

Short-Term Momentums in the Commodity Futures Market

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JEL classification: G10

Keywords: Commodity Futures; Momentum; Hedging Pressure; Liquidity Provision; Speculator; Hedger

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Abstract

Unlike in equity markets, strong short-term momentum, instead of short-term reversal, is observed in commodity futures markets. Moreover, while long-term momentum in commodity futures markets is strongly correlated with momentum in the U.S. equity market, short-term momentum does not share any common momentum factor with the equity market. We set forth the hypothesis that liquidity provision of speculators may account for the short-term momentum in commodity futures markets, and provide the following empirical evidence for it. First, speculators are momentum traders while hedgers are contrarian in the short-run, both unwinding their positions after a few weeks. Second, liquidity supply factors predict short-term momentum returns, and the short-term momentum is stronger in nearby contracts than distant contracts.

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1. Introduction

Prices of commodity futures have their momentums. Past *winner*s perform better than past *loser*s.¹ In efficient markets with a majority of rational investors, predictability using past returns is questionable. Researchers have argued about the reasons why momentums exist. However, the definitive sources which academia are all agreed on is not found yet.

In the literature, the existence of this momentum phenomenon has been documented mainly in the equity market (Chordia and Shivakumar (2002); Cooper, Gutierrez, and Hameed (2004); Jegadeesh and Titman (1993)), but many recent researches document that momentum exists in other asset markets, such as currency or commodity futures (Asness, Moskowitz, and Pedersen (2013); Moskowitz, Ooi, and Pedersen (2012)). Specifically, momentum in the commodity futures markets has been actively investigated in the past decade (Erb and Harvey (2006); G. Gorton and Rouwenhorst (2006); Miffre and Rallis (2007); Szymanowska, Roon, Nijman, and Goorbergh (2014)), and possible sources of the momentum returns in the commodity futures markets are suggested by various studies. We categorize the suggested sources into three groups, though they are not exclusive each other.

The first group of researches is based on the behavioral finance. Barberis, Shleifer, and Vishny (1998) suggests that investors are initially underreacted to recent news, and the news reflect to the price over time. The slow reflection in returns makes momentums. Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) suggest that overconfidence of investors would cause return continuation. The initial underreaction and subsequent mean-reversion is empirically supported by Miffre and Rallis (2007), Shen, Szakmary and Sharma (2007) and Moskowitz, Ooi and Pedersen (2012) which show that holding long periods of momentum portfolios performs poorly in the commodity futures markets.

The second group of researches explains the momentum returns using the hedging pressure, or

¹ Contracts with high past returns are called *winner*s and contracts with low past returns are called *loser*s.

using the theory of storage, both of which are specific to the commodity market. They argue that the commodity contracts, which are bought heavily by hedgers or which have high inventories in the physical market, have low returns in the futures market. The rationale behind the hedging pressure is that hedgers are in the commodity futures market to hedge their price risk of the physical market and as a trading partner in the futures market, speculators bear the risk. Hence the contracts which are heavily bought by hedgers and eventually which speculators are net shorting should underperform to compensate speculators for bearing the risks. And similarly to the hedging pressure theory, the theory of storage argues that the basis or roll-yield should be positive when inventories are low or in the event of a stock-out. The hedging pressure and the theory of storage are suggested long time ago by Keynes(1923), Hicks(1939), Kaldor(1939), Working (1949) and Brennan(1958). And the evidence of inventory or the hedging pressure causing the momentums are provided by many researchers, for example Miffre and Rallis (2007) shows that winners are likely to be backwardated, Gorton, Hayashi and Rouwenhorst (2013), Basu and Miffre (2013) and Dewally, Ederington and Fernando (2013) show that contracts which hedgers are net shorting and speculators are net longing outperform.

The last group, "common momentum factor" group, finds that momentums are existed in the most of the markets with regardless of asset classes and countries and those global momentums in various markets are correlated to each other. According to this point of view, the momentum in the commodity futures market also have to be interpreted in this context. They provide evidences of the high correlation between time-series returns of momentum in the equity market and those in the commodity futures markets. Asness et. al. (2013) find momentum strategies earn positive Sharpe ratios in all the major market including commodity futures market. Moskowitz et al. (2012) also finds the same results using time-series momentums rather using cross-sectional momentums and shows that time-series momentums in the commodity futures market is statistically related with the cross-sectional equity momentums. Novy-Marx(2012) also shows that the cross-sectional momentum strategies yield positive returns in many market, and they share common factors. Pirrong (2005) also provides evidence of significant correlation

between stock momentum and commodity momentums.

In this paper, we suggest that short-term momentums and long term momentums are from different sources. The former one are from the hedging pressure, and the latter one is highly related with the common momentum factors. To show the hedging pressure effect in the short-term momentum, we provide the position reaction of each trader group to the price changes on weekly basis. The marginal effect of each week's performance on position change prove that hedgers buy contracts which perform poorly during last three weeks and unwind the position afterwards, and speculators take the exact opposite positions. This suggests that the hedging pressure can induce the short-term momentum but not the long-term momentum. We also show that the short-term momentum returns are high after highly volatile market and market with high ted spreads. It can be interpreted as speculators require higher returns from their short-term momentum positions when the markets are volatile and ted spreads are high. The two conditions are known to capture market and funding liquidity states, respectively.

To verify our second main result about the long-term momentums, we show a regression results of momentum returns on the equity momentum returns, UMD. The regression shows that the intermediate to long term momentums are highly correlated with the UMD and the short-term momentums don't seem to be. It is consistent with the common momentum factor groups' idea, but we provide additional information that the short-term momentum doesn't share the common momentum factors.

Our hypothesis is also clarified by another evidence that shows the significant difference in the short-term momentum of first-nearest contracts and the short-term momentum of second-nearest contracts and no statistical difference between the long-term momentums in first-nearest and the second nearest.

This paper has contribution to the literature which address momentum phenomenon in the commodity futures market, especially which focus on the term structure of the momentum. Shen, Szakmary, and Sharma (2007) report that in the commodity futures markets the one-month momentum is the strongest compared to the longer ones, and Kang and Kwon (2017) document that the commodity

futures momentum cannot be fully explained by the basis premium or traditional risk factor models and this failure seems to be much notable for the short-term momentum. But the economic source of the difference has not been clearly documented in the literature.

We also contribute to the literature which presents the role of hedgers and speculators in the commodity futures market. In Haigh et al. (2007) and Dewally et al. (2013), speculators are regarded as liquidity providers because they are expected to fulfill the needs of hedgers, and more interestingly, Dewally et al. (2013), Fung and Hsieh (2001), Bhardwaj et al. (2014), and Rouwenhorst and Tang (2012) report that speculators are momentum traders. We additionally finds that both hedgers and speculators only pay attention to the short-term past performances and not to the older performances.

Our study is related with the researches on short-term reversal in the equity market, since we look into the source of the short-term momentum returns in the commodity market separately and there are similarities between the short-term reversal in the equity market and the short-term momentum in the commodity market. Both of them are able to be predicted by the liquidity factors, including volatility. Nagel (2012) shows that the reversal returns are high after volatile markets, and suggests that this is because the reversal returns are the compensation of the liquidity providers. Since the position of liquidity providers are contrarian in the equity market, the reversal returns can be regarded as the compensation for them.

Our results also contribute to the literature which address the relation between the stock momentum and the commodity futures momentum. Pirrong (2005) reports the positive correlation between the stock momentum and the commodity futures momentum. Asness et al. (2013) examine momentums in eight diverse markets and asset classes including both stocks and commodity futures, and find that there exists a strong common factor among them. Moskowitz et al. (2012) document that the cross-sectional and time-series momentums in the commodity futures markets seem to have a common factor, and the time-series momentum is significantly related to the stock market momentum factor (UMD) constructed by Fama and French. Their results also imply the common factor of the (cross-sectional)

commodity futures momentum and the stock momentum. Kang and Kwon (2017) examine commodity futures momentums in five countries' markets and report that the stock momentum cannot fully account for them. Kang and Kwon (2016) focus on differences in the stock and commodity futures momentums, and suggest a way to combine these two effects to generate larger returns and Sharpe ratios. They also report that from a point of view of a log-utility investor, extending an investment universe from the set of stock portfolios including stock momentum portfolios, stock portfolios sorted on the past returns, to the set with additional commodity futures momentum portfolios has a significant certainty-equivalent wealth gain. These results also support the difference between the stock and commodity futures momentums.

The rest of the paper is organized as follows. Section 2 describes data we use and summary statistics of the data. We also show the term structure of commodity momentum in Section 2. Section 3 shows the empirical results. Specifically, Section 3.1 presents the relationship between the short-term momentum and the hedging pressure, Section 3.2 shows the common momentum factor in the long-term momentum and Section 3.3 compares the momentum returns of the first-nearest contracts and those of the second-nearest contracts. Section 4 concludes.

