Are There Exploitable Trends in Commodity Future Prices?

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Abstract

We provide evidence that a simple moving average timing strategy, when applied to portfolios of commodity futures, can generate superior performance to the buy-and-hold strategy. The outperformance is very robust. It can survive the transaction costs in the futures markets, it is not concentrated in a particular subperiod, and it is robust to short-sale constraint, alternative specifications of the moving average lag length, and alternative construction of the continuous time-series of futures prices. The outperformance of the timing strategy is stronger during recession and with high investor sentiment, which likely proxies for high real interest rates. Finally, we confirm that the outperformance of the moving average timing strategy in the commodity futures comes from the successful timing of the market portfolio.

JEL Classification: G11, G14

Keywords: Commodity Futures, Moving Average, Timing, Predictability

1. Introduction

Technical analysis has been widely used in futures markets, particularly commodity futures markets, for many decades. Surveys show that a majority of traders in commodity futures markets use exclusively or moderately technical analysis to identify trends. In a sharp contrast to the views of many practitioners, however, academics tend to be skeptical about technical analysis. The skepticism is probably rooted in the wide acceptance of the efficient market hypothesis (Fama, 1970) in academics, and negative empirical findings in several early and widely cited studies of technical analysis in the stock market, such as Fama and Blume (1966), van Horne and Parker (1967, 1968), and Jensen and Benington (1970). Only a few studies have analyzed the profitability of technical analysis in commodity futures markets. Most recently, Szakmary, Shen, and Sharma (2010) find that trend-following trading strategies in commodity futures markets are profitable in at least 22 out of 28 markets. However, Marshall, Cahan, and Cahan (2008) find that quantitative market timing strategies are not consistently profitable in commodity futures markets.

This paper provides the first study on the cross-sectional profitability of technical analysis in the commodity futures markets. Unlike previous studies, which often examine individual futures contracts, we focus on portfolios of commodity futures sorted on some characteristics of futures such as volatility, trading volume, open interest, six-month past return, prior-month return, and past 60-month return. Consistent with the previous literature, we find that applying the moving average timing to individual futures produces inconsistent results. For some commodity futures, the timing strategy delivers huge profits but for others it yields negative results. For the majority of the commodity futures, the timing strategy only yields modest gains over the buy-and-hold strategy. However, when we apply the moving average timing to the sorted portfolios, we find consistent and large gains over the buy-and-hold strategy. For example, applying the moving average timing to volume sorted tercile portfolios yields average returns (t-stat) 3.29% per annum (1.81) for the portfolio with the lowest trading volume, 4.15% per annum (2.23) for the portfolio with medium level of trading volume, and 7.44% per annum (3.15) for the portfolio with the highest trading volume, respectively. Meanwhile, the buy-and-hold strategy yields average returns (t-stat) 1.16% per annum (0.45) for the lowest volume portfolio, 0.76% per annum (0.29) for the medium volume portfolio, and 3.32% (0.98) for the highest volume portfolio, respectively.

Because the moving average timing strategy delivers higher return with lower volatility, the Sharpe ratios are much higher, 0.29 versus 0.07, 0.36 versus 0.05, 0.50 versus 0.16, respectively, for the three tercile portfolios. To further appreciate the performance gains over the buy-and-hold strategy, we report the percentage increase in Modigliani-Modigliani measure ($\Delta M2$), which measures the percentage increase in the average return while keeping the volatility the same. For the moving average timing strategy, $\Delta M2$ are 304.4%, 677.1%, and 220.4%, respectively, for the three volume-sorted portfolios. In other words, if we level up the volatility of the timing strategy to the same as the volatility of the buy-and-hold strategy, the timing strategy would deliver average returns that are more than four times for the lowest volume portfolio, about eight times for the medium volume portfolio, and more than three times for the highest volume portfolio, respectively, of those delivered by the buy-and-hold strategy.

The performance gains are fairly robust. We conduct extensive robustness tests in several dimensions. First, we examine the trading behavior and break-even transaction cost (BETC). It turns out that the moving average timing strategy does not trade very often (less than 13%) and thus the break-even transaction cost (BETC) is reasonably large, and certainly higher than the typical transaction costs encountered in the commodity futures markets.

Second, we examine the subperiod performance by arbitrarily dividing the whole sample period into three subperiods. The moving average timing performs much better than the buy-and-hold strategy in all subperiods. For example, in the first subperiod from January 2, 1975 to December 31, 1990, the Sharpe ratios on the volatility tercile portfolios are 0.58, 0.31, and 0.29 for the timing strategy versus -0.03, 0.05, and 0.15 for the buy-and-hold strategy, and $\Delta M2$ is 2317.2%, 549%, and 304.5%, respectively.

Third, similar to the timing strategy used in Han, Yang, and Zhou (2013), we do not allow for shorting in the moving average timing strategy discussed above. However, one of the advantages of futures markets is the ability to short the futures without incurring higher costs. Therefore, we also consider the timing strategy that shorts the futures portfolios, which delivers even better results. The average returns are higher than those without shorting for every portfolio considered, and even with heightened volatilities, the Sharpe ratios are mostly higher. For example, the Sharpe ratios become 0.33, 0.45, and 0.54, and $\Delta M2$ become 357.7%, 875.6%, and 247.0%, respectively, for the three volume sorted portfolios mentioned above.

Fourth, we examine the performance of the moving average timing with alternative lag window lengths for estimating the moving averages. We consider L = 3, 10, 20, and 50 days, and find that the performance gradually decreases as the lag length increases. But even with 50-day lag length, the performance is only slightly reduced. For example, with L = 3, the average returns (Sharpe ratios) are 4.61% (0.66), 4.43% (0.45), and 8.86% (0.65), respectively, for the three volatility sorted portfolios, and are 3.49% (0.49), 4.80% (0.49), and 4.03% (0.29), respectively, with L = 50.

Finally, we consider alternative construction of the continuous time series of futures prices. Unlike stocks, futures have expiration dates. As a result, expired futures have to be rolled over to adjacent futures to continue the trade and to construct a continuous time series for futures prices. As a result of rollover, prices gaps are artificially introduced to the time series of futures prices because futures with different expiration are traded at different prices on the same day (backwardation or contango). Therefore, futures prices are often adjusted to smooth out the gaps. However, there is no standard procedure to roll over the futures and to smooth out the prices in the industry and in the literature. We roll over the futures at the expiration date and smooth out the gaps using the ratio of the two futures prices at the expiration as our standard procedure. But we also consider three alternative procedures. The first alternative procedure only differs from our standard procedure by the date of rollover, which is now 15 days before the expiration. The performance gains are similar to the ones delivered by the standard procedure even though the buy-and-hold strategy now performs better than with the standard procedure. The second alternative procedure differs from the standard procedure by how the prices are smoothed out. Now the futures prices are adjusted by the difference in price between the two futures at the expiration. In this case, both the buy-and-hold and moving average timing strategies perform much worse than with the standard procedure, nevertheless the moving average timing still significantly outperforms the buy-and-hold strategy. The last alternative procedure differs from the standard procedure in that futures prices are not adjusted at all. The outperformance is largely similar to that with the standard procedure. For example, the average returns are 4.37% versus 2.89% per annum, the Sharpe ratios are 0.62 versus 0.29, and $\Delta M2$ is 111.2% for the lowest volatility portfolio; the average returns are 4.35% versus -0.73% per annum, the Sharpe ratios are 0.33 versus -0.04, and $\Delta M2$ is 937.7% for the highest volatility portfolio.

To understand further the abnormal performance of moving average timing, we examine the relation of the timing performance with business cycles, investor sentiment, and several macroeconomic variables, respectively. Similar to Han, Yang, and Zhou (2013), Han, Zhu, and Zhou (2014), and Neely, Rapach, Tu, and Zhou (2014), we find that the moving average timing performs much better during recessions. Similarly, the abnormal performance of the moving average timing strategy is mainly concentrated in periods of high investor sentiment, which seems to suggest a behaviorial explanation for the abnormal performance. However, we find that the high level of sentiment may proxy for high level of real interest rate, and abnormal performance is positively associated with real interest rate. We further provide evidence that the abnormal performance of the timing strategy is indeed due to successful market timing.

This paper makes a contribution to the debate whether or not the technical analysis is profitable. Technical analysis has been widely used by investors in all sorts of financial markets. Many top traders and investors use it partially or exclusively (see, e.g., Schwager (1993), Covel (2005), Chincarini and Kim (2006), and Lo and Hasanhodzic (2009)). Despite the extensive use in the investment community, the academic studies are few and far between. The earliest empirical study dates back to Cowles (1933) who finds inconclusive evidence. Starting in 1960s, while some early studies such as Alexander (1961), Cootner (1962), and Levy (1967) find positive results, many early studies find negative results. Examples are Fama and Blume (1966), van Horne and Parker (1967, 1968), James (1968), Jensen and Benington (1970), and Levy (1971), to name a few. Recent studies, such as Brock, Lakonishok, and LeBaron (1992) and Lo, Mamaysky, and Wang (2000), however, find strong evidence of profitability of technical analysis in stock markets. More recent studies such as Neely, Rapach, Tu, and Zhou (2014), Goh, Jiang, Tu, and Zhou (2013), and Han, Yang, and Zhou (2013) also provide evidence of profitability of technical analysis, in particular the moving average.

In commodity futures markets, evidence seems more favorable. Early studies such as Houthakker (1961) and Stevenson and Bear (1970) find technical analysis is profitable, even though some studies such as Praetz (1975) find negative results. Most recently, Szakmary, Shen, and Sharma (2010) find that trend-following trading strategies in commodity futures markets are profitable in at least 22 out of 28 markets. Clare, Seaton, Smith, and Thomas (2014) show that combining momentum and trend following strategies for individual commodity futures can lead to superior performance to simple momentum strategies. However, Park and Irwin (2005) show that technical trading rules generally have not been profitable in US futures markets after correcting for data snooping biases, and Marshall, Cahan, and Cahan (2008) find that quantitative market timing strategies are not consistently profitable in commodity futures markets.

Most of the existing studies on technical analysis use either market indices or individual stocks or commodity futures. Han, Yang, and Zhou (2013) are the first to apply technical analysis to portfolios of stocks, and find significant and consistent gains using a simple moving average timing strategy. We extend the analysis to commodity futures. Compared to stock markets, commodity futures markets have both advantages and challenges. The main advantages of futures markets are the lower transaction costs and easiness to short. The challenges are much fewer contracts than stocks in cross-section and that futures have expiration dates. In addition, unlike stocks, futures are more akin to a zero-sum game and do not have inherit (fundamental) values, and the prices are mostly determined by demand and supply relation. We find that even with these differences and challenges, the moving average timing also performs well in futures markets with characteristics-sorted commodity futures portfolios.

The rest of the paper is organized as follows: Section 2 describes the data and discusses some of the unique features associated with futures. Section 3 discusses the moving average timing strategy. Section 4 provides evidence for the profitability of the moving average timing strategy. Section 5 examines the robustness of the profitability of the moving average timing in a number of dimensions. Section 6 explores the source of the profitability with business cycles, sentiment, macroeconomic variables, and the Henriksson and Merton (1981) market timing model. Section 7 concludes the paper.

