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Commodities momentum: A behavioral perspective

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ABSTRACT

The growth in commodity-related investments has sparked interest in the performance of momentum strategies in these markets. This paper introduces a behavioral proxy of the 52-week high and low momentum that explains a significant proportion of the variation of conventional momentum returns after controlling for commodity specific risk factors. Our findings show that the 52-week high strategy generates significant profits after accounting for transaction costs. We report that the 52-week high strategy is a better predictor of returns than conventional momentum. Our findings suggest that term structure and hedging pressure risk factors provide only a partial explanation of the results.

1. Introduction

The 2004–2014 boom and bust in commodity related investments has sparked renewed interest from both academia and industry in better understanding momentum strategies in these markets (see Moskowitz et al., 2012; Gorton et al., 2013; Basu and Miffre, 2013; Narayan et al., 2014; Fuertes et al, 2015; Bianchi et al., 2015).[1] The early work by Keynes (1930) and Working (1949) has led to the development of the term structure and hedging pressure risk factors as the key drivers of commodity futures returns. Erb and Harvey (2006) find that long–short momentum strategies are profitable in commodity futures. Using different datasets, Miffre and Rallis (2007) and Shen et al. (2007) support these findings and demonstrate that momentum profits in commodity futures cannot be fully attributable to systematic risk factors. Despite the intense interest in the literature, the sources of commodities momentum remain unresolved. For the first time in the literature, this paper introduces a behavioral proxy of the 52-week high momentum that explains a significant proportion of the variation of conventional momentum returns after controlling for commodity specific risk factors.

We posit that the success of the 52-week high momentum strategy rests on the anchoring bias of investors. Under a rational, efficient capital markets framework, prices adjust to new information instantaneously in a random fashion. In contrast, behavioral theorists have long argued that investors are not always rational and a delayed reaction exists as investors respond gradually to new information.[2] In the commodity futures literature, early evidence shows that futures prices do not follow random walks, and that profitable trading strategies can be used to exploit predictable patterns in prices (Stevenson and Bear, 1970; Cargill and Rausser, 1975; Leuthold, 1972). Furthermore, Ma et al., (1990) and Peterson et al. (1992) show that commodity prices do not react to information in a rational manner. These studies conclude that agricultural commodity futures prices overreact to significant events whereas financial futures prices underreact. The overreaction hypothesis is confirmed in Wang and Yu (2004) where they examine the price reversal of commodity futures, and in Shen et al. (2007) where they attribute the success of conventional commodities momentum to investors' overreaction bias. Given these behavioral

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[1] From 2003 to 2010, commodity related institutional investments have grown from less than $20 billion to more than $250 billion according to a Barclays Capital survey of over 250 institutional investors (see http://www.barcap.com/about-barclays-capital/press-office/news-releases/2010/12/). Furthermore, AUM (assets under management) for managed futures have grown from $45 billion to $340 billion from 2002 to 2013 (http://www.barclayhedge.com/). This is referred by the media, World Bank and IMF as the 'Commodity Investment Boom' or 'Commodity Super Cycle' (see CNBC, 2013; WSJ, 2013; Bloomberg, 2013; World Bank 2014; IMF, 2011).

[2] Various examples of behavioral decisions include conservatism bias (Barberis et al., 1998) and overconfidence bias (Daniel et al., 1998; Hong and Stein, 1999).

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findings, we examine the 52-week high momentum strategy to understand how the investment behavior in commodity futures is related to the conservatism bias.

The design of the 52-week high momentum strategy from George and Hwang (2004) (GH thereafter) shows that investors exhibit conservatism bias when they use the 52-week high as a reference/anchoring point in evaluating the potential impact of news on U.S. stocks. When good news pushes stock prices near or above their 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it. Similarly, when bad news pushes stock prices far from their 52-week high, investors are initially unwilling to sell at prices implied by the information. When information eventually prevails, prices adjust to a new equilibrium thus resulting in return continuation. Consequently, GH finds that strategies constructed using the 52-week high generate higher abnormal profits than conventional momentum strategies and that the 52-week high better predicts future performance. Other studies by Gupta et al. (2010) and Liu et al. (2011) support the findings of GH in various international stock market settings. We extend the understanding of commodities momentum by examining this behavioral phenomenon in commodity futures.[3]

This study makes four contributions to the literature. First, we argue that if stock investors exhibit conservatism bias in the form of anchoring behavior around the 52-week high level, then commodity investors may also exhibit similar behavior, even though commodity returns are driven by factors different from those in stock markets.[4] Grinblatt and Han (2005) predict that anchoring behavior whereby the acquisition price acts as an anchor leads to momentum effects for stocks whose prices are at or near long-run highs and long-run lows.[5] Contrary to the Grinblatt and Han (2005) predictions, GH does not find abnormal profits when momentum strategies are formed on stocks' nearness to their 52-week low. They attribute the absence of the momentum behavior at the 52-week low momentum to a tax distortion effect.[6] However, this study shows that both the 52-week high and the 52-week low momentum strategies generate statistically significant profits in commodity futures. The findings suggest that the anchoring behavior of commodity investors around the 52-week low may be different from the behavior of stocks investors.[7] Consistent with prior studies on investor irrationality in commodity futures, our results not only confirm the conservatism hypothesis but also indicate that the anchoring behaviors appear to be *stronger* than in the equities markets.

Second, our analyses suggest that the 52-week high momentum is a better predictor of future performance than the 'conventional momentum' identified by Jegadeesh and Titman (1993) and the 52-week low momentum in commodity futures. Consistent with GH, our findings suggest that the profits from the 52-week high momentum strategy are robust after controlling for conventional momentum, but not vice versa. While the 52-week low and conventional momentum can be completely subsumed by each other, the 52-week high momentum alone can explain more than half of the variation of returns of the conventional momentum portfolio. Furthermore, since nearly three-quarters of the variation in returns can be explained by the 52-week high and low momentum combined, we argue that conventional momentum can largely be explained by the anchoring behavior of investors around the 52-week high and the 52-week low of commodity prices. Furthermore, we find that the 52-week high momentum profits *do reverse* in a relatively short period of 12–30 months. Unlike in the stock market literature, whereby 52-week high momentum profits do not reverse over the long-term, our findings suggest that momentum and reversal can co-exist in commodity futures, as predicted by the behavioral models of Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999).

Third, to link the behavior of the 52-week high and low momentum strategies to common risk factors, we find that global funding liquidity and the two commodity-specific dynamic risk factors of term structure and hedging pressure play important roles. Consistent with Asness et al. (2013) and Bianchi et al. (2015), we find that global funding liquidity is a partial information variable that can help in understanding one of the possible sources of commodity momentum returns. Furthermore, we show that a six-factor framework used by Fuertes et al. (2010) and Moskowitz et al. (2012) does not explain commodity momentum portfolio returns, although it seems to explain the winners and losers portfolios. In addition to the six-factor model, the winners and losers (but not momentum) portfolios across strategies are negatively related to the VIX and OVX, suggesting a symmetrical response by winners and losers to changes in market volatility. Moreover, the profits of the 52-week high momentum strategy are completely subsumed by the TED spread. Despite a low R^2, this finding implies that global funding liquidity is important in understanding the nature of the 52-week high momentum. Furthermore, the 52-week high momentum is negatively related to the bottom quintile of the changes in investor sentiment, suggesting that the strategy tends to perform well in stable market conditions, that is, when there are smaller shifts in market sentiment. Finally, the 52-week high momentum exhibits positive relationships with the dynamic, long–short term structure and hedging pressure risk factors, although a full risk-based explanation appears unlikely based on the evidence presented in this paper.

Fourth, remarkably consistent with the predictions of the adaptive market hypothesis (AMH), our sub-period analysis reveals a significant structural decline in all momentum profits. The AMH proposed by Amilon (2008), Charles et al. (2012), Lo (2004, 2012) and Neely et al. (2009), argue that the behavioral biases of market agents, such as anchoring, heuristics, and underreaction, continue to exist because agents must adjust their behaviors to survive in a rapidly evolving market environment. Since prior studies of the 52-week high momentum offer little guidance on this finding, we conjecture that the anchoring behavior of commodity traders has changed due to the tremendous growth in commodity investments since the early 1990s and the introduction of the Commodity Futures Modernization Act of 2000. As more professionals have entered the commodity futures markets in recent years, competition has intensified causing the gradual erosion of profitable opportunities and anomalies.[8]

[3] Schwager (1989) documents commodity speculators Richard Dennis and William Eckhardt and the famous 'turtle' trading strategy, which constructs long and short speculative positions at a market's intermediate term high and low price levels. This speculative commodity futures strategy reflects and exhibits similarities to the 52-week high momentum strategy examined in this paper.

[4] Studies have shown that commodity investments exhibit low correlations with traditional asset classes, thereby reducing the overall risk associated with traditional portfolios (see Bodie and Rosansky, 1980; Jensen et al., 2000, 2002; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). However, recent studies such as Tang and Xiong (2012), Choi and Hammoudeh (2010), Silvennoinen and Thorp (2013) and Basak and Pavlova (2016) argue that commodity futures returns exhibit high correlations with traditional asset classes during crisis periods.

[5] Grinblatt and Han (2005) argue that investors are subject to a disposition effect, which causes the aversion to sell shares that result in the recognition of losses.

[6] GH states that locked-in capital gains make investors unwilling to sell a stock. Thus, prices of stocks that are winners relative to the 52-week low tend to be above their fundamental values. When the mispricing is corrected, the reversal may offset any momentum generated by the 52-week low.

[7] Perhaps there is little or no tax distortion effect because investors, on aggregate, hold lower levels of investments in commodities compared to stocks.

[8] One may also attribute the declining trading profits of the various momentum strategies to the development of information technology and the emergence of algorithmic and high frequency trading in commodity futures markets.

The findings presented in this paper complements the commodities pricing literature. Previous behavioral proxies such as VIX, investor sentiment and OVX have shown to be poor at explaining the variation of conventional momentum returns. We introduce a behavioral proxy of the 52-week high/low with risk-based factors that can explain commodity momentum returns. Our findings suggest that risk based factors (i.e. term-structure and hedging pressure) provide a partial explanation of the behavior of commodities momentum. After controlling for these risks, the driving forces of conventional momentum in commodities are largely behavioral. While a three-factor model that consists of term structure, hedging pressure and momentum factors continues to gain acceptance in the commodities pricing literature (Gorton et al., 2013, Yang, 2013, Basu and Miffre, 2013; Daskalaki et al., 2014; Szymanowska et al., 2014; Bakshi et al., 2015), our findings suggest that the 52-week high momentum may be considered as a substitute for the conventional momentum in understanding the cross-sectional variation of commodity futures returns.

The remainder of the paper proceeds as follows. Section 2 describes the data sources and the methodology of the 52-week high and 52-week low momentum strategies compared to the conventional momentum strategy. Section 3 presents the empirical results, and Section 4 provides concluding remarks.

2. Data and portfolio formation

This study employs data from the benchmark provider Standard and Poor's. The Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) is a production-weighted, broadly diversified index that tracks the overall performance of the commodities markets. The S&P GSCI (GSCI hereafter) is a widely used benchmark for investments in commodity futures. However, since construction of momentum strategies requires the transactions of multiple commodity futures markets simultaneously, we use the individual commodity futures indexes published by S&P.

Our sample consists of 30 commodities from six sectors, namely, Energy (Brent crude, gas oil, heating oil, natural gas, RBOB gas and WTI crude), Precious Metals (gold, platinum, palladium and silver), Industrial Metals (aluminum, copper, lead, nickel, tin and zinc), Livestock (feeder cattle, lean hogs and live cattle), Grains (corn, soybean, soy oil, soy meal, Chicago wheat and Kansas wheat) and Softs (cocoa coffee, cotton, frozen orange juice and sugar). We obtain daily excess returns of these commodity futures indexes from December 1969 through July 2013. All data are sourced from Datastream International.

