Short-Term Momentums in the Commodity Futures Market

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Abstract

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JEL classification: G10

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

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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 *losers*.[1] In efficient markets with a majority of rational investors, predictability using past returns is questionable. Researchers still argue about the reasons why momentums exist. While some researchers use the behavioral approach to solve the problem as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) did, others use the risk-based approaches (Chordia and Shivakumar (2002); Johnson (2002); Moskowitz and Grinblatt (1999)).

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 many possible explanations for it have been suggested. For example, G. B. Gorton, Hayashi, and Rouwenhorst (2013) provide the theoretical model that the past return of commodity futures has information about the inventory state, and thus it is related to the future return. Szymanowska et al. (2014) empirically show that the 12-month commodity futures momentum can be explained by the basis premium, which is the positive premium for the difference in the prices of the commodity futures and the underlying commodity.

However, one issue that has not been highlighted in the previous studies on momentums in the commodity futures is the difference between momentum strategies based on short-term past returns and momentum strategies based on long-term past returns. Though both strategies exhibit positive performances on average, the two have very different implications. Shen, Szakmary, and Sharma (2007) report that in the

[1] Contracts with high past returns are called *winners* and contracts with low past returns are called *losers*.

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.

In this paper, we pay attention to the term structure of the commodity momentums and suggest the rationale that plays a part in it. And when we interpret the term structure, comparing the commodity momentum to the stock momentum helps us to get a sense. We mainly focus on momentum strategies based on short-term (less than two months) past returns. There are two reasons. First, the short-term momentums in the stock and commodity futures markets show a substantial difference compared to longer ones. In the equity market, it is well-known that there is no short-term momentum; rather, strong reversal is found in periods shorter than one-month (Nagel, 2012). However, in the commodity futures markets, short-term momentum is the strongest (Shen et al., 2007; Kang and Kwon, 2017). Second, we expect that the short-term momentum can be closely related to compensation for liquidity providers. For the short-term reversal in equity markets, Nagel (2012) suggests that the returns of short-term reversal strategies in equity markets can be a proxy for the returns from liquidity provision under the assumption that liquidity providers in equity markets take contrarian strategies. 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, 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. 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.

We first construct momentum strategies by buying winners and selling losers sorted on the various lengths of past returns. To compare the result with equity momentums, we use two methods. One is to look at the average returns of momentum strategies in the commodity futures market and in the equity market varying the length of past returns. The other way is to regress the returns of the commodity momentum strategies on the equity momentum factor--UMD. In the first method, to compare the result with Novy-Marx (2012)'s result on the equity market, we form the portfolios based on the one-month returns on the *j*-th month prior to the portfolio formation with *j*=1 to 36. We find that momentum in the commodity futures markets exhibits notably different patterns compared to the equity market's momentum especially when based on short-term performances. In the second approach, the cross-sectional momentum factor of equity –UMD— seems to be highly related to the momentum returns in the commodity futures when based on the long-term past returns, but UMD cannot explain the short-term momentum returns. It may indicate that momentum based on the long-term past performance shares the common momentum factor with other assets but momentum based on the short-term past performance does not, and has different implications.

To link momentum to the trading activities of hedgers and speculators, we analyze how each investor group reacts to the price movement. As Dewally, Ederington, and Fernando (2013), Fung and Hsieh (2001), Bhardwaj, Gorton, and Rouwenhorst (2014), and Rouwenhorst and Tang (2012) address in their studies, we find that speculators are momentum players and hedgers are contrarians. Furthermore, we also discover that they do not pay attention to the longer performance. The changes in position of both investor groups are only related to the short term past returns, and both reverse their positions in the long run. So we can say that the speculators are the one who earn the strong performance of the short-term momentum strategies at the expense of hedgers. Also, long-term momentum is not relevant to any specific investor groups' strategy.