2. Data

We obtain the daily settlement price, trading volume, and open interest on 35 US commodity futures contracts from Bloomberg. The data span the period from December 31, 1974 to December 31, 2013. To avoid survivorship bias, we include contracts that start trading after December 31, 1974 or are delisted before December 31, 2013. The commodity futures are 14 agricultural futures (cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar, wheat, white wheat, rough rice, lumber), 5 livestock futures (feeder cattle, pork belly, hogs, live cattle, milk), 10 metal futures (aluminum, copper, gold, lead, nickel, palladium, platinum, silver, tin, zinc), and 6 energy futures (Brent crude oil, crude oil, gas oil, heating oil, natural gas, unleaded gasoline). Table 1 lists the symbol, name, starting date, starting price, end date, end price, and cumulative rate of returns over the entire sample period for the 35 commodity futures contracts. Although almost all the agriculture futures started trading earlier than December 31, 1974, many futures started to trade later than the start of the sample period. Similarly, most futures continue to trade after December 31, 2013, but a few stop trading before the end of the sample period. For example, white wheat futures contracts end on June 26, 2008, and pork belly contracts trade until July 15, 2011. It is of interest to note that some commodities have experienced dramatic price increase but others have barely moved. For example, palladium started to trade on October 30, 1986 with a price of \$0.35, but by the end of 2013, the price has gone up to \$717.40, so the total rate of return is a whopping 2048.71 (not in percentage). On the other hand, sugar futures are priced around \$47.20 on December 31, 1974, but the price has come down to \$16.41 by December 31, 2013, with a total rate of return of -65%. These two are of course extreme cases, and the majority of the commodities have appreciated about 2 to 3 times during the sample period of 49 years, which is small relative to the stocks market. For example, the S&P 500 index has appreciated about 27 times from 68.56 on December 31, 1974 to 1848.36 on December 31, 2013. Therefore returns on commodity futures are much lower than returns on stocks in general. This is likely because futures prices are mainly driven by the supply and demand relation, while stock prices are mainly driven by the profit-generating operations of the underlying firms.

Because individual futures contracts have expiration dates, adjacent futures are rolled over to construct a continuous time series of prices for futures. Bloomberg can produce a continuous time series of futures prices with appropriate specification and provides several different ways to roll over the contracts. In our standard case, we assume that we always hold the first nearest-to-maturity contract (front month contract) up to the expiration. Then we roll our position over to the second nearest-to-maturity contract and hold that contract up to maturity. The procedure is repeated to the next set of nearest and second nearest contracts to construct the continuous time series of futures prices. Because of backwardation or contango, the two contracts have different prices on the same day and thus will produce jumps in prices on the expiration day of the first contract. To smooth out the jumps, we adjust the futures prices before the expiration day including those of the previously expired futures by the ratio of the prices of the new contract and expiring contract on the expiration day. Therefore, the previous futures prices are adjusted by the cumulative ratios of the two contracts on the expiration days. As a robustness test, we also examine three alternative constructions. First, we roll over the contracts 15 days before expiration. Second, we smooth out the jumps using cumulative differences of futures prices of the new contract and expiring contract on the expiration day. Finally, we use the raw prices without any adjustment.

Consistent with previous literature on commodity research, such as Bessembinder (1992), Erb and Harvey (2006), Miffre and Rallis (2007), Marshall, Cahan, and Cahan (2008), Fuertes, Miffre, and Rallis (2010), and de Groot, Karstanje, and Zhou (2014), we assume that investors are fully collateralized and thus earn total return on a fully-collateralized position in futures markets, which equals to the sum of the collateral return (e.g. U.S. Treasury-bill rate earned on the notional amount of the futures contract) and the futures return. In other words, we assume that investors fully fund their positions rather than using margin in futures markets, and refer to the futures returns as excess returns. We calculate futures returns as percentage changes in the futures prices (Gorton, Hayashi, and Rouwenhorst, 2012).

3. Methodology

In this paper, we argue that it is more profitable to focus on portfolios of commodity futures instead of individual commodity futures. Thus we first discuss how to form portfolios sorted on the characteristics of futures contracts. We then discuss in details how to implement moving average timing strategy on the commodity futures portfolios.

3.1. Portfolio Sorts

In cross-section equity studies, stocks are often sorted into quintiles or deciles by certain firm characteristics. In this paper, we sort the 35 commodity futures into tercile portfolios because of the limited number of commodity contracts. We sort the futures according to their daily volatility, daily trading volume, daily open interest, past six-month momentum (cumulative return) skipping last month, last-month return, and past 60-month cumulative returns skipping last month, respectively, into six sets of tercile portfolios. Portfolios are rebalanced monthly, and therefore, daily volatility is estimated each month using the daily returns of the futures within the month, and daily trading volume and daily open interest are averaged each month. We calculate equal-weighted portfolio daily returns and daily prices.

Because of the limited number of futures contracts, changing the number of contracts in each tercile by one often induces jumps in portfolio prices. As we use moving average prices as timing signals, these discrete jumps will often cause false changes in timing signals. To mitigate the problem, instead of using the portfolio prices calculated from the individual futures prices in the portfolio, we calculate the portfolio prices from the portfolio returns assuming the initial price level is \$100 on December 31, 1974. In this way, moving average prices capture dynamics of future returns not the false jumps induced by adding or dropping one futures from the portfolio.

3.2. Moving Average Timing Strategies

Denote by r_{jt} $(j = 1, 2, 3)$ the (excess) returns on the commodity futures tercile portfolios, and by P_{jt} $(j = 1, 2, 3)$ the corresponding portfolio prices (index levels). The moving average price on day t of lag L is defined as

$$A_{jt,L} = \frac{P_{jt-L-1} + P_{jt-L-2} + \cdots + P_{jt-1} + P_{jt}}{L}, \tag{1}$$

which is the average price of the past L days including day t. Given the short maturity of futures contracts, we consider primarily 5-day moving averages in this paper, but we also examine the robustness of the results by analyzing other lag lengths as well. The moving average timing is the most popular strategy of using technical analysis and is the focus of study in the literature. On each trading day t, if the last settlement price P_{jt-1} is above the moving average price $A_{jt-1,L}$, we will invest in the tercile portfolio j for the trading day t, otherwise we will not invest in the futures markets. So the moving average prices provide an investment timing signal with a lag of one day. In another robustness test, we also consider shorting the portfolio of futures contracts when the settlement price is below the moving average price.

Mathematically, the excess returns on the moving average timing strategy are

$$\tilde{r}_{jt,L} = \begin{cases} r_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L}; \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

To measure the performance of the moving average timing strategy, we focus on the relative performance using the buy-and-hold strategy as the benchmark, which simply holds the commodity tercile portfolios over the entire sample period. The moving average timing strategy often produces higher return and lower volatility than the buy-and-hold strategy, and therefore we also compare the risk adjusted performance measured by the Sharpe ratio in addition to comparing the average returns. However, the comparison of the Sharpe ratios does not lend itself to an intuitive interpretation. We thus consider another performance measure, Modigliani-Modigliani measure (M2), which is related to the Sharpe ratio as

$$M2 = SR \times \sigma_b, \tag{3}$$

where SR is the Sharpe ratio of the moving average timing strategy, and σ_b is the standard deviation of the buy-and-hold strategy. The economic interpretation of M2 measure is that M2 is the average excess return of the moving average timing strategy if the timing strategy is leveled up (down) to have the same volatility as the buy-and-hold strategy,

$$M2 = \mu_t \times \frac{\sigma_b}{\sigma_t}, \tag{4}$$

where μ_t and σ_t are the average excess return and standard deviation of the moving average timing strategy. To appreciate the performance increase, we report the percentage change in M2 instead, which is given as

$$\Delta M2(\%) = \frac{M2 - \mu_b}{\mu_b} \times 100, \tag{5}$$

where μ_b is the average excess return of the buy-and-hold strategy.

4. Profitability of Moving Average Timing

In this section, we discuss the performance of the moving average timing strategy. We first apply the strategy to individual commodity futures and then apply the same timing strategy to the characteristics-sorted portfolios of the commodity futures. We report the summary statistics of the returns generated by the timing strategy and compare them with those generated by the buy-and-hold strategy. We finally examine the risk adjusted alphas using Fama-French three-factor model and a two-factor model with the market portfolio and an index of the commodity futures, respectively.

4.1. Individual Contracts

We apply the moving average timing strategy first to individual contracts and compare the performance of the timing strategy to that of the buy-and-hold benchmark strategy, which simply holds the individual commodity futures contracts. Table 2 reports the results using the 35 individual commodity futures. Panel A reports the results of the benchmarks, the buy-and-hold strategy, while Panel B reports the results of moving average timing. Across all the futures, the moving average timing strategy does not consistently outperform the buy-and-hold strategy. For some futures, the moving average timing strategy outperforms. For example, for C (Corn) futures, the buy-and-hold strategy yields an average return of -4.77% per annum with a rather large standard deviation of 23.1% per annum and an insignificant t value of -1.29. Therefore it has a negative Sharpe ratio of -0.21. In contrast, the moving average timing strategy delivers an average return of 4.45% per annum with a significant t value of 1.73, a difference of 9.22% per annum. In addition, the timing strategy achieves this much improved performance with much lower volatility, the standard deviation is about 16.1% per annum. As a result, the Sharpe ratio of the timing strategy is 0.28. However, for other futures, the moving average timing strategy underperforms. For example, for HG (Copper) futures, the buy-and-hold strategy yields an average return of 9.19% per annum, which is significant, but the moving average timing strategy yields only an insignificant average return of 3.97% per annum. Nevertheless the volatility of the timing strategy is still lower than that of the buy-and-hold strategy.

Out of the 35 commodity futures contracts, the moving average timing strategy delivers higher average returns (Sharpe ratios) in 23 (27) contracts but lower average returns (Sharpe ratios) in the other 12 (8) contracts. The results are largely consistent with the previous literature on technical analysis in commodity futures (see, e.g., Szakmary, Shen, and Sharma, 2010). In some contracts the performance improvement is fairly large, but in some contracts the performance deterioration is also rather large. For example, the largest improvement in the average return is 16.4% per annum achieved with LB (Lumber). On the other hand, the largest drop in the average return is -8.65% per annum with LN (Nickel) futures. If we form an equal-weighted portfolio of all the 35 commodity futures contracts, the average return is only -4.76% per annum for the buy-and-hold strategy, and 4.45% for the moving average timing strategy. The Sharpe ratio is increased from -0.21 to 0.28.

4.2. Sorted Portfolios

In this subsection, we provide evidence that the moving average timing strategy delivers better performance when applied to sorted portfolios of the commodity futures. Intuitively, the portfolios of commodity futures are much less volatile than the individual commodity futures, and thus the prices of the portfolios are much more informative than the prices of individual contracts. To apply the timing strategy to the portfolios of commodity futures, we first sort the 35 commodity futures into three groups to form three equal-weighted tercile portfolios by various attributes, including volatility, trading volume, open interest, past six-month cumulative returns from $t-2$ to $t-6$, last-month return $t-1$, and past sixty-month cumulative return from $t-2$ to $t-60$. Then we apply the moving average timing to the sorted tercile portfolios and compare the performance with that of the buy-and-hold strategy of the sorted portfolios.