Since only five commodities were available at the inception date, the commencement date is adjusted to January 1977 to maintain reasonable volatility levels in each long and short portfolio. Table 1 reports the ticker symbol, exchange information and commencement dates of the commodity futures. The end-of-the-month price is used to compute the aggregated monthly commodity futures excess returns.[9]

Although Datastream is commonly used in the commodities momentum literature, the specific use of the GSCI individual commodity futures data is limited (see Wang and Yu, 2004; Miffre and Rallis, 2007; Marshall et al., 2008). Thus, it is important to note the differences in rolling methodologies between our sample and previous studies. To compile the continuous time-series futures returns, prior studies use an 'immediate roll' approach, that is, all positions in the expiring futures contract are closed out on the same day when the new positions are opened in the nearby or distant contracts. This compares to the GSCI individual commodities time-series prices being compiled by gradually rolling all futures positions over a pre-defined roll period of 5 days (the 5th to the 9th) in each month.[10] The 'gradual roll' approach is more practical for investors because rolling large positions on a single day may create an adverse price impact in commodity futures markets, thereby reducing the value of an investment portfolio.[11]

Investors in futures markets earn a total return comprising the collateral return and the futures return. The former is the risk-free return earned on the cash position or collateral component of the futures position, and the latter is generated by the changes in the futures price. In this study, we assume no leverage in all futures positions. In other words, every long or short portfolio is fully collateralized. The combined long–short strategy is approximately 50% collateralized, therefore, the uninvested capital may be used to facilitate potential margin calls triggered before the end of each holding period. In addition to the futures returns, the long–short strategies should generate collateral returns in excess of any margin call.[12]

The conventional momentum strategy is constructed following Miffre and Rallis (2007) and Fuertes et al. (2010). At the end of each month in the sample, all commodities are sorted into terciles (winner, middle and loser) based on their past 12-months returns.[13] The momentum strategy constructs a long position in the winners portfolio and a short position in the losers portfolio. These positions are held for 1 month after portfolio formation. This procedure is repeated monthly and all futures positions are rebalanced at the end of each month. Consistent with the commodities momentum literature, no monthly gap is skipped between formation and investment period and all portfolios are equal-weighted.[14]

The 52-week high momentum strategy is constructed following GH.[15] At the end of each month, all commodities included in the sample are sorted into winner, middle and loser portfolios based on their nearness to the 52-week high ratio. The nearness ratio is calculated by $P_{i,t-1}/high_{i,t-1}$, where $P_{i,t-1}$ is the price of commodity i at the end of month $t-1$ and $high_{i,t-1}$ is the highest price of commodity i during the 12-month period before the end of month $t-1$. Consistent with the conventional momentum strategy, this proce-

[9] As a robustness check, the 15th-of-the month price is also used to construct the monthly returns time series and the results are similar to those reported using end-of month prices. These results are available upon request.

[10] For example, on the first day of the roll period for a given commodity, the first nearby contract and the roll contract will take a weight of 0.8 and 0.2, respectively. As time approaches to the end of the roll period, the weight will change to 0.6/0.4, 0.4/0.6, 0.2/0.8 until the futures contract closest to expiry takes a zero weight and the position is completely rolled-over to the next nearby contract. The compiled time series futures price included in our sample uses only the nearest and the next nearest contracts as these roll contracts mitigate liquidity concerns over the futures contracts expiring in faraway months. See Standard & Poor's (2012, p. 36) for more details on its futures contract roll weights.

[11] For robustness reasons, we also considered two alternative data providers (Dow Jones and Bloomberg) to source data on the same sample of commodities. Dow Jones-UBS employs a similar gradual role approach whereas Bloomberg implements an immediate roll approach to construct the continuous time-series commodity futures prices (see Miffre and Rallis, 2007; Fuertes et al., 2010). Consistent with the S&P dataset, results based on these alternative sources suggest that the observed strategy returns are unlikely to be a result of index construction.

[12] In this study, we report the excess return of all strategies. Thus, the total realizable profits in practice may be understated.

[13] The returns of the past 12 months are selected for two reasons. First, it is the most extensively employed formation period in the stock market literature. Second, the ranking period of the past 12 months consistently outperforms all other ranking periods (i.e. 1, 3 6 and 9 months) in previous commodity studies (see Shen et al., 2007; Moskowitz et al., 2012; Asness et al., 2013).

[14] Momentum strategies in commodity futures are not impacted by the reversal effect in the first month after formation as documented extensively in the stock market literature, thus, we do not skip one month between the portfolio formation and holding period as these returns are realized (Moskowitz and Grinblatt, 1999; Cooper et al., 2004; Boni and Womack, 2006).

[15] GH uses the classic 6/6 strategy, i.e. 6 months ranking and holding period, therefore, their portfolios are overlapping, whereas our conventional momentum strategy is non-overlapping.

Table 1
Commodity futures summary statistics.

Sector	Commodity	Ticker	Exchange	Start Date	Mean	Std. Dev.	Skew.	Kurt.
Energy	Brent crude	SPGSBRP	ICE(UK)	Jan-99	0.0166	0.0903	−0.2066	4.6608
	Gas oil	SPGSGOP	ICE(UK)	Jan-99	0.0161	0.0929	−0.0680	3.8938
	Heating oil	SPGSHOP	NYMEX	Jan-83	0.0079	0.0921	0.4035	4.6305
	Natural gas	SPGSNGP	NYMEX	Jan-94	−0.0138	0.1521	0.5633	4.0657
	RBOB gas	SPGSHUP	NYMEX	Jan-88	0.0148	0.1003	0.3878	5.6648
	WTI crude	SPGSCLP	NYMEX	Jan-87	0.0097	0.0956	0.3896	5.2863
Precious Metals	Gold	SPGSGCP	COMEX	Jan-78	0.0018	0.0570	0.5219	6.4708
	Platinum	SPGSPLP	NYMEX	Jan-84	0.0054	0.0646	−0.0064	6.6750
	Palladium	SPGSPAP	NYMEX	Dec-08	0.0271	0.0808	−0.7581	3.5468
	Silver	SPGSSIP	COMEX	Jan-77	0.0030	0.0959	0.5494	8.3917
Livestock	Feeder cattle	SPGSFCP	CME	Jan-02	0.0014	0.0439	−0.2205	3.7071
	Lean hogs	SPGSLHP	CME	Jan-77	−0.0004	0.0707	−0.0157	3.4048
	Live cattle	SPGSLCP	CME	Jan-77	0.0030	0.0431	−0.1517	4.6587
Industrial Metals	Aluminum	SPGSIAP	LME	Jan-91	−0.0026	0.0558	0.1547	3.3997
	Copper	SPGSICP	LME	Jan-77	0.0071	0.0783	0.2537	6.0713
	Lead	SPGSILP	LME	Jan-95	0.0072	0.0854	−0.0220	4.0244
	Nickel	SPGSIKP	LME	Jan-93	0.0083	0.1017	0.1822	3.3713
	Tin	SPGCISP	LME	Mar-07	0.0106	0.0926	0.1063	2.9046
	Zinc	SPGSIZP	LME	Jan-91	0.0003	0.0739	−0.0186	4.9976
Softs	Cocoa	SPGSCCP	ICE(US)	Jan-84	−0.0034	0.0835	0.6107	4.2089
	Coffee	SPGSKCP	ICE(US)	Jan-81	0.0009	0.1078	1.0452	5.9413
	Cotton	SPGSCTP	ICE(US)	Jan-77	0.0007	0.0707	0.4013	4.3263
	Orange juice	SPGSOJP	ICE(US)	Jan-99	−0.0003	0.0875	0.1517	2.9880
	Sugar	SPGSSBP	ICE(US)	Jan-77	0.0011	0.1119	1.1449	7.4075
Grains	Corn	SPGSCNP	CBOT	Jan-77	−0.0036	0.0726	0.7371	7.2928
	Soybean	SPGSSOP	CBOT	Jan-77	0.0021	0.0683	0.0831	4.0370
	Soybean oil	SPGSBOP	CBOT	Jan-05	0.0052	0.0781	−0.3089	4.9457
	Soybean meal	SPGSSMP	CBOT	May-12	0.0174	0.0858	0.7128	2.7104
	Wheat	SPGSWHP	CBOT	Jan-77	−0.0035	0.0720	0.4064	5.0328
	Kansas wheat	SPGSKWP	KCBT	Jan-99	−0.0009	0.0839	0.5321	4.8833

This table lists all commodity futures included in this study. This table classifies the markets by sectors and includes the ticker symbol, exchange information and commencement dates of each commodity. The basic summary statistics (mean, standard deviation, skewness and kurtosis) of excess returns are also reported. The returns are computed using end-of-month prices. All commodities included in the sample are published by Standard and Poor's. Despite the variations in commencement dates, all price time-series end at July 2013.

dure is repeated monthly and all portfolios are rebalanced at the end of each month, with no monthly gap skipped between formation and holding periods. Since the holding period is limited to one month, all portfolios are non-overlapping and equal-weighted.

The 52-week low momentum strategy is constructed in a similar way as the 52-week high momentum strategy. Instead of measuring the nearness to the 52-week high ratio, commodities are ranked based on their nearness to the 52-week low ratio. The nearness ratio is calculated by $P_{i,t-1}/low_{i,t-1}$, where $P_{i,t-1}$ is the price of commodity i at the end of month $t-1$ and $low_{i,t-1}$ is the lowest price of commodity i during the 12-month period before the end of month $t-1$. All portfolios are rebalanced monthly with no monthly gap skipped between ranking and holding periods, and all portfolios are non-overlapping and equal-weighted.

3. Results

3.1. Profitability of the 52-week high and low momentum strategies

Panels A, B and C of Table 2 report the performance of the conventional momentum, the 52-week high and 52-week low momentum strategies, respectively. From February 1977 through July 2013, the conventional momentum strategy reports an excess return of 12.66% per annum (1.05% per month) with a t-statistic of 3.41, while the 52-week high momentum strategy returns a stronger 14.54% p.a. (1.21% p.m.) with a t-statistic of 3.99. Consistent with GH, this finding suggests that the 52-week high momentum strategy is also profitable in commodity futures. Furthermore, while the returns to winner portfolios are almost identical, the returns in the loser portfolios of the 52-week high momentum strategy appear to be higher than those of the conventional strategy. This finding suggests that the 52-week high momentum may be a better predictor of future performance even in commodity futures.

GH does not find profits when momentum strategies are formed on stocks based on the nearness to their 52-week low and state that the lack of profits may be caused by tax distortion effects. However, our results in Table 2 show that commodity momentum portfolios formed using the 52-week low information also generate statistically significant profits of 11.36% p.a. (0.95% per month) with a t-statistic of 3.07. Although it seems inconsistent with GH, the profitability of the 52-week low strategy in commodity futures appears to be consistent with the prediction in Grinblatt and Han (2005).[16] Our findings imply that the anchoring bias behavior of commodity investors may differ from that of stock market participants.

In addition to traditional risk and return measurements in academic studies, we also report performance metrics used by industry professionals.[17] On a risk-adjusted basis, the 52-week high momentum strategy performs well, delivering a reward/risk (Sortino) ratio of 0.67 (1.16), compared to the 0.57 (0.99) and 0.51 (0.98) achieved by conventional and 52-week low momentum strategies, respectively. Table 2 also reveals that the 52-week high momentum strategy exhibits a maximum drawdown of approximately −40% compared to a far worse −60% and −54% experienced by

[16] Grinblatt and Han (2005) argue that some investors are subject to a disposition effect, which causes an aversion to sell shares that result in the recognition of losses. They demonstrate in their model that the anchoring behavior (the acquisition price acts as an anchor) leads to momentum effects for stocks whose prices are at or near long-term highs and lows.

[17] The reward/risk ratio is equivalent to the Sharpe ratio, as we use commodities excess returns data. We use 0% as the benchmark in the Sortino ratio. The 99% VaR with Cornish–Fisher expansion is the empirical estimates as no simulation is estimated to arrive at the results.

Table 2
Performance of momentum strategies.