If hedgers generally consume liquidity to construct their hedging position and speculators are the providers of that liquidity, then short term momentum profits can be thought of as a compensation for the liquidity provision. To investigate the possible implications, we delve into the relationship between momentum returns and state of liquidity. As a proxy for the liquidity states, we use two liquidity supply factors; one is ex-ante volatility, which captures market liquidity, and the other one is the TED spreads, which captures funding liquidity[2]. Both univariate and multivariate methods give us the same results. In the univariate test, short-term momentum returns are high in the bad state, and longer-term momentums are irrelevant to the liquidity states. Multivariate predictive regression presents that the liquidity factors have predictability for the short-term momentum returns, but cannot predict the long-term momentums. Compared to the Nagel (2012)'s result on the equity market which shows that the VIX can predict the reversal strategy returns and the liquidity suppliers are contrarians in the short run in the equity market, we would argue that short-term momentum strategy is the position of liquidity suppliers in the commodity futures market. Therefore, the positive returns of short-term momentum strategy in the commodity futures markets is the compensation for the liquidity provision.

We find another interesting facts about differences between first-nearest contracts and second-nearest contracts. What hedgers buy is not only underperformers but also commodities of which first-nearest contracts are worse than second-nearest contracts. Also, the differences are bounced back right after while underperformance (outperformance) has momentums. We suggest that this is because there is a rush on the first-nearest contracts of a commodity at first and then the demand spreads to distant contracts. We verify this conjecture showing the significant stronger short-term momentums in the first-nearest contracts than in the second-nearest contracts. Longer-term momentums in the first-nearest and the second-nearest are not different, which is also consistent with our conjecture.

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

[2] Brunnermeier and Pedersen (2009) find the relationship between volatility and funding liquidity. Investor sentiment is relevant to the risk premium and market liquidity (Baker and Wurgler (2006); Qiu and Welch (2006)). The TED spread is the most wide-spread variable for funding constraint.

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. Section 3 shows the term structure of momentum returns on different look-back-periods. Section 4 shows the link between the relative performances of commodities on various horizons and the position of hedgers/speculators. Section 5 shows the evidence on the hypothesis that short-term momentum in the commodity futures markets is the outcomes of liquidity provision. Section 6 documents another evidence using comparison between first-nearest contracts and second-nearest contracts. Section 7 concludes.

2. 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.[3] 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.[4] 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.[5] 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.

3. Momentum strategies based on various periods of past returns

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,

[3] 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.
[4] https://fred.stlouisfed.org/series/TEDRATES
[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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 MOMn,m. In Panel A and C of Figure 1, by setting *m*=1, we form the winner-minus-loser portfolios based on the cumulative past performances, and in Panel B and D, by setting *n* = *m*, we construct the winner-minus-loser portfolios based on a single month starting lag (*n*=*m*) months prior to the portfolio formation. 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.

[Figure1 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. However, when we take account of the results of Panel B with that of Panel A, the results of Panel A, when *n* is between 2 and 12, can be regarded as the remaining strong predictability of previous months' (*n*=1) performances. Panel B suggests 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) which shows the term structure of the equity momentum. 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.

We also 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. To control risk factors, we use the Fama-French five-factors as control variables additionally. Dependent variables are monthly returns of the momentum strategies based on different length of past returns. It is known that various types of momentum strategies, whether it is time-series or cross-sectional, share a common factor in many different markets, in different types of assets, and in many different countries. Here, 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. 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.

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

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

The results are shown in Table 2.

[Table2 about here]

In Panel A, we use MOMn,m with *m*=1, which is based on cumulative past performances from *n* months prior to the formation to the very previous month of the formation, as the dependent variables. If you look at the coefficients of the UMD for the univariate model and the multivariate model, they are insignificant when *n* is lower than 5. However, as past performances track longer past periods, 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 related with the cross-sectional equity momentum. This result is consistent with the previous research which shows 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. And we additionally find that only when they are based on from intermediate-term to long-term past returns in the commodity futures markets, they share the common factor, according to the regression results. This result is also in line with the previous result which shows that equity momentum and commodity momentum are different in the short-term but not very different in the longer term.

In Panel B, the momentum strategies based on a single month also confirm our assertion. Risk-adjusted profits are the strongest when looking-back-month is one month, but the coefficients of UMD are all insignificant when *n* is less than 4. Additionally, the coefficients of UMD for looking-back-month of 5, 6, 8 and 11 months are all significantly positive though their returns are not as high as those with looking-back-month of 1 and 2 months. 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, short-term momentum does not share the common factor and have different economic meanings. To look further into the economic source of the result, we study with the position data in the next section.