Table 3 reports the results. For volatility sorted portfolios (Panel A), the buy-and-hold strategy yields statistically insignificant average returns of 1.81%, 2.93% and 4.87% per annum, respectively, for the portfolios with the lowest volatility, medium volatility, and the highest volatility. The moving average timing strategy, on the other hand, delivers statistically significant average returns of 3.84%, 5.61%, and 8.46% per annum, respectively, for the same three tercile portfolios. Furthermore, because the timing strategy always achieves higher average returns with lower volatility, the Sharpe ratios are much higher. They are 0.55 versus 0.18 for the lowest volatility tercile portfolio, 0.58 versus 0.21 for the medium volatility tercile portfolio, and 0.62 versus 0.25 for the highest volatility tercile portfolio. In addition, the buy-and-hold strategy almost always produces negatively skewed returns with close to normal kurtosis, whereas the moving average timing strategy often produces positively skewed returns with positive excess kurtosis, which suggests that the timing strategy often generates large positive returns. Finally, $\Delta M2$ indicates large performance improvement over the buy-and-hold strategy after the volatility of the moving average timing strategy is leveled up. For example, the portfolio with the lowest volatility has the highest risk-adjusted performance improvement, more than 200%, i.e., the average return of the moving average timing strategy is three times of the average return of the buy-and-hold strategy after leveling up the volatility.

It is worth noting that the moving average timing strategy almost always yields higher

Sharpe ratios when applied to the three volatility sorted portfolios than when applied to individual commodity contracts. Furthermore, the Sharpe ratios of the three portfolios are also much higher than the Sharpe ratio of the portfolio of all 35 futures with moving average timing (Sharpe ratio is 0.28 as reported in Table 2). As discussed above, the better performance is likely due to much lower volatility of the sorted portfolios than the individual futures. This is true even for the portfolio with the highest volatility. For example, the most volatile portfolio has a standard deviation of 19.5% per annum, which is much lower than the volatility of all but three commodity futures.

Han, Yang, and Zhou (2013) provide evidence suggesting that information uncertainty proxied by volatility, analyst forecast dispersion, credit rating, etc. improves the performance of the moving average timing in the cross-section of stock markets. We observe similar pattern for the volatility sorted portfolios – the higher the volatility (information uncertainty) is, the better the performance the moving average timing delivers. For example, the average return increases from 3.84% to 5.61% to 8.46% per annum and the Sharpe ratio increases from 0.55 to 0.58 to 0.62 across the three volatility tercile portfolios.

Stronger performance is observed when the tercile portfolios sorted by the trading volume or open interest are used. For example, the volume sorted portfolios yield Sharpe ratios of 0.29 versus 0.07 for the lowest tercile, 0.36 versus 0.05 for the second tercile, and 0.50 versus 0.16 for the highest tercile, respectively. The increase in average return after controlling for the volatility ($\Delta M2$) is 304.4%, 677.1%, and 220.4%, respectively for the three volume sorted tercile portfolios.

Similar results are obtained for the past return sorted tercile portfolios. For the momentum portfolios (Panel D), for example, the moving average timing strategy delivers Sharpe ratios of 0.40 versus -0.09 (losers), 0.58 versus 0.35, and 0.71 versus 0.39 (winners), respectively, and improves the average return over the buy-and-hold strategy by 555.4%, 63.6%, and 61.8%, respectively after controlling for the volatility. For prior-month return (Panel E) and prior 60-month return (Panel F) sorted portfolios, the performance improvement is even larger, with $\Delta M2$ of 321.3% and 431.5% for the lowest ranked tercile, 194.4% and 165.6% for the middle tercile, and 63.2% and 235.7% for the highest ranked tercile, respectively.[1]

[1] It is of interest to note that commodity futures do not show short-term or long-term reversal but rather strong momentum. Han (2014) show that moving average timing can be used to enhance the reversal and momentum.

4.3. Risk Adjusted Performance

Higher performance generated by the moving average timing may be attributed to higher risk taking, and thus in this subsection we examine the risk-adjusted abnormal performance. We estimate the risk-adjusted abnormal returns relative to Fama-French three-factor model and CAPM with the S&P commodity index (GSCI). The alphas are reported in Table 4. For the sorted commodity portfolios, both Fama-French alphas and GSCI alphas are insignificant except for the highest prior-month return portfolio which has a highly significant alpha. The lowest momentum and prior-month return portfolios even have significantly negative GSCI alphas. In sharp contrast, most of the alphas are highly significant and positive for the moving average timing strategy. For example, for the volatility sorted portfolios, the buy-and-hold strategy yields a Fama-French alpha of 0.84%, 2.04%, and 2.80% per annum, respectively, for the three tercile portfolios, whereas the moving average timing strategy yields a Fama-French alpha of 3.03%, 5.44%, and 7.32% per annum, respectively, for the three tercile portfolios. For the GSCI alphas, they are 0.58% versus 2.98%, 1.44% versus 5.08%, and 1.55% versus 6.70% per annum, respectively, for the three tercile portfolios.

5. Robust

In this section, we examine the robustness of the results in a number of dimensions. We first examine the trading behavior to determine the effect of transaction costs on the performance of the moving average timing strategy. Then we analyze the subperiod performance of the timing strategy. We further examine the performance of an alternative moving average timing strategy which allows for shorting the futures. We then examine the performance of using alternative moving average windows. Finally, we analyze the performance using alternative roll-over methods to construct the continuous time-series of future returns from the underlying futures prices of various maturities.

5.1. Average Holding Days, Trading Frequency, and BETC

Since the moving average timing strategy is based on daily signals, it is of interest to see how often it trades. If the trades occur too often, a real concern is whether the abnormal returns can survive transaction costs. We address this issue by analyzing the average consecutive holding days of the timing strategy and the trading frequency. We also estimate the break-even costs, under which the timing strategy would yield the same average return as the buy-and-hold strategy (even though the timing strategy may still enjoy a lower return volatility).

Table 5 reports the results for the six sorted tercile portfolios. On average, all strategies hold about four consecutive days of the sorted portfolios each time, which corresponds well with the timing signal, a moving average price of the last five trading days. There seems no difference in the number of holding days across the three terciles regardless of the sorting variables. For example, the portfolio with the lowest volatility has 4.05 consecutive holding days on average, while the highest volatility tercile portfolio has an average of 4.16 consecutive holding days. Other sorted portfolios have similar consecutive holding days, too. Perhaps, it is not surprising that the average trading frequencies are almost the same across the three terciles for each set of sorted portfolios and across different sets of the sorted portfolios. The average trading frequencies are less than 13%.

Because of the low trading frequencies, we would expect low impact of transaction costs on the performance. Consider now how the abnormal returns will be affected after we impose transaction costs on the trades. Following Balduzzi and Lynch (1999), Lynch and Balduzzi (2000), Han (2006), and Han, Yang, and Zhou (2013) for example, we assume that the strategies incur transaction costs for trading the commodity tercile portfolios but no costs for trading the 30-day Treasury Bill (collateral). Then, in the presence of transaction cost τ per trade, the excess returns on the moving average timing strategy are:

$$\tilde{r}_{jt,L} = \begin{cases} r_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L} \quad \text{and} \quad P_{jt-2} > A_{jt-2,L}; \\ r_{jt} - \tau, & \text{if} \quad P_{jt-1} > A_{jt-1,L} \quad \text{and} \quad P_{jt-2} < A_{jt-2,L}; \\ 0, & \text{if} \quad P_{jt-1} < A_{jt-1,L} \quad \text{and} \quad P_{jt-2} < A_{jt-2,L}; \\ -\tau, & \text{if} \quad P_{jt-1} < A_{jt-1,L} \quad \text{and} \quad P_{jt-2} > A_{jt-2,L}. \end{cases} \tag{6}$$

Without taking a stand on the level of the appropriate transaction costs, we consider the break-even transaction costs that make the average returns of the moving average timing strategies equal to the average returns of the buy-and-hold strategies. Table 5 reports the break-even costs in basis points (bp). Unlike the number of consecutive holding days and trading frequency, the break-even costs vary largely across the three tercile portfolios. For example, the moving average timing strategy would require 6.34 bp each trade to eliminate the gains for the lowest volatility portfolio, 8.39 bp each trade for the second tercile portfolio, and 11.4 bp each trade for the highest volatility portfolio. Portfolios sorted by open interest can sustain higher transaction costs - the break-even transaction costs are 11.8 bp, 14.3 bp, and 8.97 bp per trade, respectively, for the portfolio with the lowest open interest to the portfolio with the highest open interest. In all case, the break-even transaction cost is much larger than the realistic transaction costs in the commodity futures markets. For example, Locke and Venkatesh (1997) estimate futures markets transaction costs to be in the 0.04 to 3.3 bp range. Thus the impact of transaction costs is expected to be low and the moving average timing strategy should still earn economically highly significant abnormal returns after considering appropriate transaction costs.

5.2. Subperiod

In this subsection, we divide the whole sample period into three subperiods arbitrarily and examine the performance of the timing strategy in each of the subperiods. Results are reported in Table 6. To save space, Table 6 only reports results for volatility sorted portfolios. Panel A reports the performance in the first subperiod from January 2, 1975 to December 31, 1990, Panel B reports the performance from January 2, 1991 to December 31, 2000, and Panel C reports the performance from January 2, 2001 to December 31, 2013. In each subperiod, the buy-and-hold strategy yields quite different performance. For example, the three tercile volatility portfolios yield -0.28%, 0.64%, and 3.04%, respectively, in the first subperiod, yield -0.50%, 2.31%, and 6.04% in the second subperiod, and yield 6.09%, 6.14%, and 6.18% in the last subperiod. Nevertheless, the moving average timing strategy yields better performance in each of the subperiods. In the first subperiod, for example, the timing strategy delivers an average return of 4.45%, 2.94%, and 8.59%, respectively, for the three tercile portfolios, and the associated $\Delta M2$ measure is 2317.2%, 549.9%, and 304.5%, respectively.

5.3. With Short

In the previous analysis, we do not allow for shorting the future contracts. However, a big advantage of using futures, among others, is the ability to short the contract equally easily. In this subsection, we entertain the moving average timing with short. Briefly, when the current price of the tercile portfolio of commodity futures is above the moving average price, we long the portfolio the next day, otherwise we short the portfolio the next day. Mathematically, the excess returns on the moving average timing strategy are

$$\tilde{r}_{jt,L} = \begin{cases} r_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L}; \\ -r_{jt}, & \text{otherwise.} \end{cases} \tag{7}$$

The results are reported in Table 7. We still report the timing performance of using the six sorted tercile portfolios.

The results are similar to but a little stronger than the results of no short reported Table 3. For example, for the three volatility tercile portfolios, the average returns delivered by the timing strategy are 5.87%, 8.29%, and 12.0% per annum, respectively. For comparison purpose, the no-short timing strategy delivers 3.84%, 5.61%, and 8.46% per annum, and the buy-and-hold strategy yields 1.81%, 2.93%, and 4.87% per annum. However, the timing strategy with short generates much higher volatility, which is almost the same as that of the buy-an-hold strategy. As a result, the Sharpe ratios of the timing strategy with short are only slightly higher than those of the timing strategy without short (0.59 versus 0.55, 0.60 versus 0.58, and 0.62 versus 0.62).