	Winner	Middle	Loser	W-L
Panel A: Conventional momentum strategy				
Annualized arithmetic mean	0.1083	−0.0002	−0.0183	0.1266
t-statistics	3.00	−0.01	−0.66	3.41
Annualized geometric mean	0.0852	−0.0109	−0.0318	0.1025
Annualized volatility	0.2153	0.1459	0.1647	0.2214
Reward/risk Ratio	0.5033	−0.0012	−0.1111	0.5720
Sortino ratio	0.7690	−0.0017	−0.1704	0.9920
Skewness	0.0434	−0.1678	0.2604	0.2643
Kurtosis	6.8614	4.8905	5.0318	5.1804
99%VaR (Cornish–Fisher)	0.2561	0.1390	0.1770	0.2530
% of positive months	0.5915	0.5376	0.4883	0.5986
Maximum drawdown	−0.6218	−0.7082	−0.8613	−0.6073
Drawdown length (months)				14
Max run-up (consecutive)	0.6252	0.1604	0.1781	0.5751
Run-up length (months)				3
Max 12M rolling return	1.0102	0.3307	0.4652	0.8776
Min 12M rolling return	−0.5579	−0.7380	−0.6010	−0.7749
Panel B: 52 week high momentum strategy				
Annualized arithmetic mean	0.1086	0.0240	−0.0368	0.1454
t-statistics	3.27	0.98	−1.24	3.99
Annualized geometric mean	0.0893	0.0132	−0.0525	0.1221
Annualized volatility	0.1976	0.1464	0.1771	0.2173
Reward/risk Ratio	0.5496	0.1642	−0.2076	0.6689
Sortino ratio	0.8632	0.2330	−0.3210	1.1582
Skewness	0.1560	−0.3031	0.1566	0.1734
Kurtosis	6.0166	7.6690	4.4627	4.6027
99%VaR (Cornish–Fisher)	0.2310	0.1638	0.1773	0.2365
% of positive months	0.5657	0.5282	0.4812	0.5704
Maximum drawdown	−0.4751	−0.5702	−0.9170	−0.3958
Drawdown length (months)				5
Max run-up (consecutive)	0.6113	0.2066	0.2465	0.5759
Run-up length (months)				3
Max 12M rolling return	1.0679	0.3845	0.4224	0.9253
Min 12M rolling return	−0.4970	−0.6280	−0.7327	−0.2964
Panel C: 52 week low momentum strategy				
Annualized arithmetic mean	0.0869	0.0311	−0.0267	0.1136
t-statistics	2.34	1.19	−1.09	3.07
Annualized geometric mean	0.0625	0.0190	−0.0374	0.0900
Annualized volatility	0.2210	0.1562	0.1456	0.2209
Reward/risk Ratio	0.3933	0.1993	−0.1835	0.5146
Sortino ratio	0.6149	0.3143	−0.2598	0.9848
Skewness	0.1197	0.0794	−0.2700	0.6408
Kurtosis	6.4211	4.5905	4.5934	5.2836
99%VaR (Cornish–Fisher)	0.2593	0.1596	0.1297	0.2703
% of positive months	0.5587	0.5164	0.4883	0.5446
Maximum drawdown	−0.6326	−0.5822	−0.8502	−0.4541
Drawdown length (months)				29
Max run-up (consecutive)	0.6794	0.2583	0.0835	0.7163
Run-up length (months)				4
Max 12M rolling return	1.0644	0.4202	0.3162	1.0590
Min 12M rolling return	−0.5631	−0.5751	−0.6988	−0.4727

This table presents the performance of momentum strategies. Commodities are sorted based on their previous 12-month excess return, their nearness to their 52-week high and nearness to their 52-week low. The headings Winner and Loser use the Fuertes et al. (2010, FMR hereafter) methodology of the 30% of commodities with the highest (lowest) previous 12-month excess return. The heading Middle are commodities that are neither winners nor losers. The 52-week high/low winners (losers) are the 30% of commodity futures that exhibit the highest (lowest) 52-week high/low measure; the middle group consists of those that are neither winners nor losers. This table reports the performance of conventional (Panel A), 52-week high (Panel B) and 52-week low (Panel C) momentum strategies. All portfolios are held for 1 month. W-L represents the Winners–Losers (momentum) portfolio. The sample covers the period February 1977 through July 2013.

conventional and 52-week low momentum strategies, respectively. These strategies also exhibit value-at-risk estimates of approximately 25% after incorporating the skewness and excess kurtosis at the 99% confidence level. These results highlight the fact that these strategies show statistically significant profits yet they are associated with significant levels of investment risk that are not captured by conventional statistical inferences.

We now examine how different commodity sectors affect the various momentum strategies. Various effects in commodity futures may occur due to the underlying nature of these markets rather than the presence of the 'January effect' documented in the stock literature. As agricultural commodities undergo stages of development before harvesting, Roll (1984), Kenyon et al. (1987) and Milonas (1991) demonstrate that commodity spot and futures prices are more volatile in months when weather conditions are unstable. Furthermore, energy commodities also exhibit seasonal patterns due to seasonal fluctuations in these markets (Pardo et al., 2002; Hunt et al., 2003).

Table 3
Momentum strategies (excluding commodity sectors).

	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
Panel A: Conventional momentum									
	All excl. Energy			*All excl. Grains*			*All excl. Industrial metals*		
Annualized arithmetic mean	0.0830	−0.0215	0.1045	0.1282	−0.0367	0.1649	0.0917	−0.0319	0.1235
t-statistics	(2.47)	(−0.80)	(3.07)	(3.16)	(−1.22)	(3.87)	(2.48)	(−1.11)	(3.15)
Annualized volatility	0.2007	0.1593	0.2030	0.2421	0.1790	0.2537	0.2203	0.1704	0.2338
Reward/risk ratio	0.4137	−0.1347	0.5148	0.5297	−0.2049	0.6499	0.4162	−0.1870	0.5284
	All excl. Livestock			*All excl. Precious metals*			*All excl. Softs*		
Annualized arithmetic mean	0.1125	−0.0314	0.1440	0.1028	−0.0165	0.1192	0.1124	−0.0062	0.1186
t-statistics	(2.86)	(−1.04)	(3.57)	(2.87)	(−0.57)	(3.07)	(2.82)	(−0.22)	(2.93)
Annualized volatility	0.2348	0.1799	0.2401	0.2133	0.1732	0.2315	0.2376	0.1714	0.2412
Reward/risk ratio	0.4792	−0.1747	0.5996	0.4816	−0.0952	0.5150	0.4731	−0.0362	0.4918
Panel B: 52 week high momentum									
	All excl. Energy			*All excl. Grains*			*All excl. Industrial metals*		
Annualized arithmetic mean	0.0866	−0.0504	0.137	0.1385	−0.0353	0.1738	0.0975	−0.0497	0.1473
t-statistics	(2.71)	−(1.80)	(4.03)	(3.90)	−(1.07)	(4.26)	(2.97)	−(1.59)	(3.88)
Annualized volatility	0.1905	0.1673	0.2027	0.2118	0.1966	0.2434	0.1955	0.1862	0.2262
Reward/risk ratio	0.4546	−0.3015	0.6761	0.6538	−0.1797	0.7142	0.4988	−0.2672	0.6511
	All excl. Livestock			*All excl. Precious metals*			*All excl. Softs*		
Annualized arithmetic mean	0.1201	−0.0505	0.1705	0.1073	−0.0327	0.1401	0.1153	−0.004	0.1193
t-statistics	(3.21)	−(1.57)	(4.23)	(3.29)	−(1.06)	(3.68)	(3.01)	−(0.13)	(3.03)
Annualized volatility	0.2225	0.1912	0.2405	0.1944	0.1837	0.2267	0.2286	0.1828	0.2348
Reward/risk ratio	0.5396	−0.2640	0.7091	0.5522	−0.1782	0.6180	0.5044	−0.0218	0.5081
Panel C: 52 week low momentum									
	All excl. Energy			*All excl. Grains*			*All excl. Industrial metals*		
Annualized arithmetic mean	0.0683	−0.0216	0.0899	0.1003	−0.0292	0.1294	0.0548	−0.0314	0.0862
t-statistics	(1.96)	−(0.88)	(2.61)	(2.38)	−(1.12)	(2.98)	(1.43)	−(1.25)	(2.20)
Annualized volatility	0.2075	0.1468	0.2055	0.2515	0.1550	0.2588	0.2281	0.1502	0.2333
Reward/risk ratio	0.3291	−0.1470	0.4374	0.3987	−0.1881	0.5000	0.2401	−0.2092	0.3694
	All excl. Livestock			*All excl. Precious metals*			*All excl. Softs*		
Annualized arithmetic mean	0.0907	−0.0324	0.1231	0.0835	−0.0303	0.1138	0.1034	−0.017	0.1205
t-statistics	(2.17)	−(1.19)	(2.99)	(2.16)	−(1.22)	(2.89)	(2.41)	−(0.65)	(2.78)
Annualized volatility	0.2488	0.1615	0.2457	0.2305	0.1480	0.2343	0.2562	0.1567	0.2580
Reward/risk ratio	0.3648	−0.2004	0.5011	0.3624	−0.2045	0.4856	0.4038	−0.1086	0.4670

This table reports the performance of momentum strategies by excluding one commodity sector at a time from the analysis. These sectors include Energy, Industrial Metals, Precious Metals, Livestock, Grains and Softs. Panels A, B and C report Conventional, 52-week high and 52-week low momentum strategies, respectively. The sample covers the period February 1977 to July 2013. Reward/Risk is the equivalent to the Sharpe ratio in this case since commodity futures excess returns are employed.

To examine whether the results are driven by a specific commodity sector, Table 3 reports the profitability of conventional (Panel A), 52-week high (Panel B) and 52-week low momentum (Panel C) strategies by excluding every commodity sector from the analysis. The returns reported in Panels A to C remain positive and statistically significant regardless of the commodity sector being excluded in the analysis. Notably, all strategies seem to perform the best (even on a risk-adjusted basis) when markets from the grains sector are excluded, whereas the worst performing sector specification is somewhat mixed. The findings suggest that the profitability of the 52-week high and low momentum strategies is not influenced by commodity sectors.[18]

To better understand the profitability of these strategies, Fig. 1 compares the percentage of total trades of the conventional, 52-week high and 52-week low momentum strategies classified by commodity sector. The left figure reports the winners portfolio and the right figure illustrates the losers portfolio. Based on the sample period, it is clear that the various momentum strategies trade commodities across all sectors and the percentage of total trades varies from strategy to strategy. This finding suggests that commodity futures momentum in general does not depend on any particular sector. In the winners portfolio, conventional and 52-week low momentum strategies trade energy-based commodities most extensively, whereas the 52-week high strategy trades softs-based commodities more frequently. Notably, the 52-week high strategy trades commodities more evenly across all sectors compared to the other momentum strategies. However, in the losers portfolio, all strategies consistently short-sell more commodities from the softs sector. As a result, we can see that the differences in return dynamics of conventional, 52-week high and 52-week low momentum strategies are not due to data mining, but rather are caused by the variations in portfolio composition due to the different investment decisions in each strategy.

We now examine whether the observed profitability in commodity futures momentum can be subsumed by transaction costs. First, transaction costs in futures are significantly lower than those for stocks. Lesmond et al. (2004) estimate a cost of 2.3% per trade in stocks and Jegadeesh and Titman (1993) use a more conservative 0.5% per trade. Locke and Venkatesh (1997) and Marshall et al. (2012) show that transaction costs in the futures markets are much lower at 0.0004–0.033% per trade. Furthermore, unlike in the equities market, taking a short position in the futures markets is as straightforward as taking a long position, providing additional assurance on the execution of these momentum-based investment strategies.

Second, momentum strategies in the equities market often involve transactions of a large number of stocks, which undoubtedly puts pressure on the net profitability of momentum trades (Korajczyk and Sadka, 2004). This is unlikely to be an issue in commodity futures, since the strategies outlined in this study do not require transactions of more than 20 commodities at any given time in the sample.

[18] To examine whether the results are influenced by calendar-based seasonality effects, we compute the average monthly returns across all calendar months for all strategies and find no particular seasonal patterns. Regression analysis with calendar dummies confirm these findings. The results hold even when both grains and softs commodities are excluded simultaneously. In the interests of brevity, these results and are not reported; however, they are available upon request.

