Weekly Momentum in the Commodity Futures Market

Kyung Yoon Kwon[‡], Jangkoo Kang[†], and Jaesun Yun[*]

Abstract

This paper investigates commodity futures momentums with various ranking periods in a weekly basis. Unlike in equity markets, strong short-term momentum, instead of short-term reversal, is observed in commodity futures markets. The weekly momentum remains highly significant even after controlling for various factors, such as carry, equity momentum, or hedging pressure. Our results suggest that the anomalous returns from the traditional 12-month momentum strategy in the commodity futures markets mainly stem from the strong predictability of the past week's return. Lastly, we suggest that the weekly momentum is closely related to the speculative activity in the commodity futures market.

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[‡] Department of Accounting and Finance, Strathclyde Business School, University of Strathclyde; 199 Cathedral street, Glasgow, G4 0QU, Scotland, UK; tel: +44-141-548-3935; e-mail: arari1115@gmail.com

[†] College of Business, Korea Advanced Institute of Science and Technology; 85 Hoegiro, Dongdaemoon-gu, Seoul, 02455, South Korea; tel: +82-2-958-3521; e-mail: jkkang@kaist.ac.kr

[*] Corresponding Author; College of Business, Korea Advanced Institute of Science and Technology; 85 Hoegiro, Dongdaemoon-gu, Seoul, 02455, South Korea; tel: +82-2-958-3697; e-mail: gwyneth@kaist.ac.kr

1. Introduction

This paper examines the profitability of commodity futures momentum strategies across different ranking periods on a weekly basis. In the literature on stock momentum, the question of how the profitability of momentum strategies varies depending on the ranking period has been investigated since Jegadeesh and Titman (1993) first documented the existence of stock momentum.[1] By contrast, the profitability of commodity futures momentum across different ranking periods has rarely been examined, although a body of the literature has reported the existence of momentum even in commodity futures markets.[2] More importantly, the literature on commodity futures momentum has revealed substantial differences between stock and commodity futures momentums, but the literature has mainly focused on 12-month momentum by simply following the conventional methodology of stock momentum.[3] Specifically, the literature has reported strong short-term (especially one-month) reversals and intermediate-term (generally 12-month) momentum in stock markets (Nagel, 2012; Novy-Marx, 2012; Asness et al., 2013), but Shen et al. (2007) and Kang and Kwon (2017) report that one-month momentum is especially strong in commodity futures markets.

In this paper, we construct four different momentum strategies by decomposing the past 12 months (52 weeks) into four subperiods – called weekly, monthly, half-yearly, and yearly momentums – and examine their profitability.[4] Our results are in stark contrast to the previous findings on stock momentum. We show that weekly momentum is strongest and most robust in the commodity futures market. Although Shen et al. (2007) and Kang and Kwon (2017) report the existence of one-month momentum in commodity futures markets, weekly momentum has not been reported in any literature. More importantly, our results show that weekly momentum is strongest and even fully spans monthly momentum. Our results suggest that the success of the conventional 12-month momentum strategy in

[1] For example, Novy-Marx (2012) suggests that the past performance of the intermediate horizon (12 to seven months prior to formation) contributes more to momentum profits than the past performance of the recent horizon (six to two months prior to formation).
[2] The literature on commodity futures momentum includes Erb and Harvey (2006), Miffre and Rallis (2007), Asness et al. (2013), and Kang and Kwon (2011).
[3] For example, Asness et al. (2013), Szymanowska et al. (2014), and Daniel and Moskowitz (2016).
[4] See more details in Section 3.1.

commodity futures markets that is well documented in the literature mainly stems from weekly momentum.

Motivated by Asness et al. (2013), we investigate whether commodity futures momentum is driven by the comovement of momentums across various asset markets. Our results show that weekly and monthly momentums are not significantly related to stock momentum, implying that these short-term momentums are commodity market specific. Next, we examine the hedging premium as a possible commodity market specific source for commodity momentum, but find that weekly momentum remains significant, even after controlling for hedging pressure.

We further explore the relation between commodity momentum and speculative activity as a possible driver of momentum. We first confirm that speculators are short-term momentum traders who follow the trend for only up to two weeks and weekly momentum is distinctively closely related to speculators' trading position factors, whereas yearly momentum shows an insignificant or opposite relation. Although our results cannot provide a factor that can fully explain the weekly commodity momentum, we shed light on its possible source for future research.