The results from other sorted portfolios are similar, although in some cases, the improvement in performance gained by relaxing the no-short constraint is rather large. For example, for the lowest ranked portfolios of momentum and prior-month return, the Sharp ratio increases from 0.40 to 0.65 and 0.22 to 0.40, respectively.

5.4. Alternative Moving Average Lag Length

In this subsection, we analyze the performance of using different moving average window lengths. Table 8 reports the results of moving average timing (no short) using the six sets of sorted tercile portfolios. We consider both shorter and longer lag lengths including 3-day, 10-day, 20-day, and 50-day. Across the various lag lengths, the timing performance seems to become weaker as the lag length becomes longer. For example, the average returns (Sharpe ratios) of the timing strategy using the volatility tercile portfolios are 4.61% (0.66), 4.43% (0.45), and 8.86% (0.65), respectively, when the lag length is 3-day, and are 3.49% (0.49), 4.80% (0.49), and 4.03% (0.29), respectively, when the lag length is 50-day. However, even with the lag length of 50-day, the timing strategy still delivers better performance than the buy-an-hold strategy.

5.5. Alternative Construction of Roll-Over Returns

In this subsection, we entertain the alternative ways to construct the rollover returns using the expiring (front-month) futures and the adjacent futures. As discussed previously, Bloomberg provides several rollover methods to construct the continuous time-series of futures returns. Table 9 reports the results of three alternative constructions. In Panel I, the rollover occurs 15 days before the expiration. In Panel II, prices are adjusted by the cumulative difference between the expiring futures and the next adjacent futures. In Panel III, prices are not adjusted during the rollover. Note that the returns on individual commodity futures and thus on the sorted tercile portfolios are different in each case due to different construction of the continuous time-series of futures prices. Therefore, the buy-and-hold strategy yields different performance in each case. For example, the performance is particularly poor when prices are adjusted using differences (Panel II). Nevertheless, in all cases the moving average timing strategy performs much better than the buy-and-hold strategy. For example, in Panel III where the futures prices are not adjusted, the moving average timing delivers average return (Sharpe ratios) of 4.37% (0.62), 4.08% (0.43), and 4.35% (0.33), respectively for the three volatility tercile portfolios, while the buy-and-hold strategy generates average returns (Sharp Ratios) of 2.89% (0.29), 2.91% (0.22), and -0.73% (-0.04), respectively, for the three volatility portfolios. The performance increase ($\Delta M2$) is 111.2%, 96.9%, and 937.7%, respectively, for the three volatility tercile portfolios.

6. Source of Abnormal Performance

In this section, we explore the source of abnormal performance generated by moving average timing. We first examine whether the performance displays any cyclic patterns and whether it depends on investor sentiment. We then analyze the spread portfolio, the return difference between the moving average timing and buy-and-hold strategies.

6.1. Business Cycle

Han, Yang, and Zhou (2013) find that moving average timing performs better in stock markets during recessions than during expansions. Han, Zhu, and Zhou (2014) also show that a trend factor constructed based on moving average signals in stock markets performs better during recessions. Table 10 reports separately the performance of the moving average timing strategy in expansions (Panel A) and recessions (Panel B)[2]. Not surprisingly, the buy-and-hold strategy on the volatility sorted commodity portfolios performs better during

[2]Recession periods are determined by the NBER.

expansions than during recessions. For example, the lowest volatility tercile portfolio gains on average 4.08% per annum during expansions but suffers on average −12.9% per annum during recessions. In contrast, the moving average timing strategy performs only slightly worse in recessions than in expansions. For example, the lowest volatility tercile portfolio gains on average 4.75% per annum during expansions and only lose −2.07% per annum on average during recessions. As a result, the performance difference between the moving average timing and buy-and-hold strategies is much bigger during recessions than during expansions. In other words, the moving average timing strategy preforms much better during recessions relative to the buy-and-hold strategy. Indeed, the performance increase ($\Delta M2$) is 61.4%, 43.3%, and 73.1%, respectively, for the three volatility tercile portfolios during expansions, but is 75.2%, 187.9%, and 184.9%, respectively, during recessions.

6.2. Sentiment

We next examine whether the performance of the moving average timing varies with the level of investor sentiment. If the abnormal returns of the moving average timing is due to investors' behavior biases, then it will depend on the level of investor sentiment. High investor sentiment often induces more biased behavior and thus higher abnormal returns. We use Baker and Wurgler (2007) monthly investor sentiment index to create a sentiment dummy, which takes a value of one when the level of sentiment is above the median estimated using the entire sample period. We then compare the performance of moving average timing during the periods of high sentiment with that during the periods of low sentiment. Table 11 reports the comparison results using the volatility tercile portfolios. First, the buy-and-hold strategy performs much better during periods of low sentiment than during the periods of high sentiment. For example, the lowest volatility portfolio yields an average return of 8.55% per annum when investor sentiment is low but loses −3.41% per annum when investor sentiment is high. Similarly, the moving average timing strategy performs better with low investor sentiment than with high investor sentiment. The lowest volatility portfolio yields an average return of 6.40% per annum when investor sentiment is low and only 1.49% per annum when investor sentiment is high. However, compared to the buy-and-hold strategy, the moving average timing performs much better when investor sentiment is high. For example, the performance increase is 1.82%, 13.6%, and 32.8%, respectively, for the three volatility portfolios during periods of low investor sentiment, but is 164.0%, 332.2%, and 70400%, respectively, during the periods of high investor sentiment. The performance increase for the highest volatility portfolio is remarkable as demonstrated by the extraordinary large $\Delta M2$ when investor sentiment is high. This is mainly due to virtually zero average return of the highest volatility portfolio for the buy-and-hold strategy, whereas the moving average timing strategy delivers a significant 6.56% average return.

6.3. Macroeconomic Variables

From the above discussion, it is clear that the recession dummy and sentiment dummy can explain part of the abnormal performance of the moving average timing, but these two dummy variables may proxy for other macroeconomic variables. These two dummy variables are also correlated with each other - the correlation is more than 14%. So to further analyze the source of the abnormal performance, we estimate the return difference between the moving average timing and buy-and-hold strategies, which is also a zero-cost spread portfolio that takes a long position in the moving average timing strategy and take a short position in the buy-and-hold strategy.

$$\Delta_{jt} = \tilde{r}_{jt} - r_{jt}. \tag{8}$$

To control for other macroeconomic variables, we collect the time-series of four macroeconomic variables: the term spread, the default spread, the real interest rate, and Cay. The term spread is defined as the yield difference between the 20-year and 1-year Treasury bonds; the default spread is defined as the yield difference between BAA and AAA bonds; the real interest rate is defined as the difference between the 30-year T-bill return and the CPI inflation rate; Cay is the consumption-wealth variable defined in Lettau and Ludvigson (2001).[3] Following Stambaugh, Yu, and Yuan (2012), we use the four variables because they may be correlated with certain risk premiums.

We regress the return difference (spread portfolio) on the recession dummy, investor sentiment, and the macroeconomic variables. The results are reported in Table 12. First, the recession dummy is positive and significant either alone or with other variables for all but the highest volatility portfolio. In fact, none of the variables are significant with the highest volatility portfolio, which is likely due to its very high volatility. The significantly

[3]The bond yields including treasury and corporate bonds and CPI are obtained from the St. Louis Federal Reserve, and Cay is obtained from Sydney Ludvigsons website.

positive coefficient confirms the results in Table 10 that the moving average timing performs much better in recession compared to the buy-and-hold strategy. Investor sentiment is also positive and significant alone in the regressions, consistent with Table 11. However, with the presence of the recession dummy, its significance is weakened – it is still significant with the lowest volatility portfolio but becomes insignificant with the mid level volatility portfolio. When the four macroeconomic variables are added to the regression, the recession dummy remains significant but investor sentiment becomes completely insignificant, whereas the real interest rate becomes significant with the lowest volatility portfolio. Results not reported here also show that investor sentiment loses its significance even in the presence of just the real interest rate and the recession dummy. In addition, the correlation between investor sentiment and the real interest rate is more than 37%. Therefore, the dependence of the abnormal performance of the moving average timing on the level of sentiment may not be due to investor irrational behavior, but due to reaction to the real interest rate (and recession). In other words, the abnormal return may be due to rational risk exposure. In the next subsection we further explore the issue.

6.4. Spread Portfolio and Market Timing

In this subsection, we examine further the abnormal returns of the spread portfolios, Δ_{jt}. Table 13 reports the abnormal returns relative to the Fama-French three-factor model and the commodity specific model with S&P GSCI index for all six sets of tercile portfolios. All tercile portfolios deliver positive alphas and most portfolios yield significant alpha with either model. For example, the moving average timing with the volume tercile portfolios yields Fama-French alphas of 3.12%, 4.25%, and 5.01% per annum and GSCI alphas of 3.23%, 4.51%, and 5.25% per annum, respectively, all of which are statistically significant.

It also of interest to note that almost all the beta (risk exposure) coefficients are significant, but are negative and small. For example, the lowest volatility portfolio has a market beta -0.05, a size beta of -0.04, and a book-to-market beta of -0.03 for the Fama-French model, and a market beta of -0.03 and a commodity beta of -0.12 for the GSCI model. It suggests that the moving average timing strategy is able to reduce the risk exposure relative to the buy-and-hold strategy. It also suggests that the spread portfolio would be an excellent hedging device, not only adding positive alphas but also reducing the risk exposures.

We next address the market timing issue, we employ the market timing regression of Henriksson and Merton (1981):

$$\Delta_{jt} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \gamma_{j,mkt} r_{mkt,t} I_{r_{mkt}>0} + \epsilon_{jt}, \qquad j = 1, 2, 3, \tag{9}$$

where $I_{r_{mkt}>0}$ is the indicator function taking the value of one when the market excess return is above zero, otherwise taking the value of zero. The significantly positive coefficient, γ_{mkt}, indicates successful market timing.

Table 14 reports the evidence of successful market timing for all six sets of sorted portfolios. First, the market betas are still negative, small, and significant, but the coefficients for market timing, γ_{mkt}, are positive and significant, indicating successful market timing ability. For example, for the volatility tercile portfolios, the market timing coefficients are 0.03, 0.09, and 0.09, respectively. Furthermore, the abnormal returns are now mostly negative but insignificant, additional evidence for successful market timing. Evidence in this table suggests that the abnormal performance of moving average timing is indeed due to the successful market timing of the strategy.

7. Conclusion

In this paper, we provide evidence that a simple moving average timing strategy, when applied to portfolios of commodity futures, can generate superior performance relative to the buy-and-hold strategy. The outperformance survives the risk adjustment using the Fama-French three-factor model or a two-factor model with the market portfolio and an index portfolio of commodity futures (GSCI). The moving average timing strategy using portfolios of commodity futures also generates more consistent and higher performance than using individual commodity futures.

We also show that the outperformance is very robust. It should survive the transaction costs in the futures markets, it is not concentrated in a particular subperiod, and it is robust to alternative specifications of the moving average lag length. Allowing shorting positions increases the performance of timing strategy, and finally it is robust to alternative construction of the continuous time-series of futures prices.