4. Trading behavior of hedgers and speculators

In this section, we test the relationship between past returns and the changes in position of each investor group to attain further implications on the stylized facts of commodity momentum and its term structure. 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 lowers-- 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 time t is defined as:

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

The regression equations are:

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

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

$R_{i,(t-t1,t-t2)}$ is cumulative return of commodity *i* from *t1* weeks prior to the time *t* to *t2* weeks prior to the time *t*. For example, $R_{i,(t-3,t)}$ is the cumulative return during the last 3 weeks, and $R_{i,(t-3,t-3)}$ is the weekly return on a single week of 3 weeks ago. The regression results are reported in Table 3. The second and the third columns are the result of equation (4), and the last two columns are the result of equation (5).

[Table 3 about here]

In the result of equation (4), all the coefficients have signs as we expected, and they are all statistically significant. Hedgers sell contracts which outperform, and speculators long the winners. This result is consistent with previous research which 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)). However, the last two columns provide an evidence that hedgers and speculators only care about short-term past performance, and the significant coefficients in the previous two columns when *k* is greater than 3 are the effects of strong correlation between recent three weeks' performances and the change of position. According to the last two columns, speculators buy contracts which outperform during recent 3 weeks and reverse their momentum position after 4 weeks. Hedgers conduct the very opposite positions of speculators'. They are contrarian and form their positions based only on recent 3 weeks, and they also unwind their reversal positions after 4 weeks.

In the previous chapter, we show that the short-term momentum has different feature and may have different implications. And using the position data, we provide evidence on who take that position—the short-term momentum—which exhibits strong performance, and does not share the common momentum factor in this chapter. Then the next question would be why speculators are compensated and why hedgers are willing to pay for it.

5. Predictability of liquidity supply factors

We suggest that speculators are acting as liquidity providers in the commodity futures markets and hedgers consume that liquidity for constructing hedging positions. And as a position of speculators, short-term momentum can yield high returns for compensating liquidity provision. To test the hypothesis, we adapt two variables that can capture market liquidity and funding liquidity; which are ex-ante volatility and the TED spread.

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.

At 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.[6] Average momentum returns

[6] Following Petkova and Zhang (2005), we define states 2 and 3 using the average of observations instead of the

in each state and differences in average returns of state 1 and state 4 are reported in Table 4. 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 4. 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, 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 4 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. Even though the difference between average returns in state 1 and state 4 is not significantly different when k is 1, the level jumps up in the bad state compared to the average returns in state 2, 3 and 4 which are relatively flat. This is consistent with the recent theories which argue that the liquidity premium has strong variation across states and jumps in the bad states. Furthermore, the ordered level of average returns are not found in the longer-term momentum strategies. This agrees with our expectations.

In Panel C and D, the results are much stronger. The returns from short-term momentum strategies are neatly ordered from state 1 to state 4 and the difference is statistically significant. But in the longer-term momentum strategies, 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 are required in the bad states of liquidity.

We also 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. However the correlation coefficients are -0.0649, which is not even positive. The regression

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median, but we find that the results are qualitatively the same.

equation is:

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

The regression results are reported in Table 5.

[Table 5 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 months passed. The TED spread also shows significant predictabilities for short-term momentum up to 2 months of look-back-period. 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 the time-variation of the short-term momentum but not the fluctuation of the longer-term momentum. The result from this chapter support this idea.

Panel B shows the results for the momentum returns constructed by one-month past performances (i.e. $n=m$) on n months prior to formation with n from 1 to 36. The results are much clearer in this panel. The ex-ante volatility and the TED spread predict the momentum returns only when strategies are based on short-term performances. This suggests that the risk premiums of 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.

6. First-nearest contracts versus Second-nearest contracts

In this chapter, we document another evidence that supports our main hypothesis, that speculators are liquidity suppliers and this causes the strong short-term momentum in the commodity futures markets, in a different way. We investigate the return difference, or relative return, between the first-nearest contract and the second-nearest contract, and how it relates to each trader group's position and momentum returns.

First, we carry out Fama-MacBeth cross-sectional regressions of position change for each trader group on past and present return difference between the first-nearest contract and the second-nearest contract – "relative performance" denotes the difference so far. The relative performance of commodity *i* at time *t* can be written in this form:

$$RP_{i,t} = r_{i,t,first} - r_{i,t,second} \qquad (7)$$

$r_{i,t,first}$ is log return of the first-nearest contract of commodity *i* at time *t*, and $r_{i,t,second}$ is log return of the second-nearest contract of commodity *i* at time *t*.