2. Data

We collect the daily settlement price data of 32 US commodity futures from Datastream. We construct daily, weekly, and monthly return series for each commodity future. Specifically, at the beginning of each period, we hold the nearest contract of each commodity future that does not expire in the next month. Our sample spans the period from January 1979 to June 2015. We report the list of commodities and the summary statistics of weekly returns in Table 1.

For position-related variables, we use publicly available position data from three investor groups—commercial, noncommercial, and non-reportable—provided by the US Commodity Futures Trading Commission (CFTC). Following a majority of the literature using position data from

Commitments of Traders reports (Bessembinder, 1992; Bessembinder and Chan, 1992; Basu and Miffre, 2013),[5] we regard commercial investors as hedgers and noncommercial investors as speculators.[6]

3. Empirical results

3.1. Profitability of commodity futures momentum strategies

We construct four momentum strategies by decomposing the past 12 months (52 weeks) into four subperiods.[7] In each week *t*, we construct momentum strategies based on four different past returns, namely, on week *t* - 1, weeks *t* - 4 to *t* - 2, weeks *t* - 26 to *t* - 5, and weeks *t* - 52 to *t* - 27. The returns on the resulting long–short portfolios[8] are denoted as weekly ($CMOM_{1,1}$), monthly ($CMOM_{4,2}$), half-yearly ($CMOM_{26,5}$), and yearly ($CMOM_{52,27}$) momentums, respectively.

Panel A of Table 2 shows that weekly momentum generates a large average return, which is 0.20% (t = 4.49) and even comparable to yearly momentum, which has an average return of 0.23% (t = 3.19). Shen et al. (2007) and Kang and Kwon (2017) report one-month momentum in commodity futures markets, as opposed to the one-month reversal in stock markets (Nagel, 2012; Novy-Marx, 2012); however, weekly momentum has not been reported in any literature.

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[5] Since non-reportable traders account for a small proportion of the total open interest (10–30%) and their identities, whether they are hedgers or speculators, are rather unclear, we focus on the open interest of commercial and noncommercial traders.

[6] The CFTC collects data and announces Commitments of Traders reports. These reports are released weekly since 1992 and include the open interest hold by each investor group and the spreading positions hold by noncommercial investors. The CFTC only provides aggregate levels of positions, independent of the delivery month. When we match the position data with return series, we calculate the weekly returns on every Tuesday, because the position data are collected at the end of every Tuesday on a weekly basis.

[7] Specifically, we follow Novy-Marx (2012), who suggests non-overlapping ranking periods, because this approach enables us to examine the marginal profitability of each momentum strategy.

[8] The momentum strategy is constructed by buying the top quintile portfolio and selling the bottom quintile portfolio.

To compute the risk-adjusted returns, we regress the momentum return on two risk factors suggested by Bakshi et al. (2019):[9] an average factor AVG_t, which is the equal-weighted average of the excess returns of all available commodity futures, and a carry factor $CARRY_t$, which is the return on a long–short portfolio that buys the most backwardated contracts (top quintile) and sells the most contangoed contracts (bottom quintile).

Panel B of Table 2 reports the risk-adjusted returns (Intercept) and the factor loadings. Our results show that shorter momentum tends to generate larger risk-adjusted returns. $CMOM_{1,1}$ and $CMOM_{4,2}$ show positive and significant intercepts, and the intercept for $CMOM_{1,1}$ is especially large and significant, at 0.20%, with *t* = 4.30. By contrast, $CMOM_{52,27}$ becomes insignificant when risk factors are controlled for (intercept = 0.09%, with *t* = 1.46). Miffre and Rallis (2007) report that the 12-month commodity futures momentum strategy tends to buy backwardated and sell contangoed contracts, implying that its profitability can be captured by *CARRY*. Our results show that only long-term momentums $CMOM_{5,26}$ and $CMOM_{52,27}$ are significantly and largely captured by *CARRY*, while $CMOM_{1,1}$ and $CMOM_{4,2}$ are not.

