \qquad \mathrm{R_nonQ}_{i,t} \;\equiv\; b_0 + \varepsilon_{i,t}, \tag{1}$$

the inventory persistence,

$$Q_{i,t+1} \;=\; \psi_Q\, Q_{i,t} \;+\; \alpha^*_{i,t}\, \mathrm{R_nonQ}_{i,t} \;+\; \nu_{i,t+1}, \tag{2}$$

and the orthogonal-component reduced form,

$$R_{\mathrm{nonQ},i,t+1} \;=\; \chi_R\, \mathrm{R_nonQ}_{i,t} \;+\; \chi_Q\, Q_{i,t} \;+\; \tilde{\varepsilon}_{i,t+1}. \tag{4}$$

Then

$$\begin{aligned} R_{i,t+1} &= b_1\, Q_{i,t+1} + R_{\mathrm{nonQ},i,t+1} \\ &= b_1\big(\psi_Q\, Q_{i,t} + \alpha^*_{i,t}\, \mathrm{R_nonQ}_{i,t} + \nu_{i,t+1}\big) + \chi_R\, \mathrm{R_nonQ}_{i,t} + \chi_Q\, Q_{i,t} + \tilde{\varepsilon}_{i,t+1}. \end{aligned}$$

Collecting terms in $Q_{i,t}$ and $\mathrm{R_nonQ}_{i,t}$ gives

$$\boxed{R_{i,t+1} \;=\; (b_1\psi_Q + \chi_Q)\, Q_{i,t} \;+\; (b_1\alpha^*_{i,t} + \chi_R)\, \mathrm{R_nonQ}_{i,t} \;+\; \text{shock}}, \tag{5}$$

with

$$\underbrace{c_Q}_{\text{reversal}} \;=\; b_1\psi_Q + \chi_Q \;<\; 0, \qquad \underbrace{c_{\mathrm{nonQ}}}_{\text{momentum}} \;=\; b_1\alpha^*_{i,t} + \chi_R \;>\; 0 \quad \text{(typically)}.$$

Reversal reflects the liquidity/immediacy channel ($\chi_Q < 0$), while momentum is endogenous trend-chasing (positive $b_1\alpha^*_{i,t}$ outweighs mild self-reversion $\chi_R < 0$).

Empirical Mapping Estimate

$$R_{i,t+1} = c_0 + c_{\text{nonQ}}\,\text{R_nonQ}_{i,t} + c_Q\,Q_{i,t} + \text{controls} + u_{i,t+1},$$

expecting $c_{\text{nonQ}} > 0$ and $c_Q < 0$. Auxiliary one-step tests:

$$\text{R_nonQ}_{i,t} \to Q_{i,t+1} > 0 \quad \text{(trend-chasing ramp-up)},$$

$$Q_{i,t} \to R_{\text{nonQ},i,t+1} < 0 \quad \text{(market makers' leaning)}.$$

Appendix C: Application of Machine Learning in Predicting Momentum Signal

Framework and Prediction Target. In the conventional approach, the sorting signal is defined as the cumulative *R_nonQ* from week t-1 to week t-52, which implicitly assigns equal weight to returns in each of the past 52 weeks. We label this benchmark as the classic equal-weight (EW) momentum strategy. We use machine learning models to predict a rank-friendly target variable, computed as follows: $y_{i,t} = R_{i,t} - \bar{R}_t - \sigma(R_t)$, where $R_{i,t}$ is the commodity futures return, and $\bar{R}_t$ and $\sigma(R_t)$ are the cross-sectional mean and standard deviation of returns at week t, respectively.

Based on the model prediction of the sorting signal, we rank all sample commodities into three portfolios (High, Median, and Low), and the profit of momentum strategy is calculated as the return difference between the High and Low portfolio in week t.

Feature Engineering and Experimental Design. We construct four predictive features based on historical momentum strategies. The past 52 weekly lags of the *R_nonQ* are aggregated into four distinct variables to capture momentum effects. Each $feature$ is the equal-weighted average of *R_nonQ* lags within specific range, from week t-1$\sim t$-13, week t-14$\sim t$-26, week t-27$\sim t$-39, and week t-40$\sim t$-52, respectively. Compared with using each single week's *R_nonQ* as one feature, this approach could reduce dimensionality and creates economically interpretable predictors. To evaluates out-of-sample performance, we use the framework of 15-year training windows. In detail, for each experiment, the model is trained on the specific window length, and then tested on the subsequent 1-year (52-week) period. The entire window then rolls forward by 1 year, and repeats the above process.

Specifically, we evaluate a curated set of five machine learning models, chosen to represent a diverse range of algorithmic approaches, alongside a traditional momentum benchmark. The selected models include Tree-based Models (Random Forest and eXtreme Gradient Boosting (XGBoost)). We denote these as machine learning augmented momentum strategies, as they retain the standard portfolio construction framework but replace the traditional sorting signal with a machine learning-predicted one.