We find that the outperformance of the moving average timing is much higher in recessions and during periods of high investor sentiment. However, we find that the stronger outperformance with high investor sentiment is not due to investor irrational behavior, but rather the impact of high investor sentiment proxies for the impact of high real interest rate on the outperformance of the moving average timing strategy. Indeed, even though the abnormal returns after adjusted by the Fama-French three-factor or GSCI two-factor model are still significant, they are no longer significant in the Henriksson and Merton (1981) market timing model, suggesting that outperformance of the moving average timing model comes from the successful market timing.

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Table 1: Summary of Individual Contracts

This table lists the information about the 35 US commodity futures contracts. We report the symbol, name, starting date, price at the starting date, end date, price at the end date, and cumulative return (*Cum Return*) from the start date to the end date for all contracts.

Symbol	Name	Start Date	Initial Price	End Date	End Price	Cum Return
C	Corn	31DEC1974	342.00	31DEC2013	422.00	0.23
CC	Cocoa	31DEC1974	1381.00	31DEC2013	2709.00	0.96
KC	Coffee	31DEC1974	59.62	31DEC2013	110.70	0.86
CT	Cotton	31DEC1974	36.80	31DEC2013	84.64	1.30
O	Oats	31DEC1974	166.00	31DEC2013	354.25	1.13
JO	Orange Juice	31DEC1974	50.75	31DEC2013	136.45	1.69
S	Soybean	31DEC1974	697.00	31DEC2013	1312.50	0.88
SM	Soybean Meal	31DEC1974	138.50	31DEC2013	437.70	2.16
BO	Soybean Oil	31DEC1974	36.35	31DEC2013	38.82	0.07
SB	Sugar	31DEC1974	47.20	31DEC2013	16.41	-0.65
W	Wheat	31DEC1974	458.50	31DEC2013	605.25	0.32
VK	White Wheat	16DEC1999	84.00	26JUN2008	103.00	0.23
RR	Rough Rice	06DEC1988	6.78	31DEC2013	15.51	1.29
FC	Feeder Cattle	31DEC1974	30.10	31DEC2013	166.70	4.54
PB	Pork Belly	31DEC1974	61.90	15JUL2011	121.00	0.95
LH	Hogs	01APR1986	43.60	31DEC2013	85.43	0.96
LC	Live Cattle	31DEC1974	39.55	31DEC2013	134.50	2.40
LA	Aluminum	23JUL1997	1643.75	31DEC2013	1761.75	0.07
HG	Copper	06DEC1988	146.89	31DEC2013	344.15	1.34
GC	Gold	02JAN1990	399.60	31DEC2013	1201.90	2.01

Symbol	Name	Start Date	Initial Price	End Date	End Price	Cum Return
LL	Lead	23JUL1997	647.00	31DEC2013	2197.50	2.40
LN	Nickel	23JUL1997	6701.50	31DEC2013	1.38E+04	1.07
PA	Palladium	30OCT1986	0.35	31DEC2013	717.40	2048.71
PL	Platinum	01APR1986	404.00	31DEC2013	1371.10	2.39
SI	Silver	02JAN1990	5.15	31DEC2013	19.34	2.76
LT	Tin	23JUL1997	5426.00	31DEC2013	2.23E+04	3.12
LX	Zinc	23JUL1997	1577.00	31DEC2013	2045.00	0.30
CO	Brent Crude Oil	23JUN1988	15.65	31DEC2013	110.80	6.08
CL	Crude Oil	30MAR1983	29.40	31DEC2013	98.42	2.35
QS	Gas Oil	03JUL1989	146.75	31DEC2013	944.25	5.43
HO	Heating Oil	01JUL1986	36.08	31DEC2013	307.72	7.53
NG	Natural Gas	03APR1990	1.64	31DEC2013	4.23	1.58
HU	Unleaded Gasoline	25APR1986	37.80	29DEC2006	154.19	3.08
DA	Milk	11JAN1996	12.18	31DEC2013	18.99	0.56
LB	Lumber	07APR1986	172.50	31DEC2013	360.10	1.09

Table 2: MA Timing with Individual Contracts

We calculate the 5-day moving average (MA) prices each day using the last 5 day futures closing prices including the current closing price, and compare the MA price with the current price as the timing signal. If the current price is above the MA price, it is an in-the-market signal and we will invest in the futures for the next trading day; otherwise it is an out-of-the-market signal, and we will not invest for the next trading day. We use the 35 commodity futures as the investment assets. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), skewness (Skewness), kurtosis (*Kurtosis*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy (Panel A) and the MA timing strategy (Panel B). The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Contract	**Panel A: Buy-and-Hold Individual Futures**					**Panel B: MA(5) Timing**					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
C	-4.77	23.1	-0.21	0.07	3.06	4.45*	16.1	0.28	0.37	9.57	234.1
	(-1.29)					(1.73)					
CC	4.20	30.5	0.14	0.17	1.91	2.25	21.6	0.10	0.47	7.45	-24.3
	(0.86)					(0.65)					
KC	6.46	35.2	0.18	0.53	8.74	8.74**	25.4	0.34	0.64	16.7	87.4
	(1.14)					(2.14)					
CT	2.53	24.6	0.10	0.10	2.20	5.09*	17.3	0.29	0.52	8.17	186.0
	(0.64)					(1.84)					
O	-1.86	29.5	-0.06	-0.01	2.51	9.60***	20.4	0.47	0.58	8.65	845.5
	(-0.39)					(2.93)					
JO	3.54	29.1	0.12	0.83	14.3	9.91***	21.5	0.46	1.63	30.4	278.1
	(0.76)					(2.87)					
S	2.51	23.4	0.11	-0.12	1.83	4.71*	16.6	0.28	0.18	6.22	164.7
	(0.67)					(1.77)					
SM	7.53*	25.5	0.30	0.02	2.14	11.0***	18.1	0.61	0.39	6.34	105.7
	(1.85)					(3.80)					
BO	-0.79	25.0	-0.03	0.19	1.36	7.60***	17.8	0.43	0.52	5.40	1,457.0
	(-0.20)					(2.67)					
SB	-2.85	39.4	-0.07	-0.09	3.65	4.06	27.6	0.15	-0.09	12.7	304.2
	(-0.45)					(0.92)					

Contract	Panel A: Buy-and-Hold Individual Futures					Panel B: MA(5) Timing					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
W	-5.58	26.2	-0.21	0.17	2.65	0.51	18.6	0.03	0.31	9.29	112.7
	(-1.33)					(0.17)					
VK	0.55	22.9	0.02	0.22	3.39	9.25***	16.6	0.56	0.72	10.4	2,223.4
	(0.15)					(3.48)					
RR	-5.50	23.8	-0.23	0.15	2.32	10.2***	16.3	0.62	0.65	7.86	369.2
	(-1.16)					(3.11)					
FC	3.27	14.8	0.22	-0.09	1.32	6.66***	10.1	0.66	0.37	5.03	197.3
	(1.38)					(4.11)					
PB	0.02	33.2	0.00	0.06	-0.04	12.3***	23.2	0.53	0.29	3.10	1.13E+05
	(0.00)					(3.19)					
LH	1.96	22.6	0.09	-0.07	1.35	5.78**	15.5	0.37	0.33	4.92	328.1
	(0.46)					(1.96)					
LC	4.52*	15.9	0.28	-0.06	1.05	6.41***	10.9	0.59	0.27	4.45	106.3
	(1.77)					(3.66)					
LA	-2.41	21.6	-0.11	-0.17	2.29	-4.93	15.1	-0.33	-0.20	8.04	-191.9
	(-0.45)					(-1.33)					
HG	9.19*	27.5	0.33	-0.03	4.04	3.97	19.2	0.21	0.21	10.8	-38.2
	(1.67)					(1.03)					
GC	1.27	19.8	0.06	0.01	6.94	1.60	14.1	0.11	0.67	14.8	76.4
	(0.40)					(0.71)					
LL	11.7	32.9	0.36	-0.04	3.38	9.57*	23.6	0.41	0.44	11.1	13.9
	(1.44)					(1.64)					
LN	12.1	37.5	0.32	0.07	3.37	3.48	25.9	0.13	0.73	10.3	-58.5
	(1.31)					(0.54)					
PA	9.66	31.3	0.31	0.04	5.81	15.2***	22.1	0.69	0.62	13.4	122.7
	(1.62)					(3.61)					

Contract	Panel A: Buy-and-Hold Individual Futures					Panel B: MA(5) Timing					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2$(%)
PL	5.83	22.2	0.26	-0.31	3.42	5.94**	15.6	0.38	0.18	8.23	44.5
	(1.38)					(2.00)					
SI	2.85	30.6	0.09	-0.33	5.91	3.72	21.2	0.18	0.27	12.1	88.2
	(0.58)					(1.09)					
LT	12.7*	27.3	0.47	0.06	7.19	6.15	18.8	0.33	0.27	12.4	-29.9
	(1.89)					(1.33)					
LX	1.09	30.1	0.04	-0.09	2.69	-1.05	20.8	-0.05	0.16	7.94	-239.0
	(0.15)					(-0.20)					
CO	19.4***	34.2	0.57	-0.39	11.8	12.5***	24.4	0.51	-0.91	39.7	-10.1
	(2.88)					(2.59)					
CL	13.9**	36.0	0.39	-0.37	11.2	10.8**	25.4	0.43	-0.99	36.9	9.91
	(2.14)					(2.35)					
QS	16.2***	31.9	0.51	-0.35	11.2	15.1***	23.4	0.65	-0.72	33.8	27.3
	(2.52)					(3.21)					
HO	17.9***	34.9	0.51	-0.31	10.1	13.9***	25.3	0.55	-0.71	33.3	7.35
	(2.68)					(2.88)					
NG	-2.28	51.1	-0.04	0.49	5.50	7.98	37.4	0.21	1.02	18.8	578.3
	(-0.22)					(1.04)					
HU	12.8*	34.1	0.37	-0.11	11.5	7.62	24.3	0.31	-1.06	28.8	-16.4
	(1.69)					(1.41)					
DA	0.94	13.7	0.07	-0.66	12.8	7.16***	9.08	0.79	0.05	27.0	1,044.1
	(0.29)					(3.31)					
LB	-4.11	27.7	-0.15	0.12	-0.00	12.3***	19.7	0.63	0.34	3.01	521.8
	(-0.78)					(3.29)					
Average across All Contracts											
	-4.76	23.1	-0.21	0.07	3.06	4.45*	16.1	0.28	0.37	9.56	234.4
	(-1.29)					(1.73)					