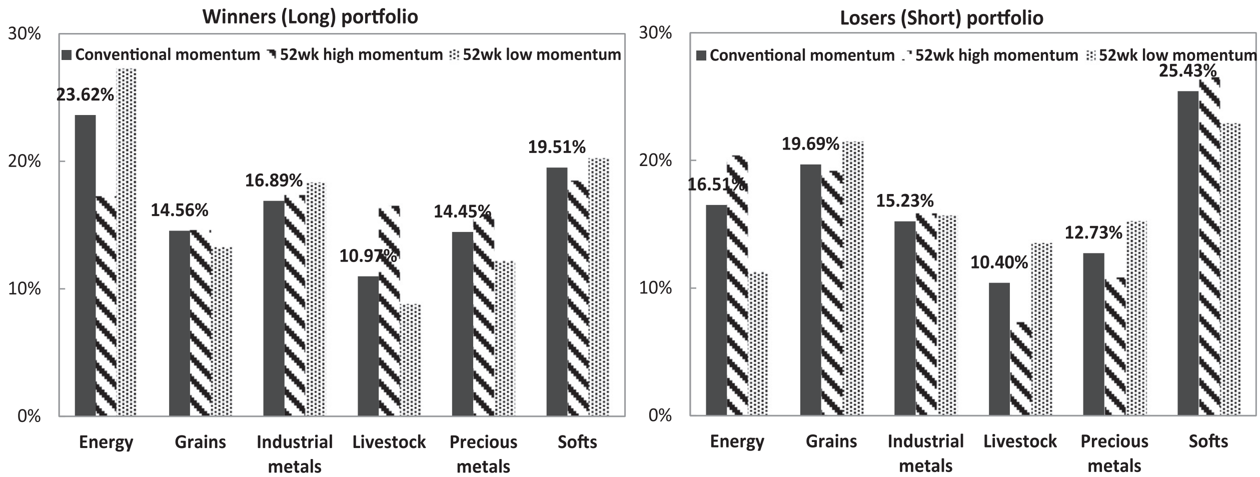

Fig. 1. Percentage of Total Trades. This figure illustrates the percentage of total trades of conventional, 52-week high and 52-week low momentum strategies. From January 1977 through July 2013, the total number of trades in long and short positions are collated. The long trades are separated from the short trades. The portfolio composition of these trades can be observed on an individual commodity sector basis. This figure presents the aggregated portfolio composition by commodity sector for both long and short positions.

To further consider these apparent advantages, we quantify the level of transaction costs by using Fuertes et al. (2010) as a proxy. This study examines long–short conventional momentum strategies in commodity futures. The authors estimate an average annual portfolio turnover of 9.24 times, based on an investment universe of 37 commodities.[19] The highest turnover ratio in their study is 10.38, which leads to a total transaction cost of just 0.69% per annum. Since their portfolio characteristics are similar to our strategies, this transaction cost is far too small to have any material impact on the profitability of the momentum strategies estimated in this study.[20]

3.2. Comparison between the conventional, 52-week high and low momentum

GH shows that conventional momentum profits are smaller when they control for the 52-week high momentum, whereas the 52-week high momentum profits remain significant even after controlling for the effects of conventional momentum. Thus, GH concludes that the 52-week high is a better predictor of future performance than the Jegadeesh and Titman (1993) methodology of past returns. We employ this methodology to determine whether the 52-week high/low momentum is a better predictor of future performance compared to the conventional momentum in commodity futures. If the 52-week high momentum strategy dominates the conventional momentum strategy, the profits from the former should still exist when conditioned on the latter. Similarly, if the 52-week low momentum dominates the conventional momentum, the profits from the 52-week low momentum must be significant after controlling for conventional momentum.

Table 4 presents the results of the comparison. Panels A and B report commodities which are sorted independently on the previous 12-month returns and the nearness to their 52-week high. Panel A reports the returns for portfolios that are long 52-week high winners and short 52-week high losers within winner, middle and loser categories identified by conventional momentum. Panel B reports the returns for portfolios constructed using the conventional strategy within groups identified as winner, middle, and loser categories by the 52-week high measure. Subsequently in Panels C and D, we perform a similar two-way dependent sorting on conventional and 52-week low momentum strategies. Panel C reports the returns for portfolios that are long 52-week low winners and short 52-week low losers within winner, middle, and loser categories identified by conventional momentum. Panel D reports the returns for portfolios constructed using the conventional momentum strategy within groups identified as winner, middle, and loser categories by the 52-week low measure.

Consistent with the findings of GH in U.S. stocks, Table 4 shows that the 52-week high momentum strategy reports positive profits in each winner, middle and loser group ranked by their previous 12-months of returns. In Panel A, a zero-cost strategy based on the 52-week high generates monthly excess returns of 0.82% and 0.42% among commodities that have already been classified by conventional momentum as winners and losers, respectively. The 52-week high strategy within winners (losers) classified by conventional momentum reports *t*-statistics of 2.17 (1.44). In Panel B however, within winners and losers classified by the 52-week high, the profitability of the conventional momentum strategy is substantially smaller at 0.61% and 0.11%, respectively, and are both insignificant. These results clearly show that the 52-week high momentum strategy is superior compared to the conventional momentum.

Nevertheless, in Panels C and D, it appears that the 52-week low momentum strategy is less superior to the conventional momentum strategy regardless of the sort order, as profits in all winner and loser groups are extremely close to zero and insignificant. Overall, the findings in Table 4 suggest that the 52-week high momentum is a better predictor of future performance, whereas the 52-week low momentum is not, which implies that using the 52-week low as an anchor in commodity futures is inferior to the conventional momentum strategy.

Table 5 presents thirteen regression results of the 52-week high, 52-week low and conventional momentum strategies' returns as dependent variables regressed against a variety of independent variables. Regression specifications 1, 5 and 9 show the average monthly returns of the 52-week high, 52-week low and conventional strategies, respectively. Specifications 2, 6 and 10 show that all strategies exhibit significant positive loadings on the U.S. momentum risk factor UMD, though the 52-week high momentum

[19] The turnover ratio considered in this case includes the rolling over of contracts and changes in portfolio composition. We do not consider price impact, commissions and monthly rebalancing.

[20] Fuertes et al. (2010) employ a 1-month holding period, terciles first-sort and median second-sort break points for portfolio formation, which results in 12 commodities being traded in each month. Our strategies involve no more than 20 commodities at any given time.

Table 4
Pairwise comparison of the 52-week high/low and the conventional momentum profits.

Panel A

Portfolios classified by Fuertes et al. (2010)	Portfolio classified by 52-week high	Ave. monthly return	*t*-statistics	Ave. standard deviation
Winner	Winner	1.37%	(3.12)	8.07%
	Loser	0.55%	(1.62)	6.95%
	Winner–loser	0.82%	(2.17)	8.25%
Middle	Winner	0.32%	(1.11)	5.22%
	Loser	−0.20%	−(0.78)	5.00%
	Winner–loser	0.51%	(2.16)	5.77%
Loser	Winner	0.06%	(0.25)	4.59%
	Loser	−0.36%	−(0.98)	6.33%
	Winner–loser	0.42%	(1.44)	5.83%

Panel B

Portfolio classified by 52-week high	Portfolios classified by Fuertes et al. (2010)	Ave. monthly return	*t*-statistics	Ave. standard deviation
Winner	Winner	1.25%	(2.81)	8.62%
	Loser	0.64%	(1.93)	5.51%
	Winner–loser	0.61%	(1.91)	7.88%
Middle	Winner	0.76%	(2.28)	6.16%
	Loser	−0.23%	−(1.05)	4.20%
	Winne–loser	0.99%	(3.38)	5.80%
Loser	Winner	−0.25%	−(0.78)	5.77%
	Loser	−0.36%	−(1.04)	6.29%
	Winner–loser	0.11%	(0.33)	6.49%

Panel C

Portfolios Classified by Fuertes et al. (2010)	Portfolio classified by 52-week low	Ave. monthly return	*t*-statistics	Ave. standard deviation
Winner	Winner	0.76%	(1.71)	9.16%
	Loser	1.03%	(3.07)	6.16%
	Winner–loser	−0.28%	−(0.76)	8.45%
Middle	Winner	0.30%	(0.98)	5.92%
	Loser	−0.21%	−(0.80)	4.55%
	Winner–loser	0.51%	(1.77)	5.91%
Loser	Winner	0.01%	(0.04)	5.92%
	Loser	−0.30%	−(1.14)	5.33%
	Winner–loser	0.31%	(1.24)	5.93%

Panel D

Portfolio classified by 52-week low	Portfolios classified by Fuertes et al. (2010)	Ave. monthly return	*t*-statistics	Ave. standard deviation
Winner	Winner	0.78%	(1.79)	9.10%
	Loser	0.69%	(1.83)	6.49%
	Winner–loser	0.09%	(0.28)	8.42%
Middle	Winner	0.61%	(1.90)	5.46%
	Loser	0.00%	(0.01)	5.59%
	Winner–loser	0.61%	(1.85)	6.27%
Loser	Winner	−0.13%	−(0.50)	4.56%
	Loser	−0.29%	−(1.11)	5.40%
	Winner–loser	0.16%	(0.68)	5.48%

This table presents the pairwise comparison of the 52-week high/low and conventional momentum profits. Commodities are sorted independently by their previous 12-month returns and by the nearness to their 52-week high. All portfolios are held for 1 month. Panel A reports the average monthly returns from February 1977 through July 2013 for equal-weighted portfolios that are long 52-week high winners and short 52-week high losers *within* winner, middle and loser categories identified by conventional momentum. Panel B reports the average monthly returns for equal-weighted portfolios constructed using conventional momentum strategy *within* groups identified as winner, middle and loser categories identified by the 52-week high strategy. Panel C reports the average monthly returns for equal-weighted portfolios that are long 52-week low winners and short 52-week low losers *within* winner, middle and loser categories identified by conventional momentum. Panel D reports the average monthly returns for equal-weighted portfolios constructed using conventional momentum strategy *within* groups identified as winner, middle and loser categories identified by the 52-week low strategy. The *t*-statistics reported in parentheses are estimated using Newey and West (1987) standard errors with a lag length of 12 months.

strategy's loading is the lowest.[21] Specifications 3 and 7 show that the 52-week high strategy reports a large, significant information ratio relative to the 52-week low strategy, but the 52-week low strategy reports an insignificant information ratio relative to the 52-week high strategy. The 52-week high strategy returns 0.60% per month relative to the 52-week low strategy, with a *t*-statistic

[21] The loadings on UMD is consistent with recent studies on momentum across asset classes. Refer to Novy-Marx (2012), Moskowitz et al. (2012) and Asness et al. (2013).

Table 5
Explanatory power of the 52-week high/low momentum.

	52WKH momentum as dependent variable				52WKL momentum as dependent variable				Conventional momentum as dependent variable				
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Intercept	1.20***	1.06***	0.60*	0.44*	0.94**	0.76*	0.14	0.09	1.06***	0.86**	0.28	0.13	0.06
	(3.95)	(3.51)	(2.49)	(2.08)	(3.04)	(2.49)	(0.58)	(0.50)	(3.41)	(2.84)	(1.51)	(0.65)	(0.35)
UMD		0.219***				0.270***				0.291***			
		(3.46)				(3.96)				(4.37)			
52WKL mom			0.648***								0.815***		0.570***
			(15.27)								(23.11)		(10.38)
52WKH mom							0.670***					0.760***	0.378***
							(12.59)					(17.86)	(6.44)
Conv. mom				0.732***				0.812***					
				(18.93)				(21.09)					
Adj. R^2		0.023	0.433	0.556		0.036	0.433	0.661		0.042	0.661	0.556	0.738

This table presents the results of 13 time-series regressions employing the returns from the commodity momentum strategies constructed using past returns and the 52-week high/low measures. 52WKH and 52WKL are the returns to the Winners-Losers portfolio (terciles), where winners and losers are based on commodities' nearness to their 52-week high and 52-week low prior to portfolio formation, respectively. Conv Mom represents the returns of the conventional Winners-Losers momentum portfolio formed using the previous 12-month returns. UMD represents the Fama–French Up-Minus-Down equity momentum factor formed using U.S. cross-sectional stock returns. The sample period covers the period February 1977 through July 2013. The *t*-statistics reported in parentheses are estimated using Newey and West (1987) standard errors with a lag length of 12 months. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

of 2.49, while the 52-week low strategy generates 0.14% per month relative to the 52-week high strategy with a *t*-statistic of 0.58 and an R^2 of 0.43. This finding suggests that the 52-week high momentum is superior to the 52-week low momentum strategy in terms of profitability.

Furthermore, specifications 4 and 12 show that while the profits of the conventional momentum strategy can be completely subsumed by the 52-week high momentum, the profits of the 52-week high momentum cannot be subsumed by the conventional momentum as the intercept of 0.44% per month remains significant with a *t*-statistic of 2.08 and an R^2 of 0.56. This finding reveals the explanatory power of the 52-week high momentum over the conventional momentum. Similar to the findings in Table 4, specifications 8 and 11 show that the 52-week low and the conventional momentum can be completely subsumed by each other with an R^2 of 0.66. Finally, specification 13 shows the combined explanatory power of the 52-week high and low momentum over the conventional momentum. Conventional momentum loads significantly on both 52-week high and low strategies with an insignificant intercept of 0.06% per month and an R^2 of 0.74. This finding is significant in the commodities momentum literature because it suggests that the profitability of conventional momentum can be largely explained by the anchoring behavior of investors around the 52-week high and the 52-week low of commodity futures prices.