2. Data and Term Structure of Commodity Momentum

2.1 Data

To analyze the momentum phenomenon in the commodity futures markets, we use commodity futures price data from Datastream. We only use futures listed on the exchanges in the U.S. After eliminating commodities with discontinued data, it consists of 32 commodity futures from 1979 to 2015. For each commodity future, we construct a daily return series. When we construct the time series returns, the nearest contracts of each commodities are used. We assume that the contracts are rolled over at the end of months ahead of maturities. Finally, we have 32 daily return series of each commodity future from 1979 to 2015.

For the purpose of comparison, we also use the equity data for calculating stock momentum

returns. We use monthly data for all common stocks (share codes 10 and 11) in the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. The data are obtained from the Center for Research in Security Prices (CRSP). For the sample period of stock portfolio returns, we use the monthly data for common stocks from January 1979 to June 2015.

We also use publicly available trading data of each investor group. The position data are provided by Commodity Futures Trading Commission (CFTC), which collects the data and makes it public via the Commitments of Traders (COT) report. The report is released on a weekly basis from 1992, so we use the data since then. It includes open interests of commercial groups, non-commercial groups and the non-reportable. Since the commercial investors are regarded as hedgers and the non-commercials are regarded as speculators in general, we follow the conventions. The COT reports on commodity futures, financial future and currency futures listed on the exchanges in the U.S., but we only use 30 commodity futures which match our return data set from Datastream. When we match the position data with the daily return data, we cumulate daily returns from the end of every Tuesday to the end of next Tuesday because the COT data are collected at the end of every Tuesday on a weekly basis.

[Table 1 about here]

Table 1 shows summary statistics of the daily returns and position of each investor groups from our data set. The first column presents the start date of the times series. The second and the third columns report annualized average daily returns and annualized standard deviation of the returns of each commodity futures. Sample means and volatilities vary significantly across the contracts. The next four columns are calculated using position data. The first two columns of the four show average and standard deviation of weekly net long position of speculators. Consistent with the results of Keynes (1923), speculators are generally net long. Standard deviations vary across the instruments. The last two columns report averages and standard deviations for the changes in net long position of speculators. The differences in volatilities and means across the contracts also can be found.

As proxies for liquidity supply factors, we use two variables.² The first variable is ex-ante volatilities which are forecasted from daily return data of the S&P Goldman Sachs Commodity Index (GSCI) using GARCH(1,1) models. On every trading day, we estimate the GARCH(1,1) model over a five-year rolling window and then forecast the ex-ante volatility for one month later. The square root of a GARCH(1,1) forecast of the variance of the daily return over a 21-trading-day horizon is used as a monthly ex-ante volatility. The S&P GSCI return is from Datastream. We use the daily TED spread as the second variable, which is provided by the Federal Reserve Bank of St. Louis.³ The TED spreads are from 1986, so when we use the TED spreads data, we match periods of other dataset to start from 1986.

We evaluate the returns of momentum strategies using the Fama-French 5-factor model from Fama and French (2015) with an equity momentum factor—UMD-- additionally. The returns of the five factors and UMD are from Ken French's Website.⁴ Most of these portfolio returns are available from July 1926, but we use the data from January 1979 to June 2015 to match the sample period with the commodity futures market data.

2.2 Term structure of the commodity momentum

We first draw attention to the different features observed in the returns of momentum strategies based on the short-term past returns and those based on the long-term past returns. Novy-Marx (2012) conducts the same analysis in the equity market. On each month, we construct momentum strategies by buying winner portfolios and selling loser portfolios. The winner and loser portfolios are defined as the top and bottom quintile of commodity futures contracts sorted on the past returns, respectively. Specifically, following Novy-Marx (2012), we define the n - m momentum strategy as the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation, and compute one-month holding return of this portfolio after formation. The return series of the n - m

² We also test the investor sentiment index of Baker and Wurgler (2006) as a state variable that captures liquidity supply, but the result was insignificant, so we drop the result using it in the following.

³ <https://fred.stlouisfed.org/series/TEDRATES>

⁴ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

momentum strategy is denoted as $MOM_{n,m}$. We construct the momentum portfolio in two ways. First, by setting $m=1$, we form the winner-minus-loser portfolios based on the cumulative past performances. Sorting by the cumulative past performances is a general way to construct momentum strategies in the literature, and thus the results from this analysis can be comparable to the previous findings (Jegadeesh and Titman, 1993; Miffre and Rallis, 2006; Shen et al., 2007; Asness et al., 2013; Kang and Kwon, 2017). However, Novy-Marx (2012) notes that the predictive power of past returns may not decay monotonically over time, and thus he tests the term-structure of momentum by varying the length of the test period and portfolio formation. Following Novy-Marx (2012), we also construct the winner-minus-loser portfolios based on a single month starting lag ($n=m$) months prior to the portfolio formation. The results from this analysis may show the term-structure of momentum and the predictive power of past returns more clearly than the first formation method.

In Figure 1, Panel A and C show the term-structures of the winner-minus-loser portfolios based on the cumulative past performances, and Panel B and D show those of the winner-minus-loser portfolios based on a past single month return. We vary the looking-back-month (n) from 1 to 36. Figure 1 shows these strategies' average monthly returns and their t -statistics. Panel A and B are the results in the commodity futures markets, and Panel C and D are the results for the equity market.

[Figure 1 about here]

According to the results from Panel A of Figure 1, the past performances do have predictability in the commodity futures markets. The momentum returns are significantly positive when looking-back-month (n) is up to 12 months. One-month momentum shows especially strong performance. This result is consistent with the results of Shen, Szakmary, and Sharma (2007) and Kang and Kwon (2017) which show the existence of strong short-term momentum in the commodity futures markets. More interestingly, when we take account of the results of Panel B with that of Panel A, the returns on the recent two months seem to mainly drive the predictability of the longer-period past returns in Panel A for n up to 12. In Panel B, the return and its significance of $MOM_{n,n}$ dramatically drop after $n=1$, and the return on $MOM_{n,n}$

strategy becomes insignificant from $n=3$. These big differences between $MOM_{n,1}$ in Panel A and $MOM_{n,n}$ in Panel B from the second month suggest that the performances of earlier than one month do not work as predictors of the future performances except abnormally strong results of $n=10$ or 11.

The results in Panel C and D reaffirm that the equities have strong one-month reversal and one-year momentum. This is consistent with Novy-Marx (2012). He reports that in the US equity market, there is a general upward trend in the returns on $MOM_{n,n}$ as n increases up to 12, and thus past performance at intermediate horizons contributes more to the profitability of momentum strategies than does past performance at recent horizons.

The notable difference between the term-structures of commodity futures momentum and stock momentum is observed from the case of $n=1$. In the stock market, Jegadeesh and Titman (1995) document existence of the negative serial covariances for stock returns, which is well-known as *short-term reversal*, and explain it by market microstructure effects. On the contrary, as we find in Figure 1, there is strong *short-term momentum* in the commodity futures markets. According to Kang and Kwon (2017), the significant one-month momentum is observed from the international commodity futures markets including five countries. Other than the results of one-month looking-back-month, the commodity momentums and the equity momentums seem to be relatively similar in Panel B and D.

3. Empirical Results

3.1 Short-term Momentum and Hedging Pressure Hypothesis

3.1.1 Trading Activities of Hedgers and Speculators

In this section, we investigate the relationship between past returns and the changes in position of each investor group to link the hedging pressure and momentum. Nagel (2012) document that the short-term reversal in equity markets can be regarded as a proxy for the returns or compensation from liquidity provision. In other words, in equity markets, liquidity providers are expected to take the contrarian strategy, buying past (short-term) losers and selling past (short-term) winners. On the other

hand, in commodity futures markets, speculators are regarded as liquidity providers in many studies (Haigh et al., 2007; Dewally et al., 2013) because they are expected to fulfill the needs of hedgers. According to the literature, however, the trading behavior of liquidity providers in the commodity futures markets is different from that in the equity market. Dewally et al. (2013), Fung and Hsieh (2001), Bhardwaj et al. (2014), and Rouwenhorst and Tang (2012) report that speculators are momentum traders, buying past winners and selling past losers. Thus, we expect that these different strategies or positions of liquidity providers in the stock and commodity futures markets may contribute to the different profitability for the short-term momentum strategy in the two markets.