And we conduct cross-sectional regression for the following regression equation on every week and average the estimates. The average estimates are reported in Table 6. Panel A is for hedgers and B is for speculators.

$$Q_{i,t,k} = a_0 + a_1 RP_{i,t-j} + \varepsilon_{i,t} \qquad (8)$$

[Table 6 about here]

In Panel A of Table 6, we find that hedgers are buying contracts of which relative performances are the lowest among other commodities, i.e., underperformance of the first-nearest compared to the second-nearest is the most severe. If we put this result with the result of Table 3 together, we can conclude that hedgers buy contracts which underperform and of which the underperformance is more evident in the first-nearest contract than second-nearest contract.

The exact opposite results can be found in Panel B for speculators.

Next, we check how long the outperformance (underperformance) and the relative performance last. This is similar to the concept of autocorrelation, but is different in a way that this is cross-sectional point of view. We regress the cross-sectional performance on the past cross-sectional performances every week, and average the estimates. This results are shown in Panel A of Table 7. We also regress the cross-sectional relative performance on the past cross-sectional relative performances every week and average the estimates. This results are shown in Panel B of Table 7.

$$r_{i,t} = a_0 + a_1 r_{i,t-j} + \varepsilon_{i,t} \qquad (9)$$

$$RP_{i,t} = a_0 + a_1 RP_{i,t-j} + \varepsilon_{i,t} \qquad (10)$$

The first equation is for Panel A and second equation is for Panel B. Data frequency is weekly here.

[Table 7 about here]

Panel A documents the cross-sectional performance gains momentum up to 3 weeks. It means that once a contract outperform (underperform), it keeps outperforming (underperforming) for next 3 weeks. It supports the cross-sectional momentum in the commodity futures market and also supports that speculators who buy outperformers in the short-run, make money using the strategies.

Panel B shows more interesting results. The relative performance have negative cross-sectional serial correlations. The mean of coefficients are significantly negative and this negative coefficients are statistically significant up to 3 weeks. This indicates that when the relative outperformance of one contracts are found, the relative outperformance starts to be reverted right away.

We interpret these results in this way; Speculators provide liquidity for contracts which are popular among hedgers who are making positions for hedging their risks with urgency. And the increased supply and demand of liquidity surges in the first-nearest contracts at first and then it spreads to more distant contracts afterwards, so the relative performances bounce back following the quick jump at the beginning. This consequences cause the position change of speculators and hedgers in the Table 6 and the return and relative performance cross-sectional serial correlations in Table 7.

If our conjectures are true, then the cross-sectional momentums are stronger in the first-nearest contracts than in the second-nearest contracts especially in the short-run. And in the longer-term, these gaps are disappeared or lessened. 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 8.

[Table 8 about here]

Table 8 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.

7. 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 reason why short-term momentum is different in the commodity futures market is that speculators are the one who take that position and they provide liquidity in the commodity futures markets. This liquidity provision encompass the compensation for the providers, speculators, and cause the strong short-term momentum returns.

We provide two supporting evidences. One is to show the predictability of short-term momentum returns using liquidity supply factors. We also show the significantly stronger short-term momentum in nearby contracts than in distant contracts. Both successfully confirm that short-term momentums are compensation for providing liquidity at the expense of hedgers.

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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%

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. 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 3. 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)