Table 6 employs an alternative correlation metric in the commodities literature. We follow Daniel et al. (1997) by constructing characteristics portfolios for the three momentum strategies. Using both the Pearson and Spearman tests, Panel A reports the average cross-sectional correlation between the momentum characteristics (*not strategy returns*) of the conventional, 52-week high and 52-week low momentum strategies. Confirming the previous results in Table 5, Panel A of Table 6 reports strong positively significant correlations between conventional momentum and 52-week high/low momentum.[22] It appears that the 52-week low momentum (0.74) is more strongly related to conventional momentum than the 52-week high momentum (0.67). Furthermore, the 52-week high strategy exhibits a correlation of 0.43 with the 52-week low strategy, suggesting differences in return dynamics. Overall, the findings suggest there is a level of commonality in the characteristics of these three strategies.

Panel B of Table 6 reports the correlations between the various momentum strategy returns with traditional asset classes. The results show that both conventional and the 52-week low momentum are positively related to the market movements of an equal-weighted commodity futures portfolio, whereas the 52-week high momentum strategy is not. Surprisingly, the 52-week low momentum seems to be more strongly related to the equal-weighted commodity futures portfolio than the conventional momentum strategy. This finding suggests that the 52-week low momentum strategy may be a poor portfolio diversification tool for investors. Furthermore, the 52-week high momentum strategy appears to exhibit a degree of commonality with U.S. Treasury bill returns as indicated by a positive and significant correlation of 0.16. None of the commodity futures momentum strategies appear to report a significant relationship with stock markets, foreign currencies and U.S. treasury bonds. Therefore, they seem to offer potential portfolio diversification benefits for traditional investments such as stocks and bonds.

We now proceed to examine the reversal effect of commodity futures momentum returns. Jegadeesh and Titman (2001) conclude that conventional momentum profits in U.S. stocks reverse in the long run after portfolio formation. GH shows that the profits from 52-week high momentum strategies do not reverse in the long term. The long-term return reversal has been studied extensively in the stock market literature; however, little research attention has been dedicated to commodity futures.[23] Using a ranking period of 2 months, Shen et al. (2007) briefly show that the returns of a conventional momentum strategy in commodity futures reverse more quickly than those in the stock market (typically 3–5 years after portfolio formation). In this study, we compare the long-term reversal effect of the 12-month conventional momentum with the 52-week high and low momentum strategies in commodity futures.

Following the event-study approach of Jegadeesh and Titman (2001), Fig. 2 illustrates the cumulative returns of conventional (left), 52-week high (middle) and 52-week low (right) momentum strategies up to 60 months post-formation. In Shen et al. (2007), momentum profits are found to peak at the 11th month after portfolio formation, and fully reverse before the 30th month post-formation. Consistent with Shen et al. (2007), the first illustration in Fig. 2 confirms the presence of return reversal experienced

[22] Despite the positive correlation between conventional and 52-week high momentum characteristics, these two strategies exhibit vastly different return dynamics over time. This will be discussed in more detail in later sections of the paper.

[23] Refer to De Bondt and Thaler (1985, 1987) and Poterba and Summers (1988).

Table 6
Correlations of characteristics and returns.

Panel A: Momentum characteristics correlation

	52-week high momentum	52-week low momentum	UMD
Conventional momentum	0.6658*	0.7374*	0.1131*
	(0.00)	(0.00)	(0.05)
52-week high momentum		0.4265*	0.1023
		(0.00)	(0.09)
52-week low momentum			0.0777
			(0.12)

Panel B: Correlation with traditional asset classes

	EW	S&P500	T-bond	FX	T-bill
Conventional momentum	0.2108*	0.0192	0.0473	−0.0711	0.0773
	(0.00)	(0.69)	(0.33)	0.14	(0.11)
52-week high momentum	0.0694	−0.0502	0.0806	−0.0159	0.1566*
	(0.16)	(0.30)	(0.10)	0.74	(0.00)
52-week low momentum	0.3242*	0.0382	0.0400	−0.0886	0.0587
	(0.00)	(0.43)	(0.41)	0.07	(0.23)

This table presents correlations with associated *p*-ratios of statistical significance. Panel A reports the average cross-correlation between the momentum characteristics (*not returns*) of conventional, 52-week high and 52-week low momentum strategies. The average correlations are computed using Pearson and Spearman correlation tests. Panel B reports the correlations of the momentum strategy returns against traditional asset classes. EW, S&P500 and T-bond represent the returns on the equal-weighted commodity futures portfolio in the sample, S&P500 and Barclays US aggregate government bond index, respectively. FX denotes the U.S. dollar effective exchange rate index return and T-bill represents the yield on the 3-month U.S. Treasury bills. UMD represents the Fama–French Up-Minus-Down momentum factor formed using U.S. cross-sectional stock returns. The sample covers the period February 1978 through July 2013. * denotes statistical significance at the 5% level or better.

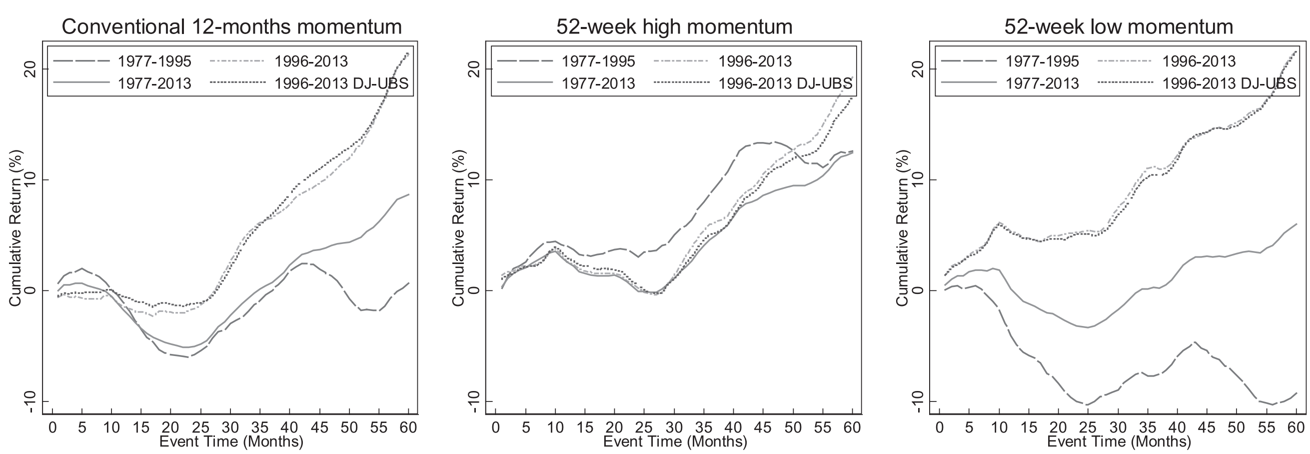

Fig. 2. Cumulative returns post-formation. This figure illustrates the cumulative post-formation returns for 12-month conventional, 52-week high and 52-week low momentum strategies. The x-axis shows event time starting from 1 month up to 60 months after portfolio formation. The sample covers 30 commodities from January 1977 through July 2013. Two sub-periods are presented with a mid-point in the sample period as January 1996. As a test of robustness, an alternate dataset (Dow Jones–UBS) is included from January 1996 through July 2013, which consists of 29 commodities (excluding Palladium).

by the conventional momentum strategy. However, the reversal clearly appears to be much stronger as the cumulative profits declines to -5% before the 25th month post-formation.[24] In the case of the 52-week high momentum (the second illustration in Fig. 2), although the reversal pattern still exists, it appears to be much smoother. The full reversal of profits takes place at around the 27th month post-formation. The reversal patterns for conventional and 52-week high are generally consistent across different sub-periods. However, it is not the case for the 52-week low momentum (the third illustration in Fig. 2) as the graph illustrates substantially different patterns in sub-periods. In the first sub-period, the cumulative returns decline to as low as −10%, whereas the cumulative profits do not seem to reverse much at all in the second half of the sample. It is difficult to rationalize such differences from a rational or behavioral framework; however, these findings suggest that the anchoring behavior by investors around the 52-week low has changed over time in commodity futures.[25]

Overall, the patterns observed in Fig. 2 suggest that the 52-week high momentum profits are smoother than the conventional momentum profits and that they reverse over a relatively short period (12–30 months). Unlike the behavior in U.S. stocks, this finding implies that momentum and reversal can co-exist in commodity futures, as predicted by behavioral models such as Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999). Fig. 2 sug-

[24] We also test the post-formation return of conventional momentum strategies using the ranking periods of 1, 2 and 3 months, respectively, and we find that the reversal patterns are consistent with Shen et al. (2007).

[25] To check the robustness of the finding, we use an approach similar to Table 3, whereby one commodity sector is excluded. The sub-sector graphs confirm the reversal pattern of the 52-week high momentum strategy.

Table 7
Multi-factor regressions.

	Conventional momentum			52-week high momentum			52-week low momentum		
	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
Intercept	0.01*	−0.00*	0.01*	0.01*	−0.01*	0.01*	0.00*	−0.00*	0.01*
	(3.59)	(−2.62)	(3.43)	(4.09)	(−3.70)	(4.21)	(2.44)	(−3.18)	(3.00)
β_{EW}	1.29*	0.91*	0.39*	1.18*	0.99*	0.19	1.35*	0.77*	0.58*
	(19.62)	(17.24)	(3.50)	(19.08)	(17.50)	(1.66)	(20.93)	(16.47)	(5.57)
β_S	−0.06	0.02	−0.09	−0.11*	0.02	−0.13*	−0.06	0.04	−0.10
	(−1.39)	(0.68)	(−1.18)	(−2.91)	(0.71)	(−2.05)	(−1.27)	(1.21)	(−1.33)
β_B	0.22	−0.08	0.30	0.29*	−0.09	0.38	0.30*	−0.08	0.39
	(1.54)	(−0.80)	(1.33)	(2.49)	(−0.82)	(1.81)	(2.14)	(−0.90)	(1.77)
β_F	0.01	−0.01	0.02	−0.02	−0.05	0.04	0.06	−0.01	0.07
	(0.10)	(−0.05)	(0.09)	(−0.14)	(−0.47)	(0.17)	(0.50)	(−0.13)	(0.37)
β_{UI}	0.17	−0.10	0.27	−0.46	0.15	−0.61	0.33	−0.07	0.40
	(0.18)	(−0.16)	(0.18)	(−0.62)	(0.22)	(−0.47)	(0.32)	(−0.11)	(0.25)
β_{UIP}	−0.54	0.20	−0.73	−0.15	0.13	−0.28	−0.31	−0.16	−0.14
	(−1.90)	(0.93)	(−1.63)	(−0.52)	(0.58)	(−0.60)	(−0.97)	(−0.70)	(−0.27)
Adj. R^2	0.647	0.582	0.044	0.616	0.613	0.008	0.661	0.544	0.104

This table presents the factor loadings of the conventional, 52-week high/low momentum strategies. Winner (Loser) are returns to the top (bottom) tercile portfolios. W-L denotes the returns to the Winners-Minus-Losers portfolio formed using conventional momentum, the nearness to their 52-week highs and lows. B_{EW}, β_S and β_B represent the coefficients of the equal-weighted commodities portfolio, S&P500 and Barclays' U.S. aggregate government bond index returns, respectively. β_F denotes the coefficients on the U.S. dollar effective exchange rate index return. β_{UI} and β_{UIP} denote the coefficients on unexpected inflation and unexpected industrial production, respectively. The U.S. dollar effective exchange rate is sourced from the Bank of International Settlements. Inflation and industrial production are sourced from the Federal Reserve Bank of St. Louis. The sample covers the period February 1978 through July 2013. The *t*-statistics reported in parentheses are estimated using Newey and West (1987) standard errors. * denotes statistical significance at the 5% level or better.

gests that the nature and dynamics of conventional, 52-week high and 52-week low momentum are structurally different in commodity futures compared to stocks and the difference is likely to be behavioral.

3.3. Understanding the 52-week high/low momentum

We have observed significant 52-week high and 52-week low momentum profits in commodity futures and significant differences in the nature and dynamics of these returns. The success of both momentum strategies relies on the anchoring bias of investors. Could these commodity futures returns reflect compensation for bearing systematic risks? In this section, we examine whether the returns of the 52-week high and 52-week low momentum strategies can be explained by risk factors proposed in the commodity futures literature.