To match the weekly position data from COT reports to the daily return data, we accumulate returns from every Wednesday to next Tuesday since the COT report is released at the end of every Tuesday. We examine whether hedgers/speculators take momentum positions--buying past winners and selling past losers-- or contrarian positions--buying past losers and selling past winners-- and which periods of returns are taken to be accounted by each investor groups. We run cross-sectional Fama-Macbeth regressions for the changes in net long positions of each investor groups on the returns from j ($j=1$ to 52) weeks ago to the time of making the position and also on the returns of a single week on the j weeks prior to the time of making the position. Net long position change of investor group k for commodity i at week t is defined as:

$$Q_{i,t,k} = \frac{(Long_{i,t,k} - Short_{i,t,k}) - (Long_{i,t-1,k} - Short_{i,t-1,k})}{OpenInterest_{i,t-1}} \quad (3)$$

where $Long_{i,t,k}$ ($Short_{i,t,k}$) indicates the long (short) position change of investor group k for commodity i at week t and $OpenInterest_{i,t-1}$ is the open interest on commodity i at week t . Using this net long position change measure as the dependent variable, we test the following regression equations to examine the relation between the trading behavior of hedgers/speculators and the past performance of the commodity futures:

$$Q_{i,t,k} = a_0 + a_1 R_{i,(t-k,t)} + \varepsilon_{i,t} \quad (4)$$

$$Q_{i,t,k} = a_0 + a_1 R_{i,(t-k,t-k)} + \varepsilon_{i,t} \quad (5)$$

where $R_{i,(t-t1,t-t2)}$ is cumulative return of commodity i from $t1$ weeks prior to the week t to $t2$ weeks prior to the week t . For example, $R_{i,(t-3,t)}$ is the cumulative return during the last three weeks, and $R_{i,(t-3,t-3)}$ is the weekly return on a single week of three weeks ago. The regression results are reported in Table 2. The second and the third columns are the result of equation (4), and the last two columns are the result of equation (5). Panel A and Panel B show the results for the trading behavior of hedgers and speculators, respectively.

[Table 2 about here]

In the result of equation (4), all the coefficients have signs as we expected, and they are all statistically significant. Panel A of Table 2 shows that the coefficients on $R_{i,(t-k,t)}$ are all negative and highly significant (t -statistics = -2.47 to -24.56), indicating that hedgers sell contracts which outperformed in the past and buy contracts which underperformed in the past. By contrast, Panel B shows that the coefficients on $R_{i,(t-k,t)}$ are all positive and highly significant (t -statistics = 3.12 to 23.15). Consistent with the literature, these results address that speculators are momentum investors and hedgers are taking the opposite positions (e.g. Dewally et al. (2013), Fung and Hsieh (2001), Bhardwaj et al. (2014), and Rouwenhorst and Tang (2012)).

More interestingly, the results of equation (5) in the last two columns in Table 2 provide an evidence that hedgers and speculators indeed only care about past short-term performance. In Panel A of Table 2, the coefficients on $R_{i,(t-k,t-k)}$ for the most recent three weeks are significant and negative, but they become negative since the fourth month ($k=4$). Hedgers are contrarian and form their positions based only on recent three weeks, and they unwind their reversal positions after four weeks. This result also suggest that the highly significant and negative relation between the hedger's position change and the past cumulative returns ($R_{i,(t-k,t)}$) attributes to the strong relation during the most recent three weeks. Among the first three weeks, we also can see the rapid decreasing pattern in the absolute value and significance of

the coefficients. This pattern also support the stronger relation with the more recent performance. Panel B shows that speculators conduct the very opposite positions of hedgers'. The significant and positive coefficients on $R_{i,(t-k,t-k)}$ become negative since the fourth month. Speculators buy contracts which outperformed during recent three weeks and reverse their momentum position after four weeks.

To summarize, we provide the evidence that the speculators in the commodity futures market are short-term momentum traders, especially focused on the recent one-month performance while the hedgers are short-term contrarian traders. The relationship between past performance and the hedging pressure occurs only in the short-term, hence, the hedging pressure can be the source of the short-term momentum, not the long-term momentum.

3.1.2 Momentum Returns conditional on Liquidity States

To verify that the short-term momentum is the result of the trading activity of hedgers who buy the short-term losers and sell the short-term winners, we look into the conditional momentum returns on liquidity states. Speculators who provide liquidity to hedgers and bear the risk which hedgers are trying to get rid of would require higher returns for holding the position when the liquidity states are tough.

To test the hypothesis, we adapt two liquidity supply factors; ex-ante volatility and the TED spread. In specific, we expect these two variables may capture different dimensions of liquidity; ex-ante volatility is expected to capture market liquidity and the TED spread is expected to capture funding liquidity. Ex-ante volatility of S&P GSCI is a natural candidate for the predictor of compensation for providing liquidity. As Brunnermeier and Pedersen (2009) argue that high volatility tightens funding constraints thereby affects liquidity risk premium, we check the predictability of ex-ante volatility of the S&P GSCI for the momentum returns. Nagel (2012) examines the same predictability in the equity market using the VIX index for the reversal returns in the equity market and finds strong predictability. The TED spread, defined as the difference between the interest rates on interbank loans and on short-term U.S. government debt, also captures funding constraints. Credit risk and flight to quality channel involve

the link between the TED spread and funding illiquidity, so to affect the liquidity risk premium.

Ex-ante volatilities are quantified by the square root of GARCH(1,1) forecasts estimated using five-year rolling windows on every trading day. To avoid the look-ahead bias, we estimate the parameters of GARCH(1,1) model on every trading day using past five-year rolling windows. Then we forecast 21-trading-day-ahead ex-ante volatilities on every trading day using the estimated parameters as one-month ex-ante volatilities.

We expect that the compensation for bearing the risk will be higher when the market liquidity and funding liquidity are in a bad state. In other words, the compensation is expected to have positive relations with the ex-ant volatility and the TED spread. According to the hedging pressure hypothesis and the results of the previous chapter about the trading activities, the short-term momentum will be positively related to those two liquidity supply factors. We investigate these relations in two folds. First, we categorize our sample period into four different states of liquidity, and then examine the difference of the momentum returns between the good and bad states. Second, we regress the momentum returns on the liquidity supply factors and test whether their coefficients are significantly positive. Moreover, we test the longer-period momentums together for comparison.

First, we divide periods into 4 different state of liquidity, according to the level of each liquidity supply factor. State 1 (High) corresponds to the 10% highest observations for each variable, state 2 corresponds to above the median, state 3 for to below the median, excluding the 10% lowest observations ,and state 4 (Low) corresponds to the 10% lowest observations.⁵ Average momentum returns in each state and differences in average returns of state 1 and state 4 are reported in Table 3. We expect that the short-term momentum returns are the highest in state 1 and the difference between returns in state 1 and state 4 are significant. The results are presented in Table 3. Panel A and B are the results for states sorted on the level of ex-ante volatility, and Panel C and D are the results for the second variable,

⁵ Following Petkova and Zhang (2005), we define states 2 and 3 using the average of observations instead of the median, but we find that the results are qualitatively the same.

the TED spreads. Momentum strategies based on cumulative past returns are used in Panel A and C, and momentum strategies based on a single month, k months prior to the formation, are used in Panel B and D.

[Table 3 about here]

In Panel A and B, the average returns of the short-term momentum strategies are the highest when ex-ante volatility is high. The one-month momentum strategy generates 0.026 monthly return on average in state 1 which is statistically significant at the 5% significance level (t -statistic = 1.95), but it generates only 0.014 monthly return on average in state 4. Even though the difference between average returns in state 1 and state 4 is not significant, we can see the pattern that the level of momentum returns jumps up in the bad state as opposed to the average returns in state 2, 3 and 4 which are relatively flat. Furthermore, the ordered level of average returns is not found in the longer-term momentum strategies. In case of $k=1$, we can see the momentum return increases as the ex-ante volatility increases, but this pattern becomes inverted as k increases. For example, in case of $k=5$ in both Panel A and B, the difference between average returns in state 1 and 4 is negative. This negative difference seems to be persistent up to about one year.

In Panel C and D, the results are much stronger than those in Panel A and B. In Panel C, the returns on short-term momentum strategies are neatly ordered from state 1 to state 4 and the difference is statistically significant. The one-month momentum returns show 0.036 monthly return on average when the TED spread is high (state 1) and only 0.002 monthly return on average when the TED spread is low (state 4). The two-month momentum strategy ($k=2$) also shows a marginally significant difference between state 1 and 4, but if we construct the strategy based on only the past second month excluding the most recent month ($k=2$ of Panel D), then the difference becomes insignificant (t -statistic = -0.52). These results also suggest that the one-month momentum return is strongly related to the liquidity state and it also contributes to the significant relation between the two-month momentum and the liquidity. For the longer-term momentum strategies, as the results in Panel C and D, the average returns are not high in the state 1 and low in the state 4. Only when k is equal to 1, the high premium is required in the bad states of

liquidity. The overall results in Table 3 are consistent with the recent theories which argue that the liquidity premium has strong variation across states and jumps in the bad states, and also support our hypothesis.