Table 3: MA Timing with Sorted Portfolios

We calculate the 5-day moving average (MA) prices each day using the last 5 day commodity futures tercile portfolio closing prices including the current closing price, and compare the MA price with the current price as the timing signal. If the current price is above the MA price, it is an in-the-market signal and we will invest in the commodity futures portfolios for the next trading day; otherwise it is an out-of-the-market signal, and we will not invest for the next trading day. We use six sets of commodity futures tercile portfolios sorted by volatility, trading volume, open interest, past six-month momentum, last-month return, and last sixty-month return, respectively, as the investment assets. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), skewness (Skewness), kurtosis (*Kurtosis*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy and the MA timing strategy. The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Rank	Buy-and-Hold Commodity Portfolios					MA(5) Timing					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
Panel A : Volatility Sorted Portfolios											
Low	1.81	9.91	0.18	-0.02	2.92	3.84***	6.99	0.55	0.43	8.38	200.5
	(1.15)					(3.45)					
2	2.93	13.9	0.21	-0.14	4.00	5.61***	9.67	0.58	0.51	10.7	174.4
	(1.33)					(3.64)					
High	4.87	19.5	0.25	-0.25	4.71	8.46***	13.7	0.62	-0.31	17.0	146.3
	(1.57)					(3.87)					
Panel B : Volume Sorted Portfolios											
Low	1.16	16.2	0.07	0.02	3.28	3.29*	11.4	0.29	0.22	10.5	304.4
	(0.45)					(1.81)					
2	0.76	16.6	0.05	-0.04	3.21	4.15**	11.7	0.36	0.26	8.52	677.1
	(0.29)					(2.23)					
High	3.32	21.2	0.16	-0.12	2.83	7.44***	14.8	0.50	0.06	8.07	220.4
	(0.98)					(3.15)					
Panel C : Open Interest Sorted Portfolios											
Low	1.71	18.9	0.09	0.23	5.08	5.51***	13.4	0.41	0.85	16.2	353.0
	(0.57)					(2.57)					
2	0.85	19.7	0.04	-1.68	54.4	5.37**	14.3	0.38	-4.43	190.5	773.7
	(0.27)					(2.36)					
High	6.63*	22.2	0.30	-0.18	8.13	9.46***	15.7	0.60	0.17	18.8	101.3
	(1.87)					(3.77)					

Rank	Buy-and-Hold Commodity Portfolios					MA(5) Timing					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
Panel D : Momentum Sorted Portfolios											
Low	-1.35	15.5	-0.09	-0.07	2.85	4.37***	10.9	0.40	0.32	9.01	555.4
	(-0.55)					(2.49)					
2	4.58**	12.9	0.35	-0.13	2.60	5.32***	9.17	0.58	0.22	6.84	63.8
	(2.21)					(3.62)					
High	6.34***	16.2	0.39	-0.48	7.58	8.04***	11.3	0.71	-0.79	27.5	81.8
	(2.44)					(4.43)					
Panel E : Prior-Month Return Sorted Portfolios											
Low	-1.58	16.2	-0.10	-0.03	2.69	2.42	11.2	0.22	0.09	8.82	321.3
	(-0.61)					(1.35)					
2	1.81	13.0	0.14	-0.17	3.86	3.70***	9.02	0.41	0.00	8.74	194.4
	(0.87)					(2.57)					
High	9.00***	15.9	0.57	-0.19	2.57	10.5***	11.3	0.93	0.11	5.96	63.2
	(3.55)					(5.80)					
Panel F : Prior 60-Month Return Sorted Portfolios											
Low	-0.75	14.2	-0.05	-0.07	2.35	1.73	9.94	0.17	0.22	7.24	431.5
	(-0.31)					(1.02)					
2	3.45	13.4	0.26	-0.10	3.01	6.32***	9.25	0.68	0.25	7.23	165.6
	(1.51)					(4.01)					
High	2.79	17.2	0.16	-0.18	3.74	6.43***	11.8	0.55	0.40	8.72	235.7
	(0.95)					(3.20)					

Table 4: Risk Adjusted Abnormal Returns

The table compares the risk-adjusted abnormal returns for the buy-and-hold (left columns) and the 5-day moving average timing (right columns) strategies on various sorted commodity futures portfolios. Panel A reports the Fama-French alpha, and Panel B reports the alpha relative to a pricing model using the market and the S&P GSCI commodity index. The abnormal returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

	Buy-and-Hold			**MA(5) Timing**		
Sorted Portfolios	Low	2	High	Low	2	High
	Panel A: Fama-French Alpha					
Volatility	0.84	2.04	2.80	3.03***	5.44***	7.32***
	(0.51)	(0.88)	(0.85)	(2.64)	(3.37)	(3.19)
Volume	-0.89	-1.93	0.73	2.36	2.48	5.83**
	(-0.35)	(-0.74)	(0.21)	(1.35)	(1.37)	(2.49)
Open Interest	-0.44	-1.29	4.51	4.42**	4.43**	8.08***
	(-0.14)	(-0.43)	(1.26)	(2.03)	(2.06)	(3.24)
Momentum	-2.88	2.68	4.17	3.52**	4.17***	6.98***
	(-1.14)	(1.30)	(1.61)	(2.02)	(2.84)	(3.89)
Prior-Month Return	-3.52	-0.00	6.79***	1.49	2.80**	8.99***
	(-1.38)	(-0.00)	(2.59)	(0.85)	(1.98)	(4.80)
Prior 60-Month Return	-2.09	1.23	0.22	1.08	5.33***	4.99**
	(-0.87)	(0.54)	(0.08)	(0.68)	(3.32)	(2.54)
	Panel B: GSCI Alpha					
Volatility	0.58	1.44	1.55	2.98***	5.08***	6.70***
	(0.39)	(0.78)	(0.66)	(2.72)	(3.46)	(3.29)
Volume	-0.83	-2.10	0.33	2.45	2.48	5.46***
	(-0.36)	(-0.92)	(0.14)	(1.44)	(1.43)	(2.69)
Open Interest	-0.34	-1.87	3.96	4.56**	4.08**	7.71***
	(-0.12)	(-0.83)	(1.50)	(2.13)	(2.12)	(3.54)
Momentum	-3.56*	2.08	3.23	3.16**	3.90***	6.56***
	(-1.69)	(1.24)	(1.64)	(1.97)	(2.90)	(4.07)
Prior-Month Return	-4.05*	-0.45	6.36***	1.25	2.59**	8.88***
	(-1.94)	(-0.27)	(3.10)	(0.77)	(2.00)	(5.29)
Prior 60-Month Return	-2.63	0.90	-0.86	0.81	5.19***	4.54***
	(-1.18)	(0.46)	(-0.44)	(0.52)	(3.43)	(2.65)

Table 5: Holding Days, Trading Frequencies, and Break-Even Transaction Costs

The table reports the average consecutive holding days (*Holding*), fraction of trading days (*Trading*), and the break-even transaction costs in basis point (BETC) for the 5-day moving average timing strategy on various sorted commodity futures portfolios. The sample period is from January 1975 to December 2013.

Rank	Holding	Trading	BETC	Holding	Trading	BETC	Holding	Trading	BETC
	Volatility			**Volume**			**Open Interest**		
Low	4.05	12.7	6.34	4.08	12.7	6.68	3.97	12.8	11.8
2	4.08	12.7	8.39	4.06	12.6	10.7	4.07	12.6	14.3
High	4.16	12.4	11.4	4.03	12.8	12.8	4.16	12.5	8.97
	Momentum			**Prior-Month Return**			**Prior 60-Month Return**		
Low	3.92	12.7	18.0	3.90	12.8	12.4	3.96	12.7	7.73
2	4.03	12.9	2.27	3.97	12.9	5.83	4.17	12.5	9.14
High	4.23	12.5	5.40	4.32	12.5	4.65	4.08	12.6	11.5

Table 6: Subperiod Performance

We compare the performance of buy-and-hold strategy with the 5-day moving average timing strategy in three arbitrarily divided subperiods. Results reported in the table are for volatility sorted tercile portfolios. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), skewness (Skewness), kurtosis (*Kurtosis*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy and the MA timing strategy. The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively.

Rank	**Buy-and-Hold Commodity Portfolios**					**MA(5) Timing**					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
					Panel A : January 2, 1975 to December 31, 1990						
Low	-0.28	10.7	-0.03	0.12	2.98	4.45**	7.62	0.58	0.78	9.61	2,317.2
	(-0.11)					(2.33)					
2	0.64	13.4	0.05	-0.04	0.99	2.94	9.45	0.31	0.24	5.37	549.9
	(0.19)					(1.24)					
High	3.04	20.3	0.15	-0.09	1.39	8.59**	14.2	0.61	0.29	5.12	304.5
	(0.60)					(2.42)					
					Panel B : January 2, 1991 to December 31, 2000						
Low	-0.50	7.32	-0.07	0.07	1.58	0.05	5.20	0.01	0.22	7.07	113.3
	(-0.22)					(0.03)					
2	2.31	10.5	0.22	-0.09	1.45	3.36	7.48	0.45	0.15	5.77	102.9
	(0.70)					(1.43)					
High	6.04	16.0	0.38	-1.20	26.0	7.75**	12.1	0.64	-2.90	78.5	69.2
	(1.20)					(2.04)					
					Panel C : January 2, 2001 to December 31, 2013						
Low	6.09**	10.6	0.57	-0.23	2.17	6.00***	7.37	0.81	-0.04	5.04	41.8
	(2.09)					(2.96)					
2	6.14	16.4	0.37	-0.23	4.89	10.5***	11.3	0.93	0.72	12.7	149.2
	(1.37)					(3.40)					
High	6.18	20.8	0.30	-0.10	2.07	8.83**	14.3	0.62	0.19	5.99	108.1
	(1.08)					(2.25)					

Table 7: MA Timing with Shorting

We calculate the 5-day moving average (MA) prices each day using the last 5 day commodity futures tercile portfolio closing prices including the current closing price, and compare the MA price with the current price as the timing signal. If the current price is above the MA price, we will long the commodity futures portfolios for the next trading day; otherwise we will short the commodity futures portfolios for the next trading day. We use six sets of commodity futures tercile portfolios sorted by volatility, trading volume, open interest, past six-month momentum, last-month return, and last sixty-month return, respectively, as the investment assets. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), skewness (Skewness), kurtosis (*Kurtosis*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy and the MA timing strategy. The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Rank	**Buy-and-Hold Commodity Portfolios**					**MA(5) Timing**					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
					Panel A : Volatility Sorted Portfolios						
Low	1.81	9.91	0.18	-0.02	2.92	5.87***	9.90	0.59	0.25	2.89	224.1
	(1.15)					(3.72)					
2	2.93	13.9	0.21	-0.14	4.00	8.29***	13.8	0.60	0.41	3.94	183.3
	(1.33)					(3.75)					
High	4.87	19.5	0.25	-0.25	4.71	12.0***	19.4	0.62	-0.04	4.71	147.1
	(1.57)					(3.88)					
					Panel B : Volume Sorted Portfolios						
Low	1.16	16.2	0.07	0.02	3.28	5.31**	16.2	0.33	0.09	3.27	357.7
	(0.45)					(2.05)					
2	0.76	16.6	0.05	-0.04	3.21	7.40***	16.6	0.45	0.17	3.20	875.6
	(0.29)					(2.80)					
High	3.32	21.2	0.16	-0.12	2.83	11.5***	21.2	0.54	0.10	2.82	247.0
	(0.98)					(3.41)					
					Panel C : Open Interest Sorted Portfolios						
Low	1.71	18.9	0.09	0.23	5.08	9.24***	18.9	0.49	0.33	5.06	440.8
	(0.57)					(3.07)					
2	0.85	19.7	0.04	-1.68	54.4	9.72***	19.7	0.49	-1.77	54.9	1,048.9
	(0.27)					(3.10)					
High	6.63*	22.2	0.30	-0.18	8.13	12.3***	22.2	0.55	0.23	8.11	85.2
	(1.87)					(3.47)					