Table 7 reports the regression results of conventional, 52-week high and 52-week low momentum strategies. Due to the current debate of a commonly accepted pricing model in commodity futures, we follow Miffre and Rallis (2007), Fuertes et al. (2010) and Moskowitz et al. (2012) and use a six-factor framework for risk adjustments. We augment the original six-factor model by removing the S&P GSCI Total Return Index as the commodities proxy and include the equal-weighted commodity futures portfolio.

$$R_{i,t} = \alpha_i + \beta_{EW,i}R_{EW,t} + \beta_{S,i}R_{S\&P500,t} + \beta_{B,i}R_{bond,t} + \beta_{F,i}R_{fx,t} + \beta_{UI,i}UI_t + \beta_{UIP,i}UIP_t + \varepsilon_{i,t} \quad (1)$$

where R_{EW} is the return of the equal-weighted commodity futures portfolio, $R_{S\&P500}$ is the return of the S&P 500 index and R_{bond} is the return of the U.S. 10-year Government Bond. All of these factors are in excess of the risk-free rate. R_{fx} denotes the return of the U.S. dollar effective (vis-à-vis main currencies) exchange rate index. *UI* denotes unexpected inflation and *UIP* is the unexpected change in U.S. industrial production. The unexpected component at month t is constructed as the difference between the economic variable at t and its most recent 12-month moving average.[26]

Consistent across strategies, the returns of the winners portfolio appear to load positively on broad commodity market movements with an adjusted R^2 ranging from 0.62 to 0.66. The intercepts of all winner portfolios remain statistically significant for all strategies. Similar to momentum winners, the momentum losers consistently load positively on commodity futures returns; however, they exhibit insignificant sensitivities to S&P 500 returns, U.S. bond market returns and foreign exchange movements, with an adjusted R^2 ranging from 0.54 to 0.61. The intercepts of all loser portfolio returns remain significant.

The six-factor model seems inadequate at explaining the winners-minus-losers (W-L) portfolio of all three strategies. The intercepts are significant across all momentum portfolios with adjusted R^2s of 0.008, 0.044 and 0.104 for the 52-week high, conventional and 52-week low momentum strategies, respectively. While the conventional and the 52-week low momentum portfolios still load positively on commodity futures returns, the 52-week high momentum portfolio no longer exhibits significant loadings. Overall, the results in Table 7 suggest that the profitability of the 52-week high/low momentum strategies cannot be attributed to broad market or macroeconomic risks. However, the 52-week low momentum profits are at least partially related to broad commodity market risks.[27]

We now proceed to explore other market related independent variables that may explain commodity futures momentum returns. Table 8 reports the factor loadings of momentum strategies on liquidity risk, market volatility, sentiment factors and extremes. Sadka (2006) shows that liquidity risk plays an important role

[26] For robustness reasons, we also employ the MSCI World Index return, and the JP Morgan Global Government Bond Index return. The results are consistent with those presented in this study despite the JP Morgan bond index being available from 1990. Newey and West (1987) standard errors are used in all regressions throughout this study.

[27] We also test the Miffre and Rallis (2007) three-factor model, which employs commodity, stock and bond market risk factors. The three-factor model reports similar results.

Table 8
Liquidity, volatility and sentiment extremes.

Independent Variables	Conventional momentum Winners	Conventional momentum Losers	Conventional momentum W-L	52-week high momentum Winners	52-week high momentum Losers	52-week high momentum W-L	52-week low momentum Winners	52-week low momentum Losers	52-week low momentum W-L
Intercept	0.01*	−0.00	0.01*	0.01*	−0.00	0.01*	0.01*	−0.00	0.01*
	(3.72)	(−0.35)	(3.84)	(4.36)	(−0.86)	(4.58)	(3.31)	(−0.41)	(3.53)
US liquidity	0.08	0.02	0.06	0.10	0.03	0.07	0.113*	0.05	0.07
	(1.37)	(0.42)	(1.21)	(1.95)	(0.55)	(1.40)	(2.01)	(1.01)	(1.21)
R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00
Top 20%	−0.02	−0.07	−0.13	0.03	−0.04	−0.08	0.01	−0.05	0.02
	(−0.39)	(−1.61)	(−1.87)	(0.62)	(−0.81)	(−1.13)	(0.22)	(−1.44)	(0.22)
Intercept	0.01*	−0.00	0.01*	0.01*	0.00	0.01	0.01	−0.00	0.01*
	(2.57)	(−0.03)	(2.54)	(2.07)	(0.05)	(1.85)	(1.75)	(−0.33)	(2.03)
Amihud illiquidity	0.001	−0.001	0.004	0.002	0.001	0.001	0.004	0.001	0.003
	(0.59)	(−0.32)	(1.39)	(0.46)	(0.40)	(0.37)	(1.03)	(0.58)	(0.97)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Intercept	0.02*	0.01*	0.01	0.01	0.02*	−0.00	0.02*	0.01*	0.00
	(2.44)	(2.39)	(1.18)	(1.73)	(2.98)	(−0.88)	(2.07)	(2.58)	(0.57)
TED spread	−1.51	−2.01*	0.50	−0.54	−2.68*	2.14*	−1.45	−2.18*	0.73
	(−1.18)	(−2.53)	(0.64)	(−0.49)	(−3.23)	(3.07)	(−1.13)	(−2.66)	(0.85)
R^2	0.01	0.04	0.00	0.00	0.06	0.02	0.01	0.06	0.00
Top 20%	0.95	−0.62	0.56	1.36	−0.76	2.91*	0.26	−0.78	1.25
	(0.94)	(−0.94)	(0.48)	(1.24)	(−1.02)	(2.55)	(0.23)	(−1.00)	(0.90)
Intercept	0.01*	0.00	0.01*	0.01*	0.00	0.01*	0.01*	0.00	0.01*
	(3.63)	(0.29)	(3.14)	(3.11)	(0.37)	(2.41)	(2.67)	(0.06)	(2.54)
VIX	−0.06*	−0.04*	−0.01	−0.03*	−0.05*	0.01	−0.06*	−0.03*	−0.02
	(−3.46)	(−2.61)	(−1.08)	(−2.27)	(−2.57)	(0.99)	(−3.30)	(−2.11)	(−1.65)
R^2	0.05	0.04	0.00	0.02	0.04	0.00	0.04	0.03	0.00
Top 20%	−0.05*	−0.01	−0.04*	−0.02	−0.02	−0.01	−0.05	−0.03	−0.05*
	(−2.10)	(−0.41)	(−2.21)	(−1.03)	(−0.93)	(−0.25)	(−1.96)	(−1.64)	(−2.92)
Intercept	0.00	0.00	0.00	0.00	−0.00	0.00	0.00	−0.00	0.01
	(0.51)	(0.57)	(0.03)	(0.30)	(−0.09)	(0.42)	(0.63)	(−0.32)	(1.02)
OVX	−0.198*	−0.185*	−0.012	−0.174*	−0.197*	0.0225	−0.197*	−0.171*	−0.026
	(−2.99)	(−3.77)	(−0.30)	(−3.05)	(−3.42)	(0.50)	(−2.98)	(−3.39)	(−0.66)
R^2	0.17	0.21	0.00	0.13	0.19	0.00	0.16	0.19	0.00
Intercept	0.01*	0.00	0.01*	0.01*	0.00	0.01*	0.01*	0.00	0.01*
	(3.72)	(0.66)	(3.20)	(4.10)	(0.12)	(3.64)	(3.26)	(0.04)	(3.26)
Sentiment	−0.01*	−0.01*	0.00	−0.01*	−0.01*	0.00	−0.01*	−0.01*	0.00
	(−3.04)	(−4.03)	(0.36)	(−2.89)	(−4.09)	(0.94)	(−3.57)	(−3.41)	(−0.74)
R^2	0.01	0.03	0.00	0.01	0.03	0.00	0.02	0.03	0.00
Top 20%	−0.01*	0.00	0.00	−0.02*	−0.01	0.01	−0.02*	0.00	0.00
	(−2.07)	(−0.93)	(0.64)	(−3.37)	(−1.32)	(0.68)	(−2.78)	(−1.08)	(−0.48)
Bottom 20%	−0.01	−0.01*	0.00	−0.01*	−0.01*	0.01	−0.01	−0.02*	0.00
	(−1.59)	(−2.91)	(0.65)	(−2.66)	(−2.96)	(1.56)	(−1.81)	(−4.24)	(0.20)
Intercept	0.01*	−0.00	0.01*	0.01*	−0.01	0.01*	0.01*	−0.00	0.01*
	(3.22)	(−0.61)	(3.52)	(3.68)	(−1.16)	(4.19)	(2.57)	(−1.16)	(3.28)
Changes in sentiment	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00*	0.00
	(0.94)	(1.93)	(−0.35)	(1.18)	(1.71)	(−0.21)	(0.81)	(1.99)	(−0.24)
R^2	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00
Top 20%	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00
	(1.26)	(1.72)	(1.11)	(1.27)	(0.47)	(1.57)	(0.91)	(0.94)	(0.21)
Bottom 20%	0.00	0.00	−0.01	0.00	0.01	−0.01*	0.00	0.00	0.00
	(1.05)	(0.63)	(−1.80)	(1.13)	(1.28)	(−3.17)	(0.85)	(1.25)	(−1.17)

This table presents the factor loadings of the conventional, 52-week high and 52-week low momentum strategies on liquidity, market volatility and investor sentiment. Winners (Losers) are returns of the top (bottom) tercile portfolios. W-L denotes the returns to Winners-Minus-Losers portfolio formed using conventional momentum and the nearness to their 52-week highs and lows. U.S. liquidity denotes the aggregate liquidity factor constructed from Pastor and Stambaugh (2003). Amihud illiquidity denotes the commodities cross-sectional illiquidity factor constructed by Daskalaki et al. (2014). The TED spread is the difference between the yield on the 3-month T-bill and LIBOR. VIX denotes changes in the Chicago Board Options Exchange (CBOE) market volatility index. OVX denotes changes in the CBOE crude oil volatility index. Sentiment factors are obtained from Jeffrey Wurgler's NYU website. Quantile regressions are estimated for all extremes. Intercepts are omitted for quantile regressions. The *t*-statistics reported in parentheses are estimated using Newey and West (1987) standard errors with a lag length of 12 months. * denotes statistical significance at the 5% level or better. The sample covers the period February 1977 through July 2013.

in explaining momentum profits in U.S. stocks. Similarly, Asness et al. (2013) find that global funding liquidity (measured by the TED-spread) is also related to momentum profits, not only in U.S. stocks but also across asset classes. Furthermore, Antoniou et al. (2013) show that stock market momentum can be explained by changes in sentiment. Accordingly, we test whether the observed 52-week high and low momentum profits in commodity futures are related to these variables. Furthermore, we include the VIX index as a proxy of market volatility. As a robustness check, the OVX is employed as a proxy for commodity market volatility. The Amihud illiquidity factor (Daskalaki et al., 2014) is employed to test whether momentum strategy returns are related to commodities cross-sectional liquidity. We also isolate the largest quintile of observations in these variables to capture the most extreme market volatility environment, which correlates with liquidity shocks.[28]

[28] U.S. liquidity denotes the aggregate liquidity factor constructed by Pastor and Stambaugh (2003). The TED spread is the difference between the yield on the

The results in Table 8 show that the 52-week low winners (the only portfolio in all strategies) load positively on the U.S. liquidity factor with an R^2 of only 0.011.[29] Consistent across strategies, the losers portfolios exhibit significantly negative loadings on the TED spread with an R^2 of around 0.056. Strikingly, the profitability of the 52-week high momentum strategy is completely subsumed by the TED spread as the intercept becomes negative, and the momentum portfolio loads strongly positively on the TED spread with an R^2 of 0.024. The relation with the TED spread suggests that global funding liquidity plays a key role in determining the profitability of the 52-week high momentum strategy.[30] Moreover, both winners and losers portfolios across strategies appear to be negatively related to the VIX, suggesting a symmetrical (as opposed to an asymmetrical) response between winners and losers to changes in stock market volatility.[31] However, the effect disappears when winners and losers portfolios are combined in a momentum portfolio. Similar patterns are observed on the OVX, although the R^2s are unsurprisingly higher compared to the VIX.