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 4. 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	0.013	0.018	0.022	0.016	0.015	0.007	0.008	0.010	0.004	0.014	0.013	0.015	0.018
	(1.95)	(0.97)	(1.46)	(1.70)	(1.26)	(1.16)	(0.54)	(0.57)	(0.80)	(0.32)	(1.00)	(0.99)	(1.55)	(1.72)
2	0.013	0.022	0.017	0.016	0.012	0.009	0.011	0.013	0.008	0.014	0.019	0.015	0.000	-0.004
	(2.03)	(3.49)	(2.71)	(2.80)	(1.92)	(1.57)	(1.74)	(2.14)	(1.32)	(2.28)	(2.99)	(2.39)	(-0.02)	(-0.75)
3	0.012	0.009	0.012	0.008	0.007	0.008	0.009	0.008	0.010	0.010	0.016	0.015	0.011	0.007
	(2.25)	(1.42)	(2.05)	(1.41)	(1.21)	(1.46)	(1.70)	(1.55)	(1.86)	(1.94)	(3.14)	(2.83)	(2.01)	(1.28)
4 (Low)	0.014	0.017	0.009	0.007	0.021	0.014	0.023	0.026	0.025	0.023	0.019	0.016	-0.003	0.010
	(1.04)	(1.74)	(0.83)	(0.53)	(1.77)	(1.18)	(1.86)	(1.94)	(1.84)	(1.74)	(1.64)	(1.39)	(-0.32)	(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	-0.002	0.009	0.026	0.006	-0.005	-0.008	-0.005	0.000	0.009	0.019	0.009	0.014	0.005
	(1.95)	(-0.15)	(0.80)	(2.29)	(0.59)	(-0.38)	(-0.59)	(-0.55)	(-0.03)	(0.70)	(1.65)	(0.75)	(1.51)	(0.48)
2	0.013	0.016	0.003	0.003	-0.004	0.007	0.002	0.005	-0.008	0.022	0.015	-0.008	-0.008	0.004
	(2.03)	(2.60)	(0.60)	(0.58)	(-0.62)	(1.20)	(0.46)	(0.93)	(-1.32)	(3.69)	(2.74)	(-1.41)	(-1.55)	(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 $MOM_{k,1}$ 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 5. 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	-0.014	-0.009	-0.018	-0.008	-0.012	-0.004	0.003	0.003	0.010	0.010	0.009	-0.008	-0.005
	(-1.12)	(-1.39)	(-1.00)	(-1.82)	(-0.81)	(-1.27)	(-0.47)	(0.30)	(0.34)	(1.01)	(1.16)	(1.04)	(-1.14)	(-0.80)
Ex-ante volatility	1.248	1.630	1.502	2.084	1.064	1.219	0.491	0.422	0.276	0.078	0.349	0.195	0.802	0.708
	(2.00)	(2.47)	(2.63)	(3.04)	(1.66)	(2.10)	(0.82)	(0.61)	(0.45)	(0.12)	(0.67)	(0.32)	(2.20)	(1.56)
TED spread	0.021	0.021	0.012	0.014	0.012	0.012	0.015	0.006	0.006	0.002	0.006	0.007	0.008	0.000
	(2.75)	(2.77)	(1.37)	(1.51)	(1.31)	(1.44)	(1.86)	(0.71)	(0.79)	(0.26)	(0.74)	(0.83)	(1.10)	(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	-0.005	-0.006	-0.013	-0.002	0.006	0.018	0.009	0.014	0.012	0.018	-0.005	-0.010	0.007
	(-1.12)	(-0.59)	(-0.68)	(-1.39)	(-0.24)	(0.69)	(2.10)	(1.10)	(1.77)	(1.48)	(1.96)	(-0.75)	(-2.23)	(1.07)
Ex-ante volatility	1.248	1.011	0.397	1.414	-0.076	-0.057	-1.296	-0.209	-1.193	0.558	-0.428	0.006	0.283	-0.291
	(2.00)	(1.42)	(0.67)	(1.97)	(-0.14)	(-0.09)	(-2.02)	(-0.35)	(-1.77)	(1.09)	(-0.50)	(0.01)	(0.62)	(-0.69)
TED spread	0.021	0.001	0.007	0.005	0.002	-0.003	-0.001	-0.007	0.000	-0.006	0.004	0.005	0.006	0.004
	(2.75)	(0.15)	(1.18)	(0.76)	(0.38)	(-0.59)	(-0.08)	(-0.82)	(-0.05)	(-1.07)	(0.71)	(0.80)	(1.14)	(0.62)

Table 6. Trading behavior of hedgers and speculator and relative performance of futures

This table shows the relation between the relative performance of the commodity futures and net-long position change of hedgers (Panel A) and speculators (non-commercials). The relative performance of the commodity futures (RP) is defined as the (log) return difference between the first-nearest contract and the second-nearest contract as equation (7). In each panel, we regress the net-long position change at week *t* on the relative performance at week t-j for j = 0 to 11. This table shows the coefficients of RP_{t-k} 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.