Our results in Table 2 offer new insights to commodity futures momentum studies. Unlike previous studies, which are mainly focused on the traditional 12-month momentum, our findings suggest that weekly momentum is the strongest and most robust. We also regress each momentum on other momentums to see whether the momentums can span each other. In untabulated results, we find that weekly momentum is not fully spanned by other momentums, generating significant intercepts in all regressions. However, we find that, if we regress $CMOM_{4,2}$ on $CMOM_{1,1}$, then $CMOM_{4,2}$ is largely captured by $CMOM_{1,1}$ and generates an insignificant intercept (*t* = -0.40). These results suggest that commodity futures momentum profits mainly stem from short-term momentum, especially weekly momentum.[10]

[9] Bakshi et al. (2019) originally suggest a three-factor model including an average factor, a carry factor, and a six-month momentum factor. However, we drop the momentum factor, since momentum is of our variable of interest, to be explained in this paper.

[10] We additionally investigate whether our findings in Section 3.1. are robust to the characteristic of

3.2. Momentum everywhere

Asness et al. (2013) show that the 12-month momentum in various asset classes have significant relations with stock momentum (*UMD*), which is regarded as a common momentum factor.[11] However, the relation between weekly momentum, which is stronger and more robust, especially in the commodity futures market, and *UMD* has not yet been examined. We therefore revisit the relation with *UMD* using our four test strategies.[12] We regress $CMOM_{k_1,k_2}$ on *UMD* without and with controlling factors (Panels A and B of Table 3, respectively).

Both panels of Table 3 exhibit consistent results. The results show that all momentums, except weekly momentum, have significant and positive relations with *UMD*. Both weekly and monthly momentums show significant intercepts, even after we control for *UMD* and other risk factors, but weekly momentum shows much stronger and more significant results.

Compared to Table 2, weekly momentum shows robust profits, regardless of whether other effects are controlled for, whereas other momentums, especially yearly momentum, show much less robust results. For example, Panel A of Table 2 shows that the raw excess return on $CMOM_{1,1}$ is 0.20% and Panel B of Table 3 shows that its risk-adjusted return is 0.19%. By contrast, the raw excess return on $CMOM_{52,27}$ is 0.23% (Panel A of Table 2), but its risk-adjusted return is 0.08% and even insignificant.

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commodities. First, we construct the sector-momentum portfolio, which is the portfolio buying the sector whose past return over the ranking period is highest and selling the sector portfolio past return over the ranking period is lowest. Second, we control the commodity sector by constructing double-sorted portfolios. From both approaches, we confirm the consistent results that the weekly momentum is the robust to the various sets of controlling factors and not significantly related to *UMD*. See details from Supplementary Material (available online).

[11] In addition to Asness et al. (2013), Moskowitz et al. (2012) also document that the time-series momentum in commodity futures has significant comovement with *UMD*. Novy-Marx (2012) tests two commodity futures momentum strategies, based on returns from month t - 12 to month t - 7 (12-7 momentum) and from month t - 6 to month t - 2 (6-2 momentum), and reports that both are positively correlated with *UMD*, with 12-7 momentum showing a slightly weaker correlation. Novy-Marx (2012) also documents that 12-7 momentum is a robust and common phenomenon over various asset classes, such as commodity futures and currency.

[12] The equity momentum factor (*UMD*) is obtained from Ken French's Website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). We use the data from January 1979 to June 2015 to match the sample period with the commodity futures market data.

These results suggest that weekly momentum in the commodity futures market can be commodity market specific, since it exceptionally shows an insignificant relation with *UMD*.

3.3. Hedging premium

Traditional theories of commodity futures explain risk premiums on commodity futures with the net position of hedgers in commodity futures. Specifically, according to the hedging pressure hypothesis (Cootner, 1960), hedgers pay a premium for transferring prick risk, and speculators receive the premium for bearing the risk. The literature has also provided empirical evidence that the hedging pressure can explain commodity futures momentum (Basu and Miffre, 2013; Dewally et al., 2013).

Motivated by these previous findings, we examine whether the hedging premium can explain the commodity futures momentum. Following Kang et al. (2019), we first define the hedging pressure for commodity *i* in week *t* as

$$Hedging\ Pressure_{i,t} = -\frac{(hedgers\ net\ long\ position)_{i,t}}{OI_{i,t}} \tag{1}$$

where *OI* indicates the open interest, the total number of contracts outstanding. Then, we form a hedging pressure–mimicking portfolio sorted on the past 12-month hedging pressure average. The resulting factor is denoted *HP*. Next, we regress $CMOM_{k_1,k_2}$ on *HP* with two controlling variables, *AVG* and *CARRY*, to investigate whether the hedging premium can explain our test momentums.