The results of the sentiment regressions in Table 8 also warrant attention. By definition, sentiment is the perception of market conditions by investors, whereas the 52-week high and low momentum represent investors' anchoring behavior around the 52-week high and the 52-week low futures price levels. Consistent across strategies, the winners and losers portfolios seem to be negatively related to sentiment. Thus, it is not surprising that no such effects are observed in the winners-losers (momentum) portfolios. This finding suggests that commodity investors not only make use of past returns but also the 52-week high and low prices to anticipate market movements. Furthermore, the 52-week high momentum is negatively related to the bottom 20% of the changes in sentiment, suggesting that the 52-week high momentum strategy tends to perform well during episodes of small shifts in market sentiment.[32] Finally, Table 8 also reveals that U.S. market aggregate liquidity and volatility cannot explain the profitability of commodity momentum strategies.

We now turn our attention to commodity-specific risk factors. Recently, there has been a resurgence in the commodities pricing literature (Gorton et al., 2013; Yang, 2013; Basu and Miffre, 2013; Daskalaki et al., 2014; Szymanowska et al., 2014; Bakshi et al., 2015). These studies find that the slope of the term structure and hedging pressure are important risk factors when pricing commodity futures. To examine whether the profitability of the 52-week high momentum strategy can be explained by these commodity-specific risk factors, we construct long–short factor mimicking portfolios on term structure and hedging pressure following Fuertes et al. (2010) and Basu and Miffre (2013), respectively.[33] However, there is one important distinction. To include as many commodities as possible (27 commodities), the sample period in Basu and Miffre (2013) is 1992 through 2011. This covers less than half of our sample period. Therefore, to obtain robust results, we employ 21 commodities with a longer sample period commencing from March 1986.[34]

Table 9 reports the regression results of conventional, 52-week high and 52-week low momentum strategies on the term structure (Panel A) and the hedging pressure (Panel B) risk factors. Consistent with Miffre and Rallis (2007), the results show that conventional momentum loads positively on term structure but not on hedging pressure. Interestingly, the 52-week high momentum also loads positively on both the term structure and the hedging pressure factors, whereas the 52-week low momentum shows a relationship with the hedging pressure factor only. However, once again, the intercepts of these regressions remain large and statistically significant with low R^2s.

Panel C combines the term structure and hedging pressure risk factors in a multi-factor model, and the intercepts remain significant. Clearly, these results suggest that the success of the 52-week high/low momentum strategies that exploit the anchoring behavior of investors cannot be attributed to the dynamic, long–short commodity-specific risk factors. While the term structure and the hedging pressure risk factors do not offer a full explanation, both help in understanding the dynamics of long–short momentum-based strategies. Overall, the findings suggest the classical term structure and hedging pressure hypotheses do not adequately explain the variation of conventional and 52-week high/low momentum returns. These findings reinforce the notion of a behavior-induced explanation of momentum returns in commodity futures.

Panel D includes term structure and hedging pressure risk factors with conventional, 52-week high and 52-week low momentum as additional explanatory variables to test whether the profits of these strategies would remain. Consistent with the findings presented in Table 5, the results in Panel D of Table 9 suggest that conventional momentum can be explained by the anchoring behavior as the term-structure risk factor (although statistically significant) adds little explanatory power over the 52-week high and low momentum factors. However, after controlling for commodity-specific risk factors, the intercept of the 52-week high momentum is no longer statistically significant, whereas the constant is significant in Table 5 model four when the 52-week high is regressed only on the conventional momentum. Although the intercepts of the strategies are insignificant, the adjusted R^2 confirm the finding that the 52-week high momentum is indeed superior to the

3-month T-bill and LIBOR. VIX denotes changes in the Chicago Board Options Exchange market volatility index. Sentiment factors are obtained from Jeffrey Wurgler's NYU website (see Baker and Wurgler, 2007). Quantile regressions are estimated for all extremes. The Baker and Wurgler sentiment index is available until 2010.

[29] In addition to regression analysis, we also examine whether the profitability of these active strategies can be explained by the illiquidity of individual commodities in our sample. To achieve this, we exclude seven relatively illiquid commodities from the sample: feeder cattle, Kansas wheat, orange juice, tin, soybean meal, soybean oil and palladium. The profitability based on the restricted sample appears to be almost identical compared to the full sample results. These results suggest that the profits cannot be accounted for by illiquidity effects of individual commodity futures.

[30] Our findings in relation to the TED spread are consistent with Asness et al. (2013) who find that the TED spread is related to the returns of a global, multi-market momentum portfolio; however, the TED spread offers only a partial explanation.

[31] Li et al. (2008) find that winners and losers respond to news in an asymmetric fashion in the U.K. stock market Using a GJR-GARCH-M model, they show that losers respond to news (volatility) more slowly but to a greater extent than the winners. Our findings of a symmetrical response of winners and losers to market volatility suggest that the dynamics of loser commodities may be very different from losers in stocks.

[32] Antoniou et al. (2013) find that loser stocks become under-priced under during optimistic market conditions and winner stocks become under-priced during pessimistic periods. They conclude that momentum in stock markets is strengthened only during optimistic periods because of the short-selling constraints on losers. Although the short-selling constraint is not an issue in commodity futures, our results are not directly comparable to Antoniou et al. (2013) due to differences in sentiment measures.

[33] We follow Fuertes et al. (2010) for the construction of long-short term structure risk factor. At the end of each month, commodities are sorted into tertiles based on their previous month's roll-yields. The term structure portfolio takes long (short) positions in commodities with the highest (lowest) roll-yield. To construct the hedging pressure risk factor, we follow Basu and Miffre (2013), in which commodities are sorted into tertiles based on the average hedging pressure of hedgers over a ranking period of 4 weeks. The hedging pressure portfolio takes long (short) positions in commodities with the lowest (highest) hedging pressure. For robustness reasons, we also tested medium breakpoints and found consistent results. These results are reported in Table 9.

[34] Consistent with Szymanowska et al. (2014), the sample covers cocoa, coffee, copper, corn cotton, feeder cattle, orange juice, RBOB gas, gold, heating oil, live hogs, crude oil, live cattle, oats, lumber, rice, silver soybean meal, soybean oil soybeans and wheat. The Commitment of Traders (COT) data from March 1986 are downloaded from the CFTC website.

Table 9
Commodity-specific risk factors.

	Conventional momentum			52-week high momentum			52-week low momentum		
	Winner	Loser	W-L	Winner	Loser	W-L	Winner	Loser	W-L
Panel A: Term structure									
Intercept	0.01*	−0.00	0.01*	0.01*	−0.00	0.01*	0.01*	−0.00	0.01*
	(2.97)	(−0.23)	(3.02)	(3.42)	(−0.83)	(3.80)	(2.48)	(−0.91)	(3.08)
β_{TS}	0.07	−0.14*	0.21*	0.03	−0.13*	0.17*	0.01	−0.05	0.06
	(0.95)	(−2.50)	(2.33)	(0.57)	(−2.64)	(2.66)	(0.18)	(−1.20)	(0.97)
R^2	0.001	0.018	0.024	−0.002	0.014	0.015	−0.002	0.001	−0.000
Panel B: Hedging pressure									
Intercept	0.01*	−0.00	0.01*	0.01*	−0.00	0.01*	0.01*	−0.00	0.01*
	(3.11)	(−0.15)	(3.13)	(2.94)	(−0.17)	(2.77)	(2.29)	(−0.32)	(2.51)
β_{HP}	0.23*	0.07	0.16	0.25*	0.07	0.19*	0.26*	0.01	0.25*
	(3.27)	(0.93)	(1.67)	(4.46)	(1.21)	(2.96)	(4.08)	(0.13)	(3.98)
R^2	0.038	−0.003	0.016	0.054	0.001	0.023	0.045	−0.003	0.043
Panel C: Term structure and hedging pressure									
Intercept	0.01*	0.00	0.01*	0.01*	0.00	0.01*	0.01*	−0.00	0.01*
	(2.80)	(0.46)	(2.30)	(2.88)	(0.42)	(2.16)	(2.23)	(−0.11)	(2.26)
β_{TS}	0.18*	−0.15*	0.34**	0.09	−0.15*	0.25*	0.09	−0.04	0.13
	(2.52)	(−2.49)	(3.75)	(1.42)	(−2.32)	(2.78)	(1.18)	(−0.76)	(1.45)
β_{HP}	0.25*	0.03	0.22*	0.25*	0.03	0.22*	0.26*	−0.0104	0.27*
	(3.48)	(0.47)	(2.44)	(3.89)	(0.43)	(2.67)	(3.40)	(−0.19)	(3.15)
Adj. R^2	0.053	0.025	0.084	0.053	0.019	0.059	0.041	−0.004	0.048
Panel D: Term structure, hedging pressure and momentum									
Intercept	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.49)	(1.31)	(0.53)	(1.40)	(0.88)	(0.59)	(0.91)	(0.71)	(0.42)
β_{TS}	0.12*	−0.06	0.18*	−0.01	−0.04	0.03	−0.12*	0.04	−0.15
	(2.32)	−(1.60)	(4.36)	−(0.16)	−(0.76)	(0.58)	−(2.35)	(0.84)	−(3.27)
β_{HP}	0.07	0.09	−0.01	0.11	0.06	0.05	0.13*	0.06	0.08
	(1.37)	(1.56)	−(0.34)	(1.78)	(0.75)	(0.88)	(2.00)	(1.18)	(1.80)
$\beta_{Convmom}$				0.14*	−0.43*	0.56*	0.71*	−0.01	0.72*
				(2.11)	−(3.78)	(5.85)	(8.45)	−(0.16)	(12.13)
β_{52WKH}	−0.12*	−0.46*	0.34*				−0.14	−0.28*	0.15*
	−(2.03)	−(5.31)	(4.16)				−(1.79)	−(3.81)	(2.59)
β_{52WKL}	0.76*	0.17*	0.58*	0.44*	0.25*	0.20*			
	(10.25)	(2.89)	(7.37)	(6.93)	(2.68)	(2.24)			
Adj. R^2	0.52	0.24	0.75	0.43	0.11	0.57	0.40	0.17	0.69

This table presents the factor loadings of the conventional, 52-week high and 52-week low momentum strategies on term structure and hedging pressure factors. Winners (Losers) are returns of the top (bottom) tercile portfolios. W-L denotes the returns to Winners-Minus-Losers portfolio formed using conventional momentum and the nearness to their 52-week highs and lows. Panel A summarizes the regression result of the slope of the term structure factor in Fuertes et al. (2010) and Panel B summarizes the hedging pressure factor in Basu and Miffre (2013). β_{TS} and β_{HP} represent long–short term structure and hedging pressure factors, respectively. $\beta_{Convmom}$, β_{52WKH} and β_{52WKL} represent conventional, 52-week high and 52-week low momentum, respectively. The *t*-statistics reported in parentheses are estimated using Newey and West (1987) standard errors with a lag length of 12 months. * denotes statistical significance at the 5% level or better. The sample in Panel A covers the period February 1977 through July 2013. Due to the availability of CFTC's commitment of traders data, the sample period in Panels B, C and D covers March 1986 through July 2013.

conventional momentum in commodity futures.[35] Overall, these findings suggest that the behavioral proxy of the 52-week high and low momentum is a stronger explanatory variable of conventional momentum than the term structure and hedging pressure risk factors.

3.4. Sub-period results and the adaptive market hypothesis

As a robustness check, this study examines the profitability of these momentum strategies by employing a sub-sample analysis. It is surprising that previous studies have not examined the sub-period performance of the 52-week high momentum. The sub-period analysis is an important method for checking robustness because it provides information on the persistence of momentum strategy returns across different periods in the sample.

The choice of the sub-period is motivated by the Commodity Futures Modernization Act of 2000 (CFMA). The enactment of the CFMA provided the catalyst which led to the unprecedented surge in commodity-related investments from 2002 to 2008. The growth of commodity-related investments hints at a shift in market dynamics. Traditionally, commodity futures markets are dominated by producers who engage in hedging activities. Following the introduction of the CFMA, an enormous amount of speculative and professionally managed investment capital entered the commodity markets. Consequently, it is important to examine whether the performance of momentum strategies have remained stable as a result of the shift in market dynamics.