Rank	Buy-and-Hold Commodity Portfolios					MA(5) Timing					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
Panel D : Momentum Sorted Portfolios											
Low	-1.35	15.5	-0.09	-0.07	2.85	10.1***	15.4	0.65	0.25	2.82	845.7
	(-0.55)					(4.07)					
2	4.58**	12.9	0.35	-0.13	2.60	6.06***	12.9	0.47	0.20	2.56	32.3
	(2.21)					(2.92)					
High	6.34***	16.2	0.39	-0.48	7.58	9.74***	16.2	0.60	-0.15	7.57	53.8
	(2.44)					(3.75)					
Panel E : Prior-Month Return Sorted Portfolios											
Low	-1.58	16.2	-0.10	-0.03	2.69	6.48***	16.2	0.40	0.06	2.70	510.7
	(-0.61)					(2.51)					
2	1.81	13.0	0.14	-0.17	3.86	5.59***	13.0	0.43	0.12	3.85	208.9
	(0.87)					(2.70)					
High	9.00***	15.9	0.57	-0.19	2.57	11.9***	15.9	0.75	0.15	2.52	32.6
	(3.55)					(4.71)					
Panel F : Prior 60-Month Return Sorted Portfolios											
Low	-0.75	14.2	-0.05	-0.07	2.35	4.12*	14.2	0.29	0.20	2.34	651.7
	(-0.31)					(1.70)					
2	3.45	13.4	0.26	-0.10	3.01	9.16***	13.4	0.68	0.17	2.98	166.0
	(1.51)					(4.01)					
High	2.79	17.2	0.16	-0.18	3.74	10.0***	17.2	0.58	0.37	3.69	259.6
	(0.95)					(3.43)					

Table 8: Alternative Lag Lengths

This table reports the performance of the moving average timing with no short using various lag length to calculate the moving average prices. For each lag length, we report the average return (*Avg Ret*), the standard deviation (*Std Dev*), and the Sharpe ratio (*Sharpe*) of the timing strategy for the six sets of tercile commodity futures portfolios. The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Rank	MA = 3			MA = 10			MA = 20			MA = 50		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe
Panel A : Volatility Sorted Portfolios												
Low	4.61***	7.01	0.66	3.59***	6.93	0.52	3.53***	7.03	0.50	3.49***	7.11	0.49
	(4.12)			(3.25)			(3.15)			(3.07)		
2	4.43***	9.78	0.45	4.69***	9.60	0.49	4.19***	9.65	0.43	4.80***	9.71	0.49
	(2.84)			(3.07)			(2.72)			(3.09)		
High	8.86***	13.7	0.65	6.01***	13.7	0.44	4.77**	13.8	0.35	4.03*	13.8	0.29
	(4.06)			(2.74)			(2.16)			(1.83)		
Panel B : Volume Sorted Portfolios												
Low	5.13***	11.3	0.45	2.99*	11.3	0.27	2.87	11.3	0.25	2.53	11.0	0.23
	(2.83)			(1.66)			(1.59)			(1.44)		
2	3.92**	11.6	0.34	2.35	11.4	0.21	3.12*	11.4	0.27	4.38**	11.5	0.38
	(2.11)			(1.29)			(1.71)			(2.38)		
High	6.86***	14.6	0.47	5.33**	15.1	0.35	4.76**	15.0	0.32	5.73**	15.0	0.38
	(2.95)			(2.22)			(1.99)			(2.39)		
Panel C : Open Interest Sorted Portfolios												
Low	8.04***	13.5	0.60	4.16**	13.3	0.31	4.96**	13.4	0.37	5.64***	13.3	0.42
	(3.73)			(1.95)			(2.32)			(2.65)		
2	5.63***	14.2	0.40	4.10*	14.1	0.29	3.32	14.2	0.23	4.74**	14.0	0.34
	(2.48)			(1.83)			(1.47)			(2.11)		
High	8.07***	15.5	0.52	6.49***	16.0	0.41	6.89***	16.1	0.43	7.77***	16.2	0.48
	(3.27)			(2.55)			(2.68)			(3.00)		

Rank	MA = 3			MA = 10			MA = 20			MA = 50		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe
Panel D : Momentum Sorted Portfolios												
Low	5.12***	11.1	0.46	1.82	10.8	0.17	2.67	10.7	0.25	0.77	10.2	0.08
	(2.87)			(1.05)			(1.56)			(0.47)		
2	5.29***	9.10	0.58	3.96***	9.21	0.43	3.08**	9.43	0.33	4.04***	9.38	0.43
	(3.62)			(2.68)			(2.03)			(2.68)		
High	8.24***	11.3	0.73	7.44***	11.4	0.66	5.68***	11.5	0.50	5.05***	12.0	0.42
	(4.56)			(4.08)			(3.09)			(2.63)		
Panel E : Prior-Month Return Sorted Portfolios												
Low	2.65	11.3	0.24	0.99	11.1	0.09	1.81	10.6	0.17	2.02	9.73	0.21
	(1.47)			(0.56)			(1.07)			(1.30)		
2	4.23***	9.09	0.47	4.33***	9.07	0.48	2.84**	9.12	0.31	2.76*	9.07	0.30
	(2.92)			(2.99)			(1.95)			(1.91)		
High	11.2***	11.2	1.00	7.92***	11.5	0.69	8.73***	11.9	0.73	8.54***	12.6	0.68
	(6.27)			(4.32)			(4.60)			(4.25)		
Panel F : Prior 60-Month Return Sorted Portfolios												
Low	2.37	10.0	0.24	1.27	9.97	0.13	1.20	10.0	0.12	1.65	9.80	0.17
	(1.39)			(0.74)			(0.70)			(0.98)		
2	5.82***	9.32	0.62	5.67***	9.23	0.61	5.23***	9.26	0.57	4.54***	9.59	0.47
	(3.66)			(3.60)			(3.31)			(2.77)		
High	6.46***	11.9	0.54	4.77**	11.9	0.40	4.32**	11.8	0.37	4.59**	11.9	0.39
	(3.18)			(2.36)			(2.15)			(2.27)		

Table 9: Alternative Construction of Rollover Returns

This table reports the performance of the moving average timing using alternatively constructed futures returns. Panel I uses the futures returns adjusted by cumulative ratios of the front-month futures and the expiring futures. The rollover occurs on the 15^{th} of the month before expiration. Panel II uses the futures returns adjusted by cumulative differences in prices between the front-month futures and expired futures. Panel III uses the unadjusted futures returns. For the latter two cases, the rollover occurs on the expiration day. We use the 5-day moving average timing with no short. We report the average return (*Avg Ret*), the standard deviation (*Std Dev*), the Sharpe ratio (*Sharpe*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy (Panel A) and the MA timing strategy (Panel B). The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

	Panel I: Construction Using Ratio at 15^{th}						
Rank	**Buy-and-Hold**			**MA(5) Timing**			
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	$\Delta M2(\%)$
	Panel A : Volatility Sorted Portfolios						
Low	2.61*	9.85	0.26	4.86***	6.90	0.70	166.3
	(1.66)			(4.42)			
2	3.71*	13.8	0.27	6.32***	9.66	0.65	143.8
	(1.68)			(4.10)			
High	4.80	19.5	0.25	8.67***	13.7	0.63	156.4
	(1.55)			(3.96)			
	Panel B : Momentum Sorted Portfolios						
Low	-1.11	15.4	-0.07	4.89***	10.9	0.45	720.2
	(-0.45)			(2.79)			
2	5.34***	12.9	0.41	6.73***	9.10	0.74	78.4
	(2.58)			(4.61)			
High	6.47***	16.3	0.40	8.40***	11.2	0.75	88.4
	(2.47)			(4.66)			
	Panel C : Prior-Month Return Sorted Portfolios						
Low	-0.79	16.2	-0.05	2.48	11.1	0.22	556.2
	(-0.31)			(1.40)			
2	2.91	13.2	0.22	4.31***	9.27	0.47	111.1
	(1.38)			(2.92)			
High	8.52***	15.7	0.54	10.7***	11.2	0.96	76.5
	(3.40)			(6.00)			
	Panel D : Prior 60-Month Return Sorted Portfolios						
Low	1.65	14.3	0.12	3.76**	10.1	0.37	221.3
	(0.68)			(2.18)			
2	3.15	13.4	0.24	5.47***	9.24	0.59	151.2
	(1.38)			(3.47)			
High	2.47	16.9	0.15	6.40***	11.6	0.55	277.8
	(0.86)			(3.25)			

Rank	Panel II: Construction Using Difference						
	Buy-and-Hold			MA(5) Timing			
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	$\Delta M2(\%)$
Panel A : Volatility Sorted Portfolios							
Low	-2.68***	4.55	-0.59	-0.09	3.07	-0.03	95.1
	(-3.69)			(-0.18)			
2	-3.68***	8.08	-0.46	0.75	5.49	0.14	130.0
	(-2.85)			(0.86)			
High	-93.7***	62.7	-1.49	-11.4***	26.2	-0.43	71.0
	(-9.37)			(-2.72)			
Panel B : Momentum Sorted Portfolios							
Low	-75.2***	43.0	-1.75	-9.09***	20.1	-0.45	74.2
	(-10.9)			(-2.82)			
2	-4.68***	7.92	-0.59	-0.62	5.17	-0.12	79.7
	(-3.69)			(-0.75)			
High	-14.8***	23.1	-0.64	0.84	13.4	0.06	109.7
	(-3.99)			(0.39)			
Panel C : Prior-Month Return Sorted Portfolios							
Low	-74.1***	46.2	-1.60	-11.1***	22.6	-0.49	69.5
	(-10.1)			(-3.07)			
2	-5.54***	7.95	-0.70	0.19	5.10	0.04	105.4
	(-4.37)			(0.24)			
High	-11.8***	20.5	-0.57	2.97	12.4	0.24	141.7
	(-3.60)			(1.50)			
Panel D : Prior 60-Month Return Sorted Portfolios							
Low	-51.3***	43.0	-1.19	-7.06**	21.0	-0.34	71.8
	(-7.01)			(-1.97)			
2	-5.55***	8.90	-0.62	0.62	5.76	0.11	117.4
	(-3.65)			(0.64)			
High	-25.9***	22.7	-1.14	1.57	12.2	0.13	111.3
	(-6.69)			(0.75)			

Rank	Panel III: Construction without Adjustment						
	Buy-and-Hold			MA(5) Timing			
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	$\Delta M2(\%)$
Panel A : Volatility Sorted Portfolios							
Low	2.89*	9.89	0.29	4.37***	7.08	0.62	111.2
	(1.83)			(3.87)			
2	2.91	13.4	0.22	4.08***	9.55	0.43	96.9
	(1.36)			(2.68)			
High	-0.73	18.4	-0.04	4.35**	13.0	0.33	937.7
	(-0.25)			(2.09)			
Panel B : Momentum Sorted Portfolios							
Low	2.32	14.9	0.16	4.35***	10.6	0.41	163.7
	(0.97)			(2.56)			
2	2.37	12.6	0.19	3.55***	8.99	0.39	110.8
	(1.17)			(2.46)			
High	-1.34	15.9	-0.08	2.02	11.0	0.18	317.3
	(-0.53)			(1.15)			
Panel C : Prior-Month Return Sorted Portfolios							
Low	2.68	15.7	0.17	3.70**	11.2	0.33	93.1
	(1.07)			(2.06)			
2	2.04	12.6	0.16	3.73***	9.03	0.41	154.5
	(1.02)			(2.59)			
High	-1.28	15.3	-0.08	4.39***	10.8	0.41	586.1
	(-0.53)			(2.55)			
Panel D : Prior 60-Month Return Sorted Portfolios							
Low	7.26***	13.5	0.54	8.30***	9.77	0.85	58.3
	(3.14)			(4.97)			
2	1.29	12.7	0.10	4.01***	9.02	0.44	337.0
	(0.60)			(2.60)			
High	-5.36*	17.2	-0.31	0.95	12.1	0.08	125.1
	(-1.83)			(0.46)			