Table 4 shows that *HP* is significantly and positively related to all momentums, consistent with the literature (Basu and Miffre, 2013; Dewally et al., 2013), but weekly momentum shows the smallest and least significant coefficient on *HP*. More importantly, weekly momentum remains significant, even after *HP* is controlled for, while the other momentums exhibit insignificant intercepts.

3.4. Possible sources: Speculative activity

Our results in Sections 3.2 and 3.3 show that weekly momentum cannot be fully explained by common momentum movement or the traditional hedging pressure hypothesis. We thus further examine other possible economic sources underlying the strong weekly momentum. Specifically, we examine whether trading activities in commodity futures markets are related to momentum. Although traditional theories of commodity futures have paid more attention to hedgers, recent studies on commodity futures also highlight the importance of speculators, the counterparty of hedgers.[13] The literature on commodity futures has thus reported that the risk premium of commodity futures is closely associated with hedgers' and speculators' trading activities, and we expect these to be commodity market specific features distinctive of other financial markets.

More importantly, we expect momentum to be closely associated with speculators. The literature has reported that speculators tend to be momentum traders (Fung and Hsieh, 2001; Dewally et al., 2013; Kang et al., 2019), and Bakshi et al. (2019) show that growth in aggregate speculative activity can explain the risk premium of the six-month momentum strategy, and it is unique to commodity markets. We therefore expect weekly momentum to be more closely associated with speculative activity than with hedging pressure.

We first examine whether speculators are momentum traders, as previous studies document. Following Kang et al. (2019), we measure the net long position change of each investor group ($Q_{i,t,k}$)[14] and conduct cross-sectional Fama–MacBeth (1973) regressions of weekly net position changes on past returns for each trader group:

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[13] For example, Kang et al. (2019) document two types of risk premiums in commodity futures: one from the trading demands of impatient speculators and the other from the hedging demands of commercial hedgers. Acharya et al. (2013) also address the importance of speculators' risk capacity in determining the risk premium of commodity futures.

[14] More precisely, it is defined as follows:

$$Q_{i,t,k} = \frac{\left(Long_{i,t,k} - Short_{i,t,k}\right) - \left(Long_{i,t-1,k} - Short_{i,t-1,k}\right)}{OI_{i,t-1}}$$

where $Long_{i,t,k}$ ($Short_{i,t,k}$) indicates the number of long (short) positions of investor group k for commodity i in week t, and $OI_{i,t-1}$ is total open interest on commodity i in week t - 1.

$$Q_{i,t,k} = a_0 + a_1 R_{i,t-j} + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t-k}$ is the excess return on commodity i in week t - j, j = 0, …, 11.

In Table 5, when j = 0, the coefficient is strongly negative for hedgers and positive for speculators. A similar pattern is observed up to j = 2. This result indicates that hedgers trade as contrarian players, while speculators are trend chasers, as we expected, but speculators unwind their momentum positions after two weeks and hedgers also reverse their positions after two weeks.

More importantly, Table 5 shows that the speculators' trend-following trading behavior is especially notable in the first week (j = 1). Table 5 shows that speculators strongly buy the previous week's winners and sell the previous week's losers, and their trend-following behavior substantially drops the second week and then even becomes negative the third week. These results suggest that weekly momentum can be a consequence of the trading activities of speculators.

Next, we construct more direct factors regarding speculators' trading activities: speculators' directional and spreading position factors. Following Bakshi et al. (2019), we measure aggregate speculative activity with the directional positions of speculators as

$$Directional\ Position_{i,t} = \frac{long_{i,t,spec} + short_{i,t,spec}}{OI_{i,t}} \tag{3}$$

where $long_{i,t,spec}$ ($short_{i,t,spec}$) indicates the total long (short) position of speculators on commodity i in week t. We then equally weight *Directional Position*$_{i,t}$ in the cross section and compute its first differential. The resulting factor is denoted ΔDP.