Table 10 reports the profitability of the conventional, 52-week high and 52-week low momentum strategies across two sub-periods: 1978–2000 and 2001–2013, along with the full sample results from 1978 through 2013. Based on the sub-samples, it appears that the profitability of all momentum strategies has declined considerably. Most notably, the annualized average return of the 52-week high momentum strategy is significantly higher in the pre-2001 sample. The results show all three momentum strategies

[35] We also employ the Fama and MacBeth (1973) approach to test the predictive power of all three signals. The findings suggest that the 52-week high momentum dominates the conventional momentum. These results are available upon request.

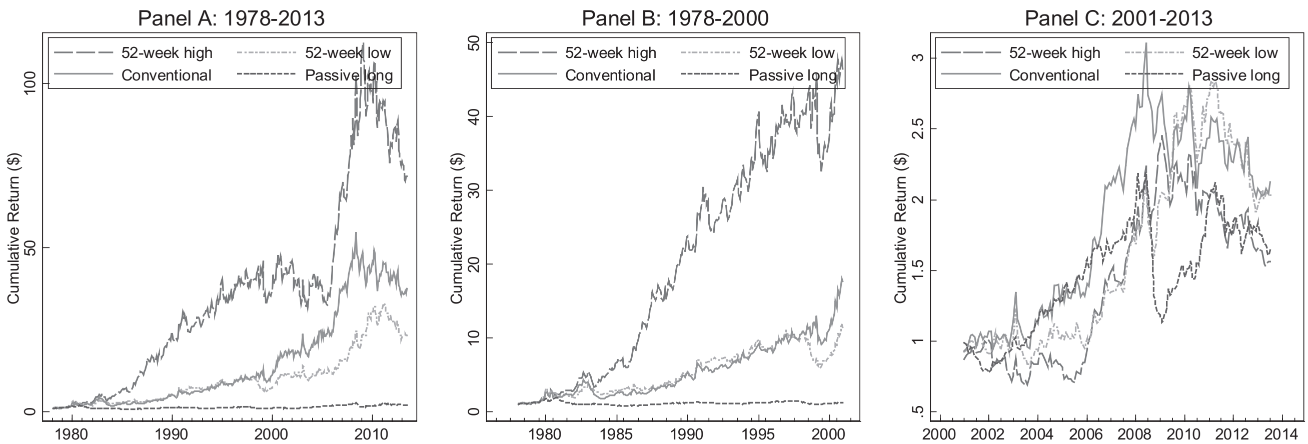

Fig. 3. Cumulative absolute profits. This figure illustrates the value of $1 invested in the conventional, 52-week high and 52-week low momentum strategies, benchmarked against the long only portfolio (passive long) which is an equal-weighted portfolio of all commodities. The left figure illustrates the performance of the strategies in the full sample (Panel A), the middle and right figures exhibit the results for 1978–2000 (Panel B) and the 2001–2013 sample (Panel C), respectively.

Table 10
Sub-period results.

	Sample period		
	1978–2013	1978–2000	2001–2013
Conventional momentum			
Annualized	12.58%	15.24%	7.92%
Monthly	1.05%	1.27%	0.66%
t-statistics	(3.38)	(3.12)	(1.44)
52-week high momentum			
Annualized	14.54%	19.32%	5.88%
Monthly	1.21%	1.61%	0.49%
t-statistics	(3.99)	(4.12)	(1.04)
52-week low momentum			
Annualized	11.36%	13.32%	7.56%
Monthly	0.95%	1.11%	0.63%
t-statistics	(3.07)	(2.73)	(1.41)

This table presents the profitability and statistical significance of conventional, 52-week high and 52-week low momentum strategies in sub-periods. The conventional strategy ranks commodities based on their prior 12-month returns whereas the 52-week high/low momentum strategies rank commodities based on their nearness to their 52-week high/low price levels. For each strategy, all commodities are sorted into terciles (Winners, Middle, and Losers). Both annualized and monthly arithmetic mean returns are reported for each sub-period. Two sub-periods are presented. The full sample covers the period February 1978 through July 2013. The *t*-statistics reported in parentheses are estimated using Newey and West (1987) standard errors with a lag length of 12 months.

continue to be profitable in the 2001–2013 period; however, they lose statistical significance.[36]

The decline in profitability in commodities momentum can be more directly observed in Fig. 3. The left, middle and right figures depict the performance of all strategies in the 1978–2013, 1978–2000 and 2001–13 sample periods, respectively. Conventional, 52-week high and low momentum strategies are also benchmarked against the passive long-only strategy, which is an equal-weighted commodity futures portfolio. Clearly, the profitability of all strategies has declined from the early years to the more recent sub-sample period. More specifically, the 52-week high strategy has seen a large decline in profitability in the second sub-sample period and no longer dominates the other strategies. Instead, the 52-week high strategy exhibits significant underperformance compared to the conventional strategy.[37] Interestingly, the 52-week low momentum strategy appears to perform exceptionally well in the recovery period subsequent to the 2008 global financial crisis (GFC).[38]

Furthermore, Fig. 4 presents the rolling 1-year returns of the conventional, the 52-week high and the 52-week low momentum strategies. As illustrated, the profitability of all strategies has gradually declined over time, especially for the 52-week high strategy, which appears to perform poorly in the second half of the sample. Also worth noting is that all rolling returns, on average, become negative following the 2008 GFC.

It is unclear why all three momentum strategies have declined in profitability in the second half of the sample. Since prior studies omit any form of sub-period analysis, the literature provides little guidance on this issue. This is especially the case given that the returns of the 52-week high momentum have declined markedly in comparison to conventional momentum. However, one explanation may be that the anchoring behavior of commodity traders has changed over time, due to the growth of the commodity investment industry, with the introduction of the CFMA. Since these strategies still generate profits even after the enactment of the CFMA, the efficient market hypothesis leaves little room for such conjecture. On the other hand, existing behavioral theories do not explain why the profits in these momentum strategies have declined. However, the findings uncovered in this study are consistent with the recently proposed adaptive market hypothesis (AMH).

The AMH by Lo (2004) suggests that irrational agents portrayed by the behavioral theorists can exist in the world of efficient markets. Lo (2012) argues that the behavioral biases of market agents are actually adaptive behaviors taken out of their natural context. Lo (2004, 2012) asserts that the 'sub-optimal' behaviors (anchoring, heuristics, underreaction and others) persist because they help ease the pressures from 'extinction'. Accordingly, agents must adjust their behaviors to 'survive' in a market environment that is

[36] We employ equality in mean, median, and variance tests. We also employ a Chow (1960) breakpoint test estimated from a mean equation. These results suggest no difference in returns over the two sub-sample periods. The results also hold after including a 12-month delay (i.e. the second sub-sample with a January 2002 commencement date).

[37] This is attributable to the 52-week high momentum strategy's lower weighting assigned to energy commodities during the energy boom period from 2001 to 2005, which is the period preceding the 2008 GFC.

[38] We also perform sub-period analysis on the return of all strategies tested by classifying the high/low volatility periods based on the GSCI index. We define high (low) volatility periods when the 12-months rolling standard deviation of the GSCI returns is larger (smaller) than the sample standard deviation of the GSCI. The findings suggest that momentum profits are stronger in low volatility periods both quantitatively and statistically.

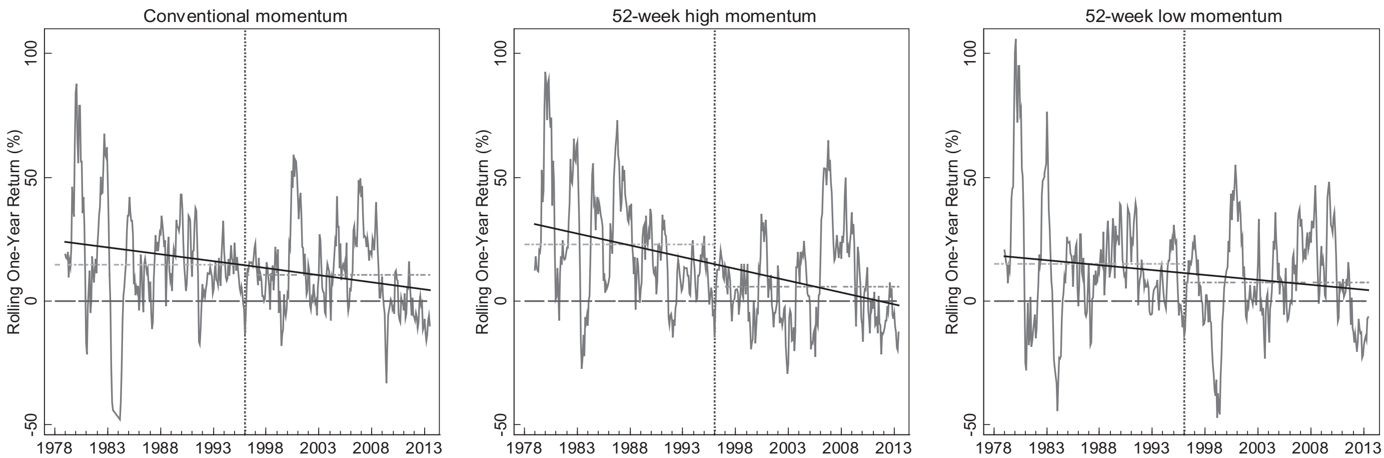

Fig. 4. Rolling 1-year returns. This figure illustrates the rolling 1-year return of conventional, 52-week high and 52-week low momentum strategies. The horizontal lines denote the first half sample (1977–1995) mean return, the second half sample return (1996–2013), and a zero line. The vertical line denotes the end of the first half sample. The diagonal line represents the fitted values of the strategy returns from a regression with a constant and time trend.

constantly changing and evolving. Although still in its infancy, the AMH has generated interest from both academia and the investment profession. Amilon (2008) and Kim et al. (2011) present supporting evidence of the AMH in the stock market Furthermore, Neely et al. (2009) and Charles et al. (2012) show that foreign exchange market behavior can also be explained by the AMH. In this study, we argue that commodity futures are also adaptive.

The AMH presents two predictions that have direct implications to our results. First, profitable opportunities generally exist in markets, and investment strategies will perform well in certain environments but poorly in others. Second, the learning and competition pressures will gradually erode the profits of successful investment strategies. As more arbitrageurs and speculators enter the commodity futures markets, the AMH suggests that competition for survival intensifies, resulting in diminishing opportunities and anomalies. AMH explains why the profitability of the 52-week high momentum strategy has declined more than the conventional and 52-week low momentum strategies. The 52-week high momentum was far more profitable than the other strategies in the earlier part of the sample. By way of contrast, conventional momentum profits are more stable, therefore, it implies, at least in commodity futures, that conventional momentum is not driven by behavioral biases alone.

The results in Table 9 confirm this conjecture. Panels A to D show that conventional momentum exhibits higher risk factor loadings to the term structure and hedging pressure risk factor in comparison to the 52-week high/low. Panel D suggests that conventional momentum returns are a combination of risk-factors and behavioral factors while the 52-week high strategy is dominated by behavioral factors only. This finding suggests that the behavioral effects in the 52-week high strategy are slowly being eroded while the source of risk and return from conventional momentum continues to exhibit exposure to the term structure risk factor.

4. Conclusion

This study examines the profitability of the 52-week high and 52-week low momentum strategies in comparison to the conventional momentum strategy of Jegadeesh and Titman (1993) in a commodity futures setting. Consistent with the Grinblatt and Han (2005) prediction of investors' anchoring behavior, the findings in this study suggest that both the 52-week high and low momentum strategies are profitable in commodity futures. Furthermore, through extensive comparative analysis, we show that the nearness to the 52-week high is a superior predictor of future returns in comparison to both conventional momentum and the nearness to the 52-week low. The findings suggest that conventional momentum can be largely explained by the anchoring behavior of investors around the 52-week high and the 52-week low of commodity futures prices after controlling for commodity specific term structure and hedging pressure risk factors.

Our sub-period analysis reveals an overall decline in the profitability of these momentum strategies, especially in the second half of the sample. Since these findings cannot be grounded easily by either the efficient market hypothesis or behavioral theories, we conjecture that the anchoring behavior of commodity traders has changed over time, likely due to the growth in hedge funds, commodity trading advisors, managed futures and commodity index products since the introduction of the *Commodities Futures Modernization Act of 2001*. The recently proposed AMH offers a sound explanation for the results observed. In the world of adaptive markets, irrational agents portrayed by behavioral theorists can exist in a market environment that is informationally efficient. A more rigorous and complete test of the AMH in commodity futures presents an interesting avenue for future research.

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