j	Panel A. Hedgers		Panel B. Speculators	
	RP_{t-j}		RP_{t-j}	
0	-3.139	(-9.25)	2.408	(7.55)
1	-2.021	(-8.61)	1.843	(8.80)
2	-0.634	(-2.71)	0.641	(3.21)
3	-0.224	(-1.12)	0.065	(0.34)
4	0.074	(0.41)	-0.202	(-1.24)
5	0.146	(0.67)	-0.090	(-0.49)
6	0.519	(2.69)	-0.301	(-1.77)
7	0.213	(0.95)	-0.276	(-1.64)
8	0.772	(3.25)	-0.577	(-2.85)
9	0.136	(0.70)	-0.049	(-0.31)
10	-0.052	(-0.28)	-0.086	(-0.48)
11	0.190	(0.90)	-0.148	(-0.80)

Table 7. Relation with the past returns and relative performance

In this table, Panel A (Panel B) shows the relation between the return (relative performance) of the commodity futures at week *t* and the return (relative performance) at week *t-j* for *j* = 1 to 12 (1 to 11). The relative performance of the commodity futures (*RP*) is defined as the (log) return difference between the first-nearest contract and the second-nearest contract as equation (7). This table shows the coefficients of r_{t-j} (RP_{t-j}) 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.

j	Panel A. Return		Panel B. Relative performance	
	r_{t-j}		RP_{t-j}	
1	0.033	(3.80)	-0.148	(-7.96)
2	0.015	(1.78)	-0.127	(-6.02)
3	0.021	(2.55)	-0.074	(-3.53)
4	0.007	(0.67)	-0.013	(-0.78)
5	-0.001	(-0.07)	-0.038	(-1.99)
6	0.007	(0.82)	-0.061	(-3.40)
7	0.014	(1.49)	-0.020	(-1.06)
8	0.034	(3.53)	-0.008	(-0.43)
9	0.001	(0.11)	-0.034	(-2.23)
10	0.016	(1.68)	-0.032	(-1.69)
11	0.007	(0.87)	-0.035	(-1.74)
12	0.001	(0.16)		

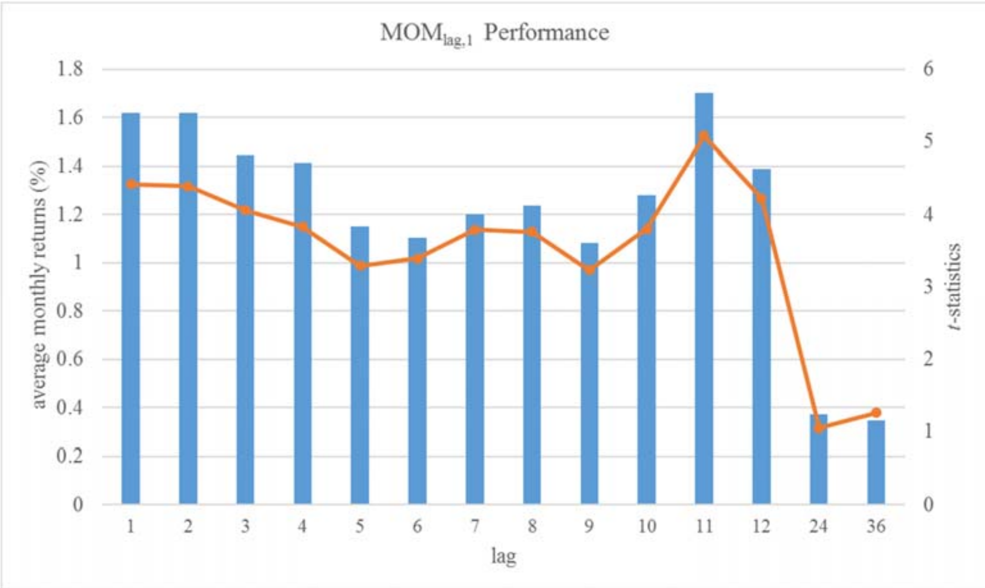
Table 8. Difference in momentum returns with the first- and second-nearest contracts

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)