The spreading position data were first introduced by Boons and Prado (2019). They show that the spreading position is significantly and negatively priced in commodity futures markets, and they explain that, in times of high uncertainty, speculators can be averse to taking a directional position and thus prefer spreading positions. It is rather unclear how the spreading position is related to momentum, but, along with the argument of Bakshi et al. (2019), we could expect the spreading position to be negatively related to commodity futures momentum, since it implies a decrease in speculators' directional trading (or speculative activity in commodity markets). Following Boons and Prado (2019), we measure the spreading position as

$$Spreading\ position_{i,t} = \frac{Spreading_{i,t,spec}}{OI_{i,t}} \tag{4}$$

where $spreading_{i,t,spec}$ indicates the total spreading position of speculators on commodity *i* in week *t*. Then, *ΔSP* is similarly defined as *ΔDP*.

Using those factors, we conduct the following time-series regression test:

$$CMOM_{(k_1,k_2),t} = a_0 + \beta' F_t + \delta' X_t + \varepsilon_{i,t} \tag{5}$$

where $CMOM_{(k_1,k_2),t}$ is the commodity futures momentum based on the return from week t - k_1 to week t - k_2 on week t, F_t is a subset of speculative activity factors $\{\Delta DP_t$ and $\Delta SP_t\}$, and X_t is a set of controlling factors, $\{AVG_t$ and $CARRY_t\}$ or $\{AVG_t$, $CARRY_t$, and $HP_t\}$.[15]

Panels A and B of Table 6 show that speculators' trading factors – ΔDP and ΔSP– are related to our test momentums in a different way. In the case of ΔDP, only $CMOM_{1,1}$ and $CMOM_{4,2}$ are positively related, while $CMOM_{52,27}$ exhibits a significantly negative relation. Interestingly, the argument of Bakshi et al. (2019) that commodity futures momentum increases when the total directional position held by speculators increase seems to hold only in the short term. This result is also consistent with our findings in Table 5, that speculators trade in momentum only in the short term. ΔSP also shows significant results only for $CMOM_{1,1}$, and the coefficient is negative, as we expected. If we include both factors together (Panel C), our results appear to be qualitatively similar.[16]

[15] More specifically, we first include each of the positions factors as F_t in Eq. (5), with $\{AVG_t$ and $CARRY_t\}$ as X_t, and the results are reported in Panels A and B of Table 6, respectively. Next, we include both speculative activity factors and *HP* as a control variable to examine the marginal effects of speculative activity (Panel C of Table 6).

[16] In Panel C of Table 6, the coefficients on ΔSP become slightly weaker, which could be due to the fact that the increase in the spreading position (ΔSP) could be related to the decrease in directional position (ΔDP), as Boons and Prado (2019) argue.

Overall, Table 6 suggests that weekly momentum is closely related to speculative activity factors. Along with our previous findings, that weekly momentum is the strongest and most robust phenomenon in the commodity futures market, our findings in this section shed light on the possible source of this puzzling weekly commodity momentum for future research, which is speculative activity in the commodity futures market.

4. Conclusion

This paper suggests that the anomalous returns of the traditional 12-month momentum strategy in commodity futures markets mainly stem from the strong predictability of the past week's return. Weekly momentum cannot be fully explained by various factors while other momentums can be explained, but we suggest that this puzzling weekly momentum is closely related speculative activity in the commodity futures market.

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Table 1. Data description

Panel A shows the list of commodity futures used in this paper. According to categorization of Gorton et al. (2012) and Kang and Kwon (2017), our sample includes five in metals, seven in soft commodities, seven in grains, six in meats, and seven in energy. Panel B shows the summary statistics of the monthly returns on each commodity futures and the sector portfolio (Average). In particular, we report the average, standard deviation (stdev), skewness (skew), and kurtosis (kurt) of the weekly returns. The sample period is from January 1979 to June 2015.

Panel A. List of Commodities

Commodity Sector	Commodity
Metals	Copper, gold, palladium, platinum, and silver
Softs	Ethanol, random length lumber, cocoa, coffee ‘C’, cotton seed, orange juice (FCOJ), and sugar
Grains	Corn, oats, rough rice, soybeans, soybean meal, No. 2 red wheat, and hard red spring wheat
Meats	Butter, feeder cattle, live cattle, dry whey, lean hogs, and milk
Energies	Coal, Brent crude oil, light sweet crude oil, heating oil, gasoline, electricity, and natural gas