Next, we execute predictive regressions of the momentum returns formed by various periods of past performances on the two liquidity factors. Before conducting regression, we calculate the correlation coefficients among two variables since the two variables are both related with liquidity and fear among investors. We find that the correlation coefficients are -0.0649, which is not even positive.⁶ We run the following time-series regression:

$$MOM_{n,m,t} = a_0 + a_1 ExVOL_{t-1} + a_2 TED_{t-1} + \varepsilon_t \quad (6)$$

where $MOM_{n,m,t}$ indicates the return on the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation at month t , and as the predictor of momentum returns, $ExVOL_{t-1}$ and TED_{t-1} are the ex-ante volatility and the TED spread at month $t-1$, respectively. The regression results are reported in Table 4.

[Table 4 about here]

Panel A describes the results of the momentum strategies using cumulative past returns (i.e. $m=1$). The ex-ante volatility predicts the momentum returns which are the winner-minus-loser portfolios sorted on cumulative past performances for from 1 to 6 months and the predictabilities are doomed after 6

⁶ The negative correlation between the ex-ante volatility of the commodity futures market and the TED spread is rather counter-intuitive as the volatility of stock markets is positively related to the TED spread. On March 27, 1980, the Hunt brothers failed to meet the margin call and so derived a large drop of the silver futures price. This event also caused the overall trough of the US commodity futures market. We expect that the GSCI movement in the early 1980s could be largely affected by this event. We expect that the negative correlation between the TED spread and the ex-ante volatility of the commodity futures markets can be driven by the early sample period. Excluding the first 10 years, from 1980 to 1989, we reexamine the correlation from January 1990 to June 2015 and find the positive correlation (0.137). For comparison, we also compute the correlation between the VIX index and the TED spread, and find the correlation (0.231) larger than that between the commodity ex-ante volatility and the TED spread. This larger correlation with the stock market is consistent with the literature that the commodity futures markets have little comovement with other financial markets that are more closely related to the TED spread (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006).

months passed. The coefficients on the ex-ante volatility appear to be positive for all cases, but they are significant only for the short-term momentum strategies with only one-exception in the long-term ($k=24$). The TED spread also shows significant predictabilities for the short-term momentum up to 2 months of look-back-period. The value and significance of coefficients on the TED spread are almost monotonically decreasing as k increases.

Panel B shows the results for the momentum returns constructed by past single month performances on k months prior to formation for $k = 1$ to 36. Compared to Panel A, Panel B more clearly shows the strong predictability of liquidity supply factors for the short-term momentum. The ex-ante volatility and the TED spread predict the momentum returns only when strategies are based on the most recent month performances ($k=1$).

If the returns from short-term momentum strategies are the compensation for liquidity provision of speculators and if the long-term momentums are not relevant to the liquidity supply, then the liquidity factors should predict only the time-variation of the short-term. In this section, our results suggest that unlike the intermediate- or the long-term momentums, the risk premiums of the short-term momentums are predicted by the factors which proximate market and funding liquidity, which means that those variables are state variables for the short-term momentum returns which happens to be the returns of the strategies among speculators.

3.2 Long-term Momentum and Common Momentum Factor

The previous chapter shows that the long-term momentums are not from the hedging pressure. To check the other possibility, we run regressions of the commodity momentum returns on the UMD factor, which is a cross-sectional momentum factor built in the equity market. Using the regression results, we reassert the distinct features of the short-term commodity momentums and approach the source where the difference stems from. By contrast to the different performances of the short-term stock and commodity futures momentum strategies, we expect that there can be a common movement between

stock and commodity futures momentums for the longer-term. Panel B and D of Figure 1 suggest this similarity and Asness et al. (2013) also document the co-movement of 12-month-momentum (skipping the most recent month) across different asset classes including stock and commodity futures. In this analysis, we verify this issue by examining the relation between the commodity futures momentum with various looking-back-periods and the UMD factor.

We use the UMD returns, which is formed by buying stocks in top decile portfolios and selling stocks in bottom decile portfolios based on past 10 months' performances from 12 months prior to the formation to 2 months prior to the formation, as a proxy for the common factor. Additionally, we control the effects of other risks using the Fama-French five-factors: stock market (MKT), value (HML), size (SMB), investment (CMA), and profitability factors (RMW). The first equation is the regression equation for the univariate model, and the second is for the multivariate model with the Fama French's five factors.

$$MOM_{n,m,t} = \alpha + \beta_{UMD}UMD_t + \varepsilon_t \quad (1)$$

$$MOM_{n,m,t} = \alpha + \beta_{MKT}MKT_t + \beta_{HML}HML_t + \beta_{SMB}SMB_t + \beta_{CMA}CMA_t + \beta_{RMW}RMW_t + \beta_{UMD}UMD_t + \varepsilon_t \quad (2)$$

In regression models (1) and (2), dependent variables ($MOM_{n,m}$) are monthly returns on the momentum strategies based on different length of past returns. As in Figure 1, we test for two types of momentum strategies, one is based on the cumulative past returns (Panel A of Table 5) and the past single-month returns (Panel B of Table 5). The results are shown in Table 5.

[Table 5 about here]

In Panel A, the coefficients of the UMD for the univariate model and the multivariate model are insignificant when n is lower than 5. As past performances track longer past periods, however, the coefficients are getting bigger and become significant when looking-back-month (n) is between 5 and 12. Though the momentum strategies are formed only with the commodity futures, the returns are strongly correlated with the cross-sectional equity momentum. This result is consistent with the previous findings

which show that many different types of momentums share a common factor even when they are constructed either with other asset classes or with different measures, e.g. time-series momentums or cross-sectional momentums (Moskowitz et al., 2012; Asness et al., 2013). We additionally find that this significant relation with the UMD factor is limited to strategies based on the intermediate- and the long-term past returns. This result is also in line with the result in Figure 1 which shows that equity momentum and commodity momentum show a notable difference in the short-term while two momentums show similar patterns in the longer term.

In Panel B, the momentum strategies based on a past single month also confirm our assertion. Risk-adjusted returns on the commodity futures momentum strategies (alphas) are the strongest when looking-back-month is one month ($n=1$), and the coefficients on UMD are insignificant in the short-term (when n is less than 4). By contrast, the coefficients on UMD for the intermediate-term (looking-back-month of 5, 6, 8 and 11 months) are significantly positive in general. It implies that while momentums formed by intermediate-term past performances can be regarded as the “momentum” which co-move with the common momentum factor, the short-term momentum does not share the common factor and have different economic meanings.

3.3 First-nearest contracts versus Second-nearest contracts

If our conjectures are true, then the cross-sectional momentums are stronger in the first-nearest contracts than in the second-nearest contracts in the short-run, because the hedging pressure must be stronger in the first-nearest than in the second-nearest. And in the longer-term, these gaps are disappeared or lessened, because the longer-term momentums are from common momentum factor, which supposed to be irrelevant of the maturity of the futures. To test this hypothesis, we compare the momentum returns of the first-nearest contracts and momentum returns of the second-nearest contracts. The results are shown in Table 6.

[Table 6 about here]

Table 6 supports our conjecture. The differences are significant in the short-run, and in the long-run, the differences are not found. The compensations of providing liquidity are higher in the first-nearest contract since the demand for liquidity is high in the nearby. But the longer-term momentum returns are not different since these are not related with the liquidity provision and compensation for it. This is consistent with our main hypothesis.

4. Conclusion

In the commodity futures markets, the cross-sectional momentums exhibit strong positive performance. The term-structure of the momentum returns in the commodity futures markets is significantly different from that of equity momentums. The difference is the most remarkable in the short-term—one-month. While there is no short-term momentum in the equity market, the one-month momentum is the most solid in the commodity futures markets. Furthermore, while the long-term momentums are positively correlated with the equity momentum factor, the short-term momentum does not commove with the equity momentum. This implies that the short-term momentum has different implications.

We suggest that the two momentums have different sources; the short-term momentum is caused by the hedging pressure and the long-term momentum is from the common momentum factor.

We provide two supporting evidences for the short-term momentum. One is to show the predictability of the short-term momentum returns using liquidity supply factors. Second, we successfully show that hedgers are contrarian in the short run, and they reverse their position after three weeks. So, the hedging pressure and the momentum are related only during the short period.

We address the regression results of momentum returns on the common momentum factor, UMD, to show that the long-term momentum is from common momentum factor. The results support our hypothesis, and presents that the short-term is irrelevant with the common momentum factor, while the

long-term momentums are highly correlated with the common factor.

We also show the significantly stronger short-term momentum in nearby contracts than in distant contracts. It also confirms our hypothesis.

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Table 1. Summary statistics on futures contracts

This table shows the summary statistics on 32 US futures contracts and two commodity futures market indices. We report the date that each contract's data start, annualized mean return and standard deviation in our sample from January 1979 to June 2015. For the period from October 1992 to June 2015, we report the mean and standard deviation of the Net speculator long positions and position changes in each contract as a percentage of open interest, covered and defined by CFTC data.