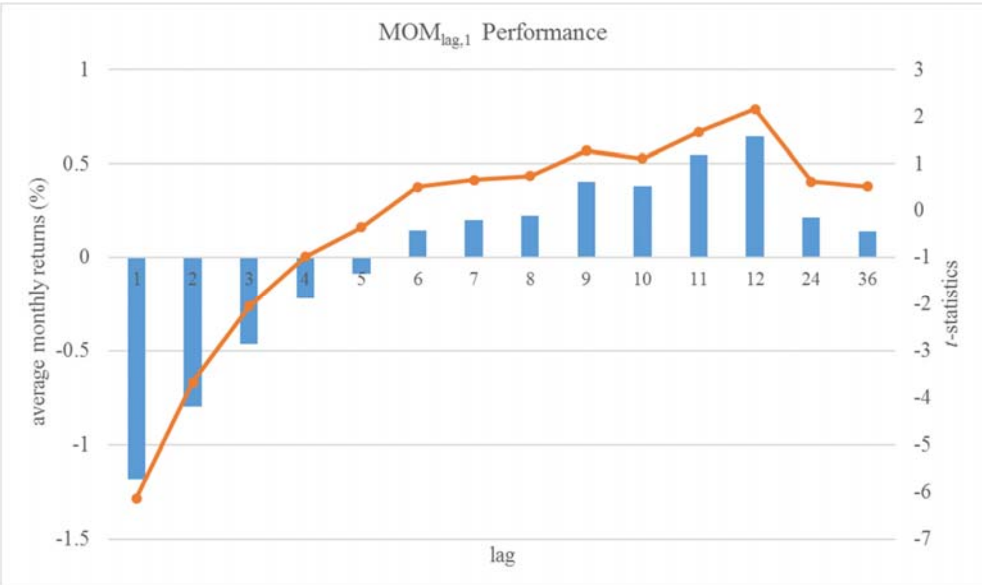
Figure 1. Momentum strategy performance

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 weekly returns and the solid line shows Newey–West (1987) adjusted *t*-statistics.

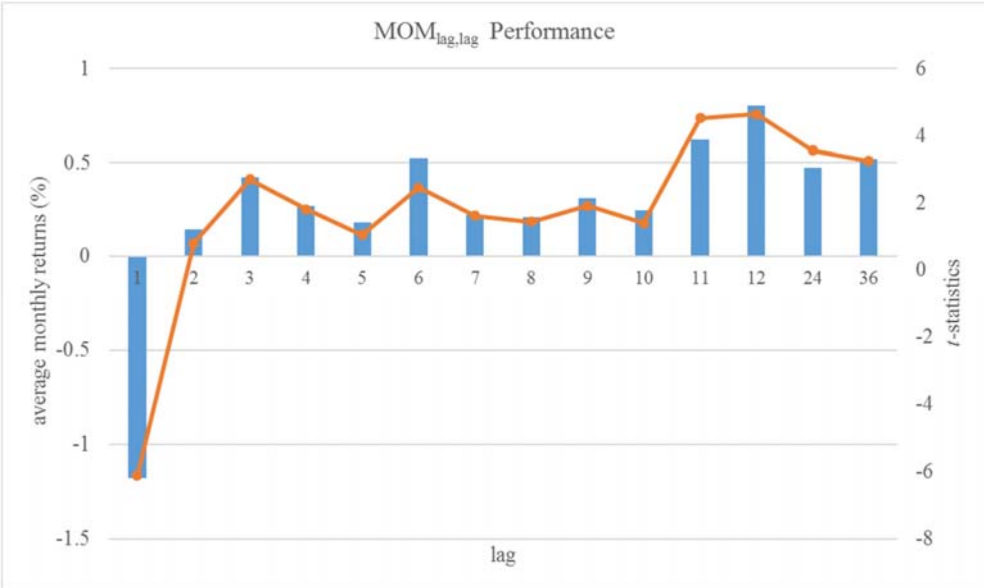


Panel A

Panel B



Panel C


$MOM_{lag,lag}$ Performance
average monthly returns (%)
t-statistics
lag
1
0.5
0
-0.5
-1
-1.5
6
4
2
0
-2
-4
-6
-8
1
2
3
4
5
6
7
8
9
10
11
12
24
36

Panel D