Panel B. Summary statistics

		Average	Stdev	Skew	Kurt
Metals					
	Copper	0.15	3.41	-0.05	2.12
	Gold	0.03	2.70	0.44	7.02
	Palladium	0.16	4.72	-0.15	3.76
	Platinum	0.08	3.67	0.12	4.58
	Silver	0.05	4.64	-0.05	9.55
	Average	0.09	3.19	-0.38	5.43
Softs					
	Ethanol	0.72	4.70	0.11	1.82
	Random Length Lumber	-0.15	4.07	0.18	0.63
	Cocoa	-0.02	4.20	0.56	2.57
	Coffee 'C'	0.04	4.94	0.62	4.28
	Cotton seed	0.04	3.57	0.09	2.48
	Orange Juice (FCOJ)	0.02	4.12	0.61	3.95
	Sugar	-0.02	5.68	0.31	4.51
	Average	0.01	2.14	0.05	0.71
Grains					
	Corn	-0.07	3.38	0.49	4.30
	Oats	0.00	4.42	0.58	5.10
	Rough Rice	-0.14	3.66	-0.06	2.50
	Soybeans	0.05	3.16	0.06	1.99
	Soybean Meal	0.18	3.57	0.26	1.49
	No.2 Red Wheat	0.04	3.29	0.34	2.04
	Hard Red Spring Wheat	0.09	3.19	0.35	4.57
	Average	0.03	2.57	0.35	2.43
Meats					

	Butter	-0.06	2.82	0.55	1.87
	Feeder Cattle	0.05	2.03	-0.22	2.54
	Live Cattle	0.08	2.14	-0.03	2.50
	Dry Whey	0.34	3.44	0.01	2.96
	Lean Hogs	0.00	3.32	0.05	2.94
	Milk	0.12	3.17	-0.12	2.27
	Average	0.07	1.83	0.00	1.83
Energies					
	Coal	-0.10	3.74	0.86	7.62
	Brent Crude Oil	-0.01	4.55	0.12	2.85
	Light Sweet Crude Oil	0.18	4.52	-0.16	3.48
	Heating Oil	0.29	4.57	0.27	2.97
	Gasoline	0.25	4.82	0.02	2.52
	Electricity	-0.17	5.83	0.49	2.11
	Natural Gas	-0.15	6.16	0.24	1.10
	Average	0.19	3.91	0.04	2.22

Table 2. Profitability of Momentum Portfolios

Panel A shows the average raw weekly returns on the four momentum strategies and Panel B reports the risk-adjusted returns on them. $CMOM_{1,1}$, $CMOM_{4,2}$, $CMOM_{26,5}$, and $CMOM_{52,27}$ indicate the weekly, monthly, half-yearly, and yearly momentums, respectively. The risk-adjusted returns in Panel B are computed by regressing the raw return on the average (AVG) and the carry (CARRY) factors. The numbers in parenthesis indicate *t*-statistics.

Panel A. Raw returns				
	$CMOM_{1,1}$	$CMOM_{4,2}$	$CMOM_{26,5}$	$CMOM_{52,27}$
	0.20	0.16	0.14	0.23
	(4.49)	(2.44)	(1.76)	(3.19)

Panel B. Risk-adjusted returns				
	$CMOM_{1,1}$	$CMOM_{4,2}$	$CMOM_{26,5}$	$CMOM_{52,27}$
Intercept	0.20	0.14	0.06	0.09
	(4.30)	(2.22)	(0.83)	(1.46)
AVG	0.03	0.07	0.04	0.13
	(0.84)	(1.19)	(0.59)	(2.49)
CARRY	0.01	0.06	0.42	0.80
	(0.24)	(1.08)	(6.19)	(18.65)

Table 3. Commodity Momentum and Equity Momentum

This table shows the regression results of each momentum returns on the equity momentum factor (UMD) without controlling factors (Panel A) and with controlling factors (Panel B). $CMOM_{1,1}$, $CMOM_{4,2}$, $CMOM_{26,5}$, and $CMOM_{52,27}$ indicate the weekly, monthly, half-yearly, and yearly momentums, respectively. The average (AVG) and the carry (CARRY) factors are employed as controlling factors in Panel B. The numbers in parenthesis indicate *t*-statistics.