	Data start date	Annualized mean	Annualized volatility	Average net speculator long position	Std. dev. net speculator long position	Average net speculator long position change	Std. dev. net speculator long position change
Butter	Oct-05	-1.91%	24.19%	-9.94%	20.65%	-0.16%	5.42%
Cattle, Feeder	Jan-79	2.82%	14.45%	11.69%	14.00%	0.08%	4.44%
Cattle, Live	Jan-79	4.16%	15.04%	10.86%	11.24%	0.03%	3.06%
Corn	Jan-79	-3.30%	25.63%	9.54%	12.08%	0.02%	3.28%
Dry Whey	Apr-07	17.41%	22.60%	-60.01%	13.05%	-3.70%	27.06%
Ethanol	Apr-06	39.58%	40.95%	12.22%	11.43%	0.20%	4.96%
Hogs, Lean	Jan-79	0.71%	26.09%	7.27%	13.70%	0.16%	6.81%
Lumber, Random Lengths	Jan-79	-7.67%	30.50%	3.25%	17.10%	0.00%	6.13%
Milk, BFP	Apr-96	7.41%	27.21%	2.77%	13.39%	0.02%	3.65%
Oats	Jan-79	0.01%	33.46%	13.95%	13.13%	0.05%	4.33%
Rough Rice	Feb-00	-7.71%	26.31%	3.28%	17.97%	0.04%	3.99%
Soybeans	Jan-79	2.83%	23.89%	10.83%	13.91%	-0.03%	4.38%
Soybean Meal	Jan-79	9.61%	26.90%	10.54%	12.18%	0.04%	3.90%
Wheat, No.2 Red	Jan-79	2.20%	24.56%	9.66%	13.05%	0.02%	3.39%
Wheat, Hard Red Spring	Jan-79	4.95%	24.62%	6.48%	13.64%	0.05%	3.05%
Cocoa	Jan-79	-1.27%	29.65%	8.85%	15.55%	0.05%	3.51%
Coffee 'C'	Jan-79	2.29%	37.73%	6.87%	14.82%	-0.03%	5.32%
Cotton Seed	Jan-79	1.92%	26.01%	2.99%	20.70%	0.11%	5.82%
Orange Juice, FCOJ	Jan-79	0.91%	30.31%	14.17%	20.26%	-0.01%	5.85%

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Sugar No. 11, World	Jan-79	-0.85%	41.91%	9.81%	13.86%	0.03%	4.57%
Coal	Apr-04	-5.14%	27.93%				
Brent Crude Oil Last day	Aug-07	-0.59%	31.80%	-17.26%	15.99%	-0.56%	3.72%
Light Sweet Crude Oil	Apr-83	9.60%	32.91%	5.04%	7.77%	0.05%	2.21%
Heating Oil	Jan-79	15.90%	35.80%	2.85%	6.42%	-0.02%	2.63%
RBOB Gasoline	Nov-05	13.79%	35.57%	19.90%	5.18%	0.13%	2.43%
PJM Electricity	Apr-04	-5.82%	51.40%				
Copper	Sep-89	8.15%	26.07%	2.93%	16.14%	-0.02%	4.72%
Gold, 100 Troy oz	Jan-79	1.34%	19.02%	15.00%	23.93%	0.11%	5.98%
Palladium	Jan-79	8.63%	35.57%	31.19%	25.24%	0.19%	5.56%
Platinum	Jan-79	4.20%	25.84%	38.23%	21.40%	0.21%	8.16%
Silver, 5000 Troy oz	Jan-79	3.33%	35.93%	23.21%	13.55%	0.06%	5.14%
Henry Hub Natural Gas	Apr-90	-5.78%	48.77%	-5.57%	10.28%	-0.03%	2.18%
Equal weighted	Jan-79	2.48%	11.98%				
S&P GSCI	Jan-79	4.93%	20.00%				

Table 2. Trading behavior of hedgers (commercials) and speculator (non-commercials)

This table shows the relation between the past returns on the commodity futures and net-long position change of hedgers (Panel A) and speculators (non-commercials). In each panel, we regress the net-long position change at week t on the commodity futures returns from week $t-k+1$ to week t or to week $t-k$ (single week return) for $k = 1$ to 52. This table shows the coefficients of the commodity futures returns estimated from the Fama-MacBeth regression. Newey–West (1987) adjusted t -statistics are reported in parentheses. The sample period is from October 1992 to June 2015.

Panel A. Hedgers				
k	From week $t-k$ to week t		From week $t-k$ to week $t-k$	
1	-0.630	(-24.46)	-0.630	(-24.46)
2	-0.455	(-24.56)	-0.289	(-21.21)
3	-0.327	(-24.21)	-0.065	(-5.17)
4	-0.235	(-22.96)	0.040	(4.20)
5	-0.173	(-21.10)	0.077	(5.58)
6	-0.131	(-20.15)	0.089	(7.60)
7	-0.101	(-18.29)	0.079	(7.50)
8	-0.081	(-16.13)	0.072	(6.29)
9	-0.067	(-14.91)	0.043	(3.92)
10	-0.057	(-14.02)	0.043	(3.82)
11	-0.049	(-13.00)	0.028	(2.94)
12	-0.042	(-11.96)	0.036	(3.82)
16	-0.024	(-8.10)	0.039	(3.93)
20	-0.015	(-5.85)	0.022	(2.43)
24	-0.008	(-3.91)	0.018	(1.73)
26	-0.007	(-3.49)	-0.001	(-0.08)
52	-0.003	(-2.47)	0.000	(-0.01)
Panel B. Speculators				
k	From week $t-k$ to week t		From week $t-k$ to week $t-k$	
1	0.493	(23.15)	0.493	(23.15)
2	0.386	(21.40)	0.280	(19.72)
3	0.277	(22.65)	0.061	(6.39)
4	0.199	(21.99)	-0.028	(-3.26)
5	0.149	(20.10)	-0.051	(-5.38)
6	0.113	(19.45)	-0.075	(-8.51)
7	0.089	(17.68)	-0.062	(-7.23)
8	0.071	(16.06)	-0.060	(-6.09)
9	0.059	(15.10)	-0.035	(-3.75)
10	0.051	(13.67)	-0.033	(-2.89)

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11	0.043	(13.09)	-0.028	(-3.35)
12	0.038	(12.25)	-0.019	(-2.37)
16	0.022	(8.92)	-0.033	(-3.91)
20	0.014	(6.40)	-0.012	(-1.50)
24	0.008	(4.69)	-0.011	(-1.18)
26	0.007	(4.34)	0.009	(0.77)
52	0.004	(3.12)	-0.004	(-0.46)

Table 3. Momentum profits in different liquidity states

This table shows the average monthly returns on the momentum strategy in four different market liquidity states. Following Novy-Marx (2012), we define the n - m momentum strategy as the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation. The return series of the n - m momentum strategy is denoted as $MOM_{n,m}$. We define four states by sorting on either the ex-ante volatility (Panel A and Panel B) or the TED spread (Panel C and Panel D). The ex-ante volatility is based on GARCH (1,1) model. We estimate the model using the S&P GSCI daily data for the past 5 years, then compute the ex-ante volatility at month $t+1$ using the variable at month $t-1$. State 1 (High) corresponds to the 10% highest observations for the sorting variable; state 2 corresponds to above the median; state 3 corresponds to below the median, excluding the 10% lowest observations; and state 4 (Low) corresponds to the 10% lowest observations. The last row (1-4) in each panel shows the significance of the difference on returns in 1 and 4 states. Panel A and Panel C (Panel B and Panel D) report the average monthly returns on $MOM_{k,1}$ ($MOM_{k,k}$) for $k = 1$ to 36 in different market liquidity states. Newey–West (1987) adjusted t -statistics are reported in parentheses. The sample period of Panel A and Panel B is from January 1979 to June 2015, and that of Panel C and Panel D is from January 1986 to June 2015.

Panel A. Returns on $MOM_{k,1}$ in different ex-ante volatility states														
k	1	2	3	4	5	6	7	8	9	10	11	12	24	36
1 (High)	0.026 (1.95)	0.013 (0.97)	0.018 (1.46)	0.022 (1.70)	0.016 (1.26)	0.015 (1.16)	0.007 (0.54)	0.008 (0.57)	0.010 (0.80)	0.004 (0.32)	0.014 (1.00)	0.013 (0.99)	0.015 (1.55)	0.018 (1.72)
2	0.013 (2.03)	0.022 (3.49)	0.017 (2.71)	0.016 (2.80)	0.012 (1.92)	0.009 (1.57)	0.011 (1.74)	0.013 (2.14)	0.008 (1.32)	0.014 (2.28)	0.019 (2.99)	0.015 (2.39)	0.000 (-0.02)	-0.004 (-0.75)
3	0.012 (2.25)	0.009 (1.42)	0.012 (2.05)	0.008 (1.41)	0.007 (1.21)	0.008 (1.46)	0.009 (1.70)	0.008 (1.55)	0.010 (1.86)	0.010 (1.94)	0.016 (3.14)	0.015 (2.83)	0.011 (2.01)	0.007 (1.28)
4 (Low)	0.014 (1.04)	0.017 (1.74)	0.009 (0.83)	0.007 (0.53)	0.021 (1.77)	0.014 (1.18)	0.023 (1.86)	0.026 (1.94)	0.025 (1.84)	0.023 (1.74)	0.019 (1.64)	0.016 (1.39)	-0.003 (-0.32)	0.010 (0.94)
1-4	(0.72)	(-0.22)	(0.50)	(0.84)	(-0.32)	(0.02)	(-0.96)	(-1.11)	(-0.88)	(-1.10)	(-0.31)	(-0.16)	(1.14)	(0.52)
Panel B. Returns on $MOM_{k,k}$ in different ex-ante volatility states														
k	1	2	3	4	5	6	7	8	9	10	11	12	24	36
1 (High)	0.026 (1.95)	-0.002 (-0.15)	0.009 (0.80)	0.026 (2.29)	0.006 (0.59)	-0.005 (-0.38)	-0.008 (-0.59)	-0.005 (-0.55)	0.000 (-0.03)	0.009 (0.70)	0.019 (1.65)	0.009 (0.75)	0.014 (1.51)	0.005 (0.48)
2	0.013 (2.03)	0.016 (2.60)	0.003 (0.60)	0.003 (0.58)	-0.004 (-0.62)	0.007 (1.20)	0.002 (0.46)	0.005 (0.93)	-0.008 (-1.32)	0.022 (3.69)	0.015 (2.74)	-0.008 (-1.41)	-0.008 (-1.55)	0.004 (0.79)

3	0.012	0.001	0.004	0.002	-0.002	0.007	0.010	0.000	0.010	0.013	0.017	0.003	0.001	0.007
	(2.25)	(0.19)	(0.85)	(0.27)	(-0.37)	(1.28)	(2.07)	(0.07)	(2.03)	(2.38)	(3.66)	(0.54)	(0.27)	(1.32)
4 (Low)	0.014	-0.006	-0.007	0.002	0.019	-0.001	0.007	0.016	0.014	-0.001	0.003	-0.012	-0.015	0.011
	(1.04)	(-0.48)	(-0.54)	(0.16)	(1.51)	(-0.06)	(0.44)	(1.38)	(1.09)	(-0.15)	(0.30)	(-0.88)	(-1.32)	(1.05)
1-4	(0.72)	(0.27)	(1.01)	(1.58)	(-0.87)	(-0.25)	(-0.93)	(-1.41)	(-0.92)	(0.63)	(1.05)	(1.28)	(1.87)	(-0.42)

Panel C. Returns on $MOM_{k,l}$ in different TED spread states

k	1	2	3	4	5	6	7	8	9	10	11	12	24	36
1 (High)	0.036	0.027	0.009	0.006	0.006	0.007	0.018	0.021	0.017	0.013	0.018	0.025	0.012	0.011
	(3.01)	(2.05)	(0.68)	(0.37)	(0.46)	(0.49)	(1.43)	(1.44)	(1.18)	(0.90)	(1.33)	(1.75)	(0.86)	(0.89)
2	0.014	0.019	0.019	0.017	0.014	0.012	0.013	0.010	0.010	0.013	0.017	0.014	0.003	-0.002
	(2.40)	(2.99)	(3.13)	(2.71)	(2.13)	(2.01)	(2.07)	(1.60)	(1.65)	(2.07)	(2.74)	(2.18)	(0.44)	(-0.30)
3	0.011	0.013	0.012	0.012	0.010	0.008	0.009	0.013	0.008	0.012	0.018	0.014	0.007	0.004
	(1.83)	(2.06)	(1.96)	(2.04)	(1.67)	(1.31)	(1.53)	(2.28)	(1.41)	(1.99)	(3.17)	(2.34)	(1.31)	(0.63)
4 (Low)	0.002	-0.007	-0.002	-0.006	-0.005	-0.002	-0.010	-0.004	0.005	0.005	0.009	0.013	-0.001	0.005
	(0.12)	(-0.49)	(-0.18)	(-0.46)	(-0.37)	(-0.15)	(-0.78)	(-0.31)	(0.38)	(0.39)	(0.67)	(1.03)	(-0.13)	(0.46)
1-4	(1.96)	(1.84)	(0.63)	(0.65)	(0.62)	(0.52)	(1.65)	(1.40)	(0.76)	(0.46)	(0.54)	(0.67)	(0.78)	(0.41)

Panel D. Returns on $MOM_{k,k}$ in different TED spread states

k	1	2	3	4	5	6	7	8	9	10	11	12	24	36
1 (High)	0.036	-0.007	-0.011	0.012	0.012	0.005	0.016	-0.003	-0.004	0.000	0.026	0.014	0.002	0.028
	(3.01)	(-0.50)	(-0.87)	(1.08)	(0.88)	(0.34)	(1.00)	(-0.25)	(-0.27)	(0.03)	(2.16)	(0.99)	(0.14)	(3.08)
2	0.014	0.007	0.014	0.001	-0.002	0.006	0.004	0.003	0.009	0.008	0.011	-0.008	-0.006	0.001
	(2.40)	(1.39)	(2.37)	(0.22)	(-0.37)	(1.02)	(0.64)	(0.47)	(1.42)	(1.30)	(2.07)	(-1.16)	(-1.03)	(0.23)
3	0.011	0.009	-0.002	0.006	-0.005	-0.002	0.004	0.007	-0.006	0.023	0.016	-0.002	-0.005	0.006
	(1.83)	(1.56)	(-0.30)	(1.09)	(-0.94)	(-0.32)	(0.87)	(1.25)	(-1.07)	(4.21)	(3.02)	(-0.43)	(-0.97)	(1.03)
4 (Low)	0.002	0.002	-0.011	0.004	0.005	0.017	-0.004	-0.004	0.006	0.013	0.026	0.002	0.009	0.012
	(0.12)	(0.14)	(-1.19)	(0.35)	(0.47)	(1.66)	(-0.48)	(-0.50)	(0.68)	(0.90)	(3.16)	(0.21)	(0.98)	(1.36)
1-4	(1.96)	(-0.52)	(-0.03)	(0.50)	(0.41)	(-0.79)	(1.22)	(0.12)	(-0.58)	(-0.73)	(0.00)	(0.72)	(-0.48)	(1.13)

Table 4. Predictive regression

This table shows the estimates of the predictive regression. The ex-ante volatility is based on GARCH (1,1) model. We estimate the model using the S&P GSCI daily data for the past 5 years, then compute the ex-ante volatility at month $t+1$ using the variable at month $t-1$. In Panel A (Panel B), we regress the monthly returns on the winner-minus-loser commodity futures portfolio on the ex-ante volatility of the S&P GSCI with two control variables, the sentiment index and the TED spread. Following Novy-Marx (2012), we define the n - m momentum strategy as the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation. The return series of the n - m momentum strategy is denoted as $MOM_{n,m}$. In Panel A (Panel B), the dependent variable is $MOM_{k,1}$ ($MOM_{k,k}$) for $k = 1$ to 36. Newey–West (1987) adjusted t -statistics are reported in parentheses. The sample period is from January 1986 to June 2015.

Panel A. Predictive regression with $MOM_{k,1}$														
k	1	2	3	4	5	6	7	8	9	10	11	12	24	36
Intercept	-0.011 (-1.12)	-0.014 (-1.39)	-0.009 (-1.00)	-0.018 (-1.82)	-0.008 (-0.81)	-0.012 (-1.27)	-0.004 (-0.47)	0.003 (0.30)	0.003 (0.34)	0.010 (1.01)	0.010 (1.16)	0.009 (1.04)	-0.008 (-1.14)	-0.005 (-0.80)
Ex-ante volatility	1.248 (2.00)	1.630 (2.47)	1.502 (2.63)	2.084 (3.04)	1.064 (1.66)	1.219 (2.10)	0.491 (0.82)	0.422 (0.61)	0.276 (0.45)	0.078 (0.12)	0.349 (0.67)	0.195 (0.32)	0.802 (2.20)	0.708 (1.56)
TED spread	0.021 (2.75)	0.021 (2.77)	0.012 (1.37)	0.014 (1.51)	0.012 (1.31)	0.012 (1.44)	0.015 (1.86)	0.006 (0.71)	0.006 (0.79)	0.002 (0.26)	0.006 (0.74)	0.007 (0.83)	0.008 (1.10)	0.000 (0.04)
Panel B. Predictive regression with $MOM_{k,k}$														
k	1	2	3	4	5	6	7	8	9	10	11	12	24	36
Intercept	-0.011 (-1.12)	-0.005 (-0.59)	-0.006 (-0.68)	-0.013 (-1.39)	-0.002 (-0.24)	0.006 (0.69)	0.018 (2.10)	0.009 (1.10)	0.014 (1.77)	0.012 (1.48)	0.018 (1.96)	-0.005 (-0.75)	-0.010 (-2.23)	0.007 (1.07)
Ex-ante volatility	1.248 (2.00)	1.011 (1.42)	0.397 (0.67)	1.414 (1.97)	-0.076 (-0.14)	-0.057 (-0.09)	-1.296 (-2.02)	-0.209 (-0.35)	-1.193 (-1.77)	0.558 (1.09)	-0.428 (-0.50)	0.006 (0.01)	0.283 (0.62)	-0.291 (-0.69)
TED spread	0.021 (2.75)	0.001 (0.15)	0.007 (1.18)	0.005 (0.76)	0.002 (0.38)	-0.003 (-0.59)	-0.001 (-0.08)	-0.007 (-0.82)	0.000 (-0.05)	-0.006 (-1.07)	0.004 (0.71)	0.005 (0.80)	0.006 (1.14)	0.004 (0.62)