Panel A. Without controlling for risk factors				
	$CMOM_{1,1}$	$CMOM_{4,2}$	$CMOM_{26,5}$	$CMOM_{52,27}$
Intercept	0.20	0.14	0.11	0.22
	(4.36)	(2.17)	(1.38)	(2.98)
UMD	0.01	0.07	0.12	0.05
	(0.99)	(2.68)	(4.44)	(2.02)
Panel B. With controlling for risk factors				
	$CMOM_{1,1}$	$CMOM_{4,2}$	$CMOM_{26,5}$	$CMOM_{52,27}$
Intercept	0.19	0.13	0.03	0.08
	(4.17)	(1.92)	(0.41)	(1.19)
UMD	0.02	0.07	0.12	0.07
	(1.10)	(2.86)	(4.82)	(3.20)

Table 4. Commodity Momentum and Hedging Premium

This table shows the regression results of each momentum returns on the hedging premium (HP) with controlling factors. $CMOM_{1,1}$, $CMOM_{4,2}$, $CMOM_{26,5}$, and $CMOM_{52,27}$ indicate the weekly, monthly, half-yearly, and yearly momentums, respectively. The average (AVG) and the carry (CARRY) factors are employed as controlling factors, and the coefficients on controlling factors are excluded. The numbers in parenthesis indicate *t*-statistics.

	$CMOM_{1,1}$	$CMOM_{4,2}$	$CMOM_{26,5}$	$CMOM_{52,27}$
Intercept	0.14	0.04	0.09	0.09
	(2.60)	(0.57)	(1.08)	(1.21)
HP	0.09	0.17	0.16	0.13
	(3.07)	(3.99)	(3.29)	(3.21)

Table 5. Trading Behaviors of Hedgers and Speculators

This table shows the estimated results of Eq. (3). Panel A (Panel B) shows the coefficients of net position change of hedgers (speculators) on past returns. *j* is a time-lag between past performance and position change. The numbers in parenthesis indicate *t*-statistics.

j	Panel A. Hedger		Panel B. Speculator	
0	-0.62	(-24.89)	0.49	(23.31)
1	-0.29	(-21.48)	0.28	(20.21)
2	-0.06	(-5.74)	0.07	(7.26)
3	0.03	(3.57)	-0.02	(-2.77)
4	0.07	(6.99)	-0.05	(-5.96)
5	0.10	(8.89)	-0.08	(-9.13)
6	0.08	(7.62)	-0.06	(-7.07)
7	0.07	(6.07)	-0.06	(-6.57)
8	0.04	(4.17)	-0.04	(-4.14)
9	0.04	(3.92)	-0.03	(-3.82)
10	0.04	(4.43)	-0.03	(-3.51)
11	0.05	(4.46)	-0.04	(-4.79)

Table 6. Speculators positions and hedging pressures

This table shows the estimated results of Eq. (6). We first include each of positions factors as F_t in Eq. (6) with $\{AVG_t$, and $CARRY_t\}$ as X_t, and the results are reported in Panels A and B, respectively. Next, we include both speculative activity factors and also additionally include HP as a control variable to examine the marginal effects of speculative activity (Panel C). We exclude the coefficients on controlling factors. $CMOM_{1,1}$, $CMOM_{4,2}$, $CMOM_{26,5}$, and $CMOM_{52,27}$ indicate the weekly, monthly, half-yearly, and yearly momentums, respectively. The numbers in parenthesis indicate *t*-statistics.

	$CMOM_{1,1}$	$CMOM_{4,2}$	$CMOM_{26,5}$	$CMOM_{52,27}$
Panel A. Regressions on ΔDP				
Intercept	0.14	0.05	0.10	0.10
	(2.61)	(0.60)	(1.15)	(1.33)
ΔDP	0.30	0.43	0.30	0.02
	(4.83)	(4.85)	(2.90)	(0.26)
Panel B. Regressions on ΔSP				
Intercept	0.15	0.06	0.10	0.10
	(2.80)	(0.77)	(1.19)	(1.33)
ΔSP	-0.45	-0.28	0.38	0.03
	(-2.67)	(-1.15)	(1.39)	(0.11)
Panel C. Regressions on ΔDP and ΔSP				
Intercept	0.14	0.03	0.08	0.09
	(2.55)	(0.45)	(0.93)	(1.19)
ΔDP	0.20	0.27	0.003	-0.19
	(4.50)	(4.74)	(3.11)	(-0.21)
ΔSP	-0.38	-0.20	0.26	-0.12
	(-1.88)	(-0.29)	(1.99)	(-0.25)