Table 5. Profitability of momentum strategies

This table shows the average monthly returns of the commodity futures and stock momentum strategies, and intercepts (alphas) estimated from various risk factor models. Following Novy-Marx (2012), we define the n - m momentum strategy as the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation. Panel A shows the results for the momentum strategy based on the past cumulative returns from n to 1 month prior to portfolio formation. Panel B shows the results for the strategy based on the single month returns on past n month ($n=m$). The table also presents the alpha and the coefficient on the stock momentum factor (UMD) estimated from the univariate model and the multivariate model with Fama and French's (2015) five factors. In the last column, we report the alpha from Fama and French's (2015) five factor model for comparison. The numbers in parentheses are t -statistics corrected by the Newey–West (1987) method. The sample period is from January 1979 to June 2015.

Panel A. Cumulative return strategy															
n	m	Average monthly return				FF five factor		Univariate model				Multivariate model			
		Stock		Commodity		Alpha		Alpha		UMD		Alpha		UMD	
1	1	-1.180	(-6.13)	1.618	(4.42)	1.681	(4.05)	1.531	(4.15)	0.077	(1.42)	1.589	(3.86)	0.093	(1.57)
2	1	-0.795	(-3.66)	1.621	(4.39)	1.675	(3.85)	1.513	(4.06)	0.094	(1.41)	1.564	(3.49)	0.112	(1.52)
3	1	-0.465	(-2.04)	1.446	(4.06)	1.292	(3.03)	1.301	(3.59)	0.128	(1.82)	1.145	(2.65)	0.148	(2.00)
4	1	-0.220	(-0.99)	1.413	(3.83)	1.195	(2.65)	1.244	(3.14)	0.149	(1.73)	1.026	(2.19)	0.171	(2.09)
5	1	-0.089	(-0.36)	1.150	(3.29)	0.942	(2.28)	0.937	(2.68)	0.188	(2.24)	0.732	(1.79)	0.214	(2.84)
6	1	0.143	(0.50)	1.104	(3.39)	0.935	(2.64)	0.890	(2.76)	0.188	(2.46)	0.732	(2.11)	0.211	(2.97)
7	1	0.197	(0.65)	1.199	(3.79)	0.928	(2.65)	0.956	(3.17)	0.213	(2.92)	0.704	(2.15)	0.232	(3.32)
8	1	0.223	(0.74)	1.237	(3.76)	0.962	(2.83)	1.042	(3.30)	0.170	(2.24)	0.778	(2.34)	0.190	(2.65)
9	1	0.401	(1.27)	1.080	(3.23)	0.766	(2.20)	0.876	(2.86)	0.180	(2.86)	0.576	(1.73)	0.198	(3.52)
10	1	0.380	(1.11)	1.281	(3.80)	0.916	(2.53)	1.129	(3.55)	0.136	(2.32)	0.771	(2.16)	0.151	(2.51)
11	1	0.545	(1.67)	1.700	(5.08)	1.373	(3.91)	1.517	(4.85)	0.167	(2.61)	1.205	(3.37)	0.179	(2.79)
12	1	0.645	(2.15)	1.387	(4.22)	1.004	(2.67)	1.159	(3.86)	0.210	(3.21)	0.804	(2.19)	0.216	(3.84)
24	1	0.214	(0.62)	0.373	(1.05)	0.298	(0.79)	0.258	(0.64)	0.109	(1.24)	0.190	(0.46)	0.107	(1.68)
36	1	0.139	(0.51)	0.348	(1.26)	0.299	(1.26)	0.294	(0.84)	0.048	(0.50)	0.237	(0.85)	0.058	(0.71)

Panel B. Single month return strategy															
n	m	Average monthly return				FF five factor		Univariate model				Multivariate model			

		Stock		Commodity		Alpha		Alpha		UMD		Alpha		UMD	
1	1	-1.179	(-6.12)	1.618	(4.42)	1.681	(4.05)	1.531	(4.15)	0.077	(1.42)	1.589	(3.86)	0.093	(1.57)
2	1	0.141	(0.79)	0.645	(1.86)	0.585	(1.41)	0.571	(1.57)	0.065	(1.02)	0.487	(1.13)	0.099	(1.44)
3	1	0.422	(2.70)	0.269	(0.77)	-0.130	(-0.35)	0.262	(0.72)	0.006	(0.10)	-0.143	(-0.36)	0.014	(0.23)
4	1	0.267	(1.81)	0.557	(1.57)	0.373	(0.92)	0.509	(1.36)	0.042	(0.59)	0.296	(0.70)	0.077	(1.12)
5	1	0.182	(1.04)	0.212	(0.69)	0.224	(0.58)	0.067	(0.22)	0.128	(2.33)	0.095	(0.25)	0.132	(2.65)
6	1	0.525	(2.45)	0.512	(2.08)	0.302	(1.05)	0.414	(1.72)	0.086	(2.01)	0.202	(0.70)	0.103	(1.94)
7	1	0.220	(1.61)	0.501	(1.46)	0.476	(1.38)	0.422	(1.22)	0.069	(1.45)	0.405	(1.16)	0.074	(1.34)
8	1	0.208	(1.43)	0.187	(0.59)	-0.063	(-0.18)	0.060	(0.19)	0.111	(2.38)	-0.173	(-0.49)	0.113	(2.36)
9	1	0.311	(1.91)	0.202	(0.49)	-0.008	(-0.02)	0.147	(0.35)	0.049	(0.99)	-0.050	(-0.11)	0.044	(1.01)
10	1	0.246	(1.39)	1.291	(3.54)	1.094	(2.61)	1.295	(3.48)	-0.003	(-0.08)	1.105	(2.55)	-0.012	(-0.31)
11	1	0.618	(4.51)	1.472	(5.98)	1.325	(4.68)	1.374	(5.72)	0.090	(2.78)	1.256	(4.55)	0.074	(2.10)
12	1	0.801	(4.63)	-0.321	(-0.88)	-0.303	(-0.84)	-0.401	(-1.09)	0.074	(1.41)	-0.360	(-1.01)	0.062	(1.19)
24	1	0.472	(3.56)	-0.510	(-1.72)	-0.502	(-1.91)	-0.531	(-1.94)	0.020	(0.58)	-0.509	(-1.64)	0.007	(0.17)
36	1	0.518	(3.25)	0.761	(3.98)	0.876	(4.16)	0.791	(3.70)	-0.027	(-0.66)	0.903	(4.07)	-0.025	(-0.59)

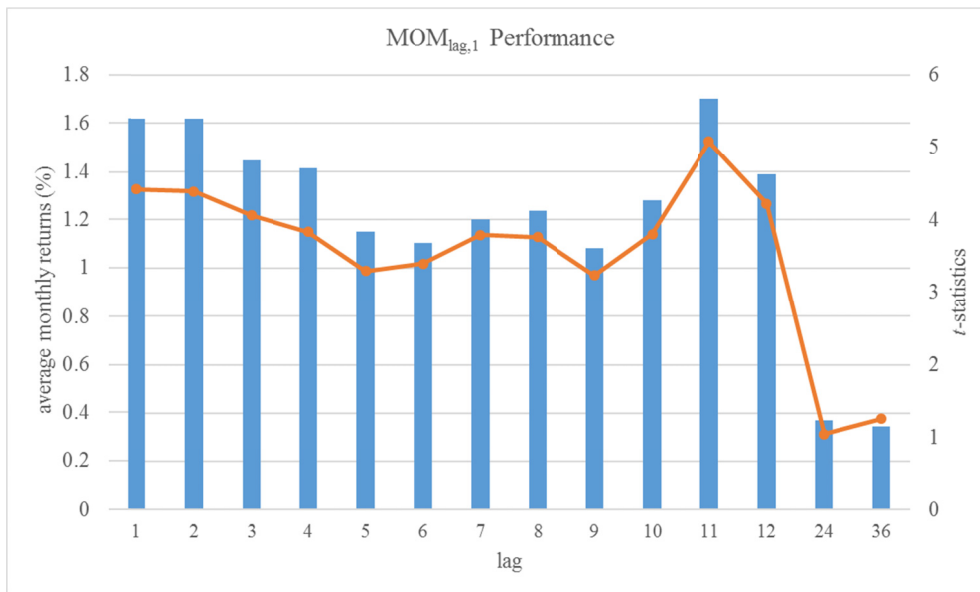
Table 6. Difference in momentum returns with the first- and second-nearest contracts

This table shows the difference in returns on momentum strategies constructed by the first- and second-nearest contracts. Following Novy-Marx (2012), we define the n - m momentum strategy as the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation. The return series of the n - m momentum strategy is denoted as $MOM_{n,m}$. Panel A (Panel B) reports the average of monthly return difference on $MOM_{k,1}$ ($MOM_{k,k}$) for $k = 1$ to 36. Matched-pair t -statistics are reported in parentheses. The sample period is from January 1979 to June 2015.

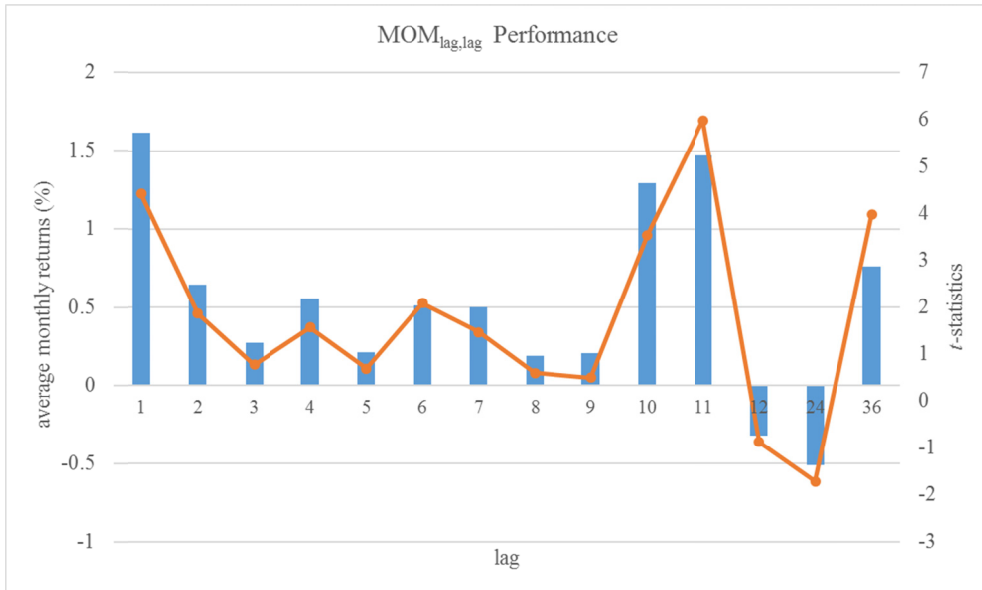
j	Panel A. Returns on $MOM_{k,1}$		Panel B. Returns on $MOM_{k,k}$	
1	0.0032	(1.86)	0.0032	(1.86)
2	0.0005	(0.26)	0.0028	(1.72)
3	0.0003	(0.14)	0.0013	(0.80)
4	0.0042	(2.22)	0.0032	(1.98)
5	0.0023	(1.42)	0.0018	(1.20)
6	0.0009	(0.49)	0.0007	(0.45)
7	0.0011	(0.65)	-0.0005	(-0.31)
8	0.0030	(1.82)	-0.0009	(-0.60)
9	0.0015	(0.92)	-0.0020	(-1.29)
10	-0.0005	(-0.29)	-0.0004	(-0.22)
11	0.0013	(0.74)	0.0025	(1.42)
12	0.0007	(0.40)	-0.0006	(-0.34)
24	0.0017	(0.88)	0.0018	(1.11)
36	0.0007	(0.36)	0.0015	(0.79)

Figure 1. Momentum strategy performance

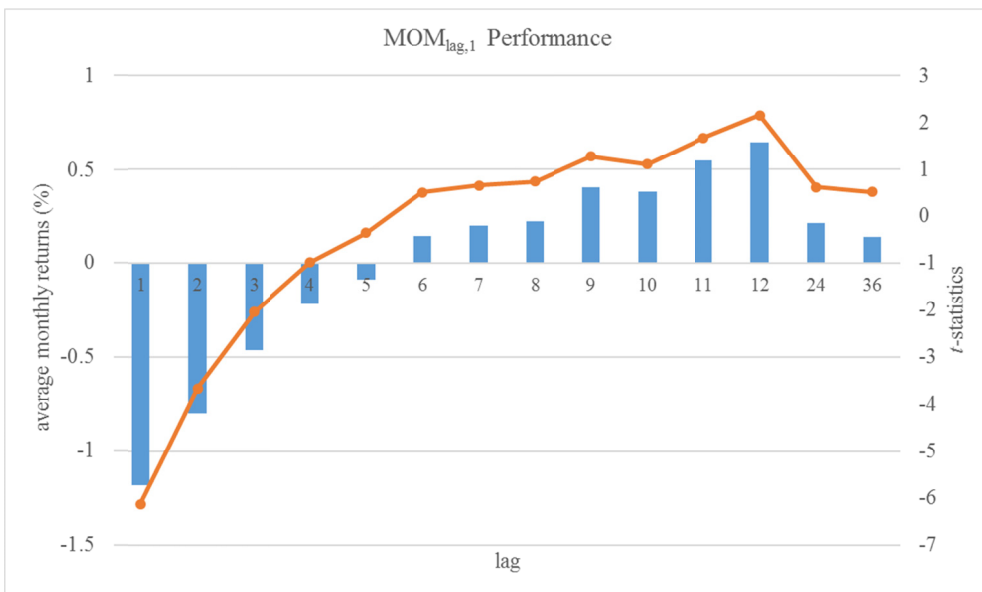
The figures show the average monthly returns on winner-minus-loser strategies. In each month, we construct a momentum strategy by buying the winner and selling the loser portfolios. The winner and loser portfolios are defined as the top and bottom quintiles (deciles) of the commodity futures contracts (stocks) sorted on the past returns, respectively. Following Novy-Marx (2012), we define the n - m momentum strategy as the winner-minus-loser portfolio based on the cumulative returns from n to m months prior to portfolio formation. The return series of the n - m momentum strategy is denoted as $MOM_{n,m}$. Panel A and B (C and D) present the average monthly returns on $MOM_{lag,1}$ and $MOM_{lag,lag}$ commodity futures (stocks) strategies, respectively. The bar shows the average monthly returns and the solid line shows Newey–West (1987) adjusted t -statistics.



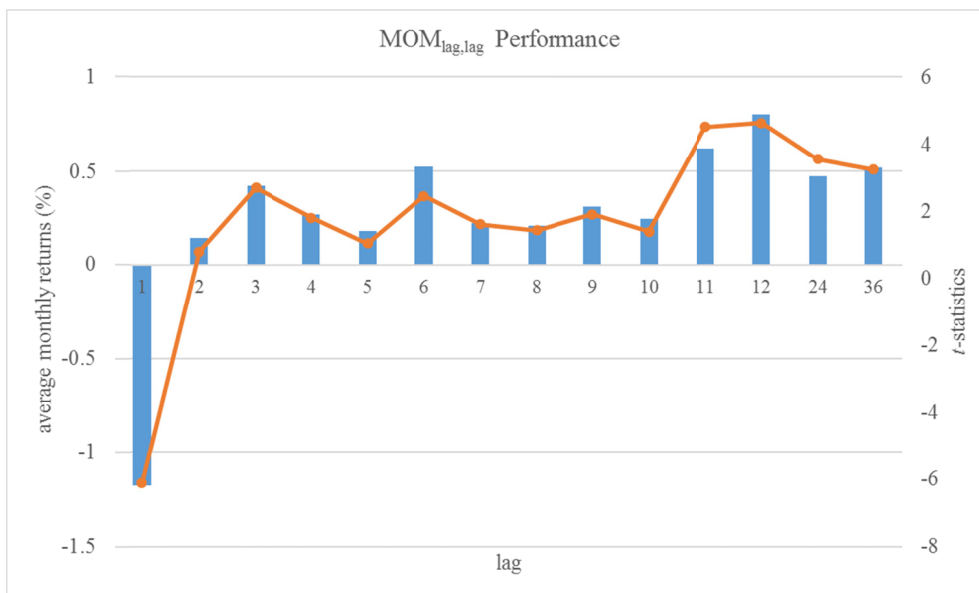
Panel A



Panel B



Panel C



Panel D