Table 10: Business Cycles

This table contrasts the performance difference between the moving average timing and the buy-and-hold strategy in expansions to that in recessions. Recession periods are determined by NBER. Results reported are for the volatility tercile portfolios. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), skewness (Skewness), kurtosis (*Kurtosis*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy and the MA timing strategy. The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Rank	**Buy-and-Hold Commodity Portfolios**					**MA(5) Timing**					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
						Panel A: Expansion					
Low	4.08***	9.36	0.44	0.04	2.59	4.75***	6.76	0.70	0.47	8.13	61.4
	(2.54)					(4.11)					
2	5.28**	12.9	0.41	-0.13	1.60	5.38***	9.15	0.59	0.13	5.15	43.3
	(2.39)					(3.43)					
High	7.19**	18.0	0.40	-0.00	1.46	8.85***	12.8	0.69	0.31	5.33	73.1
	(2.33)					(4.04)					
						Panel B: Recession					
Low	-12.9**	12.8	-1.00	-0.08	2.38	-2.07	8.33	-0.25	0.35	8.00	75.2
	(-2.30)					(-0.57)					
2	-12.3	19.1	-0.64	-0.07	5.45	7.10	12.5	0.57	1.42	18.3	187.9
	(-1.48)					(1.30)					
High	-10.1	27.1	-0.37	-0.64	6.62	5.89	18.6	0.32	-1.55	29.1	184.9
	(-0.86)					(0.73)					

Table 11: Investor Sentiment

This table contrasts the performance difference between the moving average timing and the buy-and-hold strategy in low sentiment periods to that in high sentiment periods. Results reported are for the volatility tercile portfolios. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), Sharpe ratio (*Sharpe*), skewness (Skewness), kurtosis (*Kurtosis*), and the percentage change in M2 measure ($\Delta M2(\%)$) for the buy-and-hold strategy and the MA timing strategy. The results are annualized and in percentages. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2010 due to availability of sentiment data.

Rank	**Buy-and-Hold Commodity Portfolios**					**MA(5) Timing**					
	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	Avg Ret	Std Dev	Sharpe	Skewness	Kurtosis	$\Delta M2(\%)$
	Panel A: Low Sentiment										
Low	8.55***	10.2	0.84	0.02	1.91	6.40***	7.48	0.86	0.17	6.05	1.82
	(3.41)					(3.47)					
2	11.6***	14.0	0.82	-0.06	1.88	9.64***	10.3	0.93	0.19	5.99	13.6
	(3.34)					(3.79)					
High	11.4**	19.9	0.57	-0.41	8.14	11.0***	14.4	0.76	-0.93	27.2	32.8
	(2.32)					(3.09)					
	Panel B: High Sentiment										
Low	-3.41	9.67	-0.35	-0.03	4.01	1.49	6.58	0.23	0.70	11.5	164.0
	(-1.57)					(1.01)					
2	-2.34	13.6	-0.17	-0.16	6.31	3.68*	9.17	0.40	0.99	17.6	332.2
	(-0.77)					(1.79)					
High	0.01	19.3	0.00	-0.13	1.75	6.56**	13.3	0.49	0.28	5.96	7.04E+04
	(0.00)					(2.19)					

Table 12: Effect of Business Cycle, Sentiment, and Macroeconomic Variables

This table reports the results of regressing the return difference between the moving average timing and the buy-and-hold strategies on recession dummy, investor sentiment, term spread, default spread, real interest rate, and cay. Results reported are for the volatility tercile portfolios. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2010 due to availability of sentiment data.

	Low Volatility				Mid Volatility				High Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.14	1.49	0.28	-7.74*	-0.37	2.31	-0.27	7.91	1.35	3.33	1.44	-6.58
	(0.12)	(1.29)	(0.25)	(-1.70)	(-0.24)	(1.40)	(-0.17)	(1.19)	(0.59)	(1.43)	(0.63)	(-0.70)
Recession	10.7**		8.62*	13.4**	19.7***		18.4**	21.1**	14.7		13.4	16.5
	(2.42)		(1.89)	(2.35)	(2.83)		(2.51)	(2.32)	(1.63)		(1.39)	(1.50)
Sentiment		1.59***	1.25**	0.49		1.55**	0.82	0.51		1.34	0.81	0.10
		(2.90)	(2.19)	(0.72)		(2.22)	(1.10)	(0.57)		(1.25)	(0.69)	(0.07)
Term Spread				-0.05				-0.67				0.07
				(-0.10)				(-1.14)				(0.08)
Default Spread				-1.99				0.86				-2.13
				(-1.00)				(0.30)				(-0.48)
Real Interest Rate				0.71**				-0.48				0.79
				(2.04)				(-1.00)				(1.08)
CAY				12.6				62.3				-7.94
				(0.32)				(1.09)				(-0.10)
$\bar{R}^2$ (%)	0.1	0.1	0.2	0.3	0.2	0.0	0.2	0.2	0.0	0.0	0.0	0.0

Table 13: Risk Adjusted Abnormal Returns of the Spread Portfolios

The table reports the risk-adjusted abnormal returns of the spread portfolio (return difference) between the 5-day moving average timing and the buy-and-hold strategies on various sorted commodity futures portfolios. Left columns report the Fama-French alpha and risk loadings, and right columns report the alpha and risk loadings relative to a pricing model using the market and the S&P GSCI commodity index. The abnormal returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Rank	**Fama-French**				**GSCI**		
	$\alpha(\%)$	β_{mkt}	β_{smb}	β_{hml}	$\alpha(\%)$	β_{mkt}	β_{gsci}
Panel A : Volatility Sorted Portfolios							
Low	2.18*	-0.05***	-0.04***	-0.03**	2.39**	-0.03***	-0.12***
	(1.94)	(-7.27)	(-3.04)	(-2.05)	(2.25)	(-5.25)	(-16.6)
2	3.41**	-0.09***	-0.05**	-0.08***	3.63**	-0.05***	-0.22***
	(2.07)	(-6.38)	(-2.50)	(-3.13)	(2.47)	(-4.64)	(-16.3)
High	4.59**	-0.11***	-0.08***	-0.10***	5.20***	-0.04***	-0.37***
	(1.97)	(-6.50)	(-2.91)	(-2.98)	(2.66)	(-3.65)	(-23.9)
Panel B : Volume Sorted Portfolios							
Low	3.12*	-0.08***	-0.06***	-0.05**	3.23*	-0.04***	-0.18***
	(1.67)	(-8.60)	(-2.99)	(-2.50)	(1.84)	(-5.79)	(-17.1)
2	4.25**	-0.09***	-0.03	-0.06***	4.51***	-0.05***	-0.22***
	(2.28)	(-8.45)	(-1.63)	(-2.79)	(2.62)	(-5.64)	(-18.8)
High	5.01**	-0.08***	-0.08***	-0.13***	5.25**	0.00	-0.42***
	(2.03)	(-5.44)	(-3.38)	(-4.06)	(2.55)	(0.23)	(-26.0)
Panel C : Open Interest Sorted Portfolios							
Low	4.75**	-0.08***	-0.06***	-0.05***	4.89**	-0.04***	-0.19***
	(2.19)	(-7.69)	(-2.68)	(-2.67)	(2.38)	(-4.54)	(-17.3)
2	5.52***	-0.09***	-0.07***	-0.08***	5.90***	-0.02***	-0.33***
	(2.61)	(-7.39)	(-3.14)	(-3.16)	(3.16)	(-2.68)	(-24.3)
High	3.48	-0.07***	-0.05**	-0.10***	3.86*	0.01	-0.39***
	(1.38)	(-4.87)	(-2.27)	(-3.40)	(1.76)	(0.90)	(-20.3)

Rank	Fama-French				GSCI		
	$\alpha(\%)$	β_{mkt}	β_{smb}	β_{hml}	$\alpha(\%)$	β_{mkt}	β_{gsci}
Panel D : Momentum Sorted Portfolios							
Low	6.61***	-0.10***	-0.05**	-0.07***	6.94***	-0.05***	-0.22***
	(3.71)	(-7.70)	(-2.33)	(-2.90)	(4.28)	(-5.66)	(-17.9)
2	1.62	-0.08***	-0.04***	-0.07***	1.96	-0.04***	-0.20***
	(1.12)	(-7.97)	(-2.79)	(-3.12)	(1.51)	(-5.34)	(-18.6)
High	2.78	-0.09***	-0.09***	-0.08***	3.30**	-0.02***	-0.30***
	(1.49)	(-7.17)	(-4.01)	(-3.30)	(2.03)	(-2.65)	(-22.1)
Panel E : Prior-Month Return Sorted Portfolios							
Low	5.07***	-0.10***	-0.06***	-0.07***	5.35***	-0.05***	-0.26***
	(2.73)	(-8.29)	(-3.81)	(-2.90)	(3.20)	(-5.84)	(-21.0)
2	2.81*	-0.09***	-0.06***	-0.06***	3.02**	-0.05***	-0.21***
	(1.87)	(-8.07)	(-3.40)	(-2.73)	(2.24)	(-5.82)	(-18.3)
High	2.19	-0.08***	-0.07***	-0.06***	2.50	-0.02***	-0.26***
	(1.21)	(-7.13)	(-3.82)	(-2.92)	(1.54)	(-2.75)	(-19.9)
Panel F : Prior 60-Month Return Sorted Portfolios							
Low	3.08*	-0.08***	-0.06***	-0.04*	3.36**	-0.04***	-0.16***
	(1.75)	(-7.45)	(-3.39)	(-1.82)	(2.01)	(-5.12)	(-15.3)
2	4.06**	-0.11***	-0.08***	-0.08***	4.27***	-0.07***	-0.18***
	(2.54)	(-11.2)	(-5.30)	(-4.12)	(2.92)	(-8.61)	(-17.1)
High	4.73**	-0.12***	-0.05*	-0.09***	5.40***	-0.05***	-0.35***
	(2.18)	(-7.65)	(-1.80)	(-3.00)	(2.98)	(-4.25)	(-21.8)

Table 14: Market Timing Tests of the Spread Portfolios

The table reports the market timing regression results of the spread portfolio (return difference) between the 5-day moving average timing and the buy-and-hold strategies on various sorted commodity futures portfolios. The coefficient γ_{mkt} is the market timing coefficient for the binary variable that takes a value of one when the market return is above the risk-free rate, otherwise it takes a value of zero. The abnormal returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1975 to December 2013.

Rank	$\alpha(\%)$	β_{mkt}	γ_{mkt}	$\alpha(\%)$	β_{mkt}	γ_{mkt}	$\alpha(\%)$	β_{mkt}	γ_{mkt}
	Volatility			**Volume**			**Open Interest**		
Low	-0.74	-0.06***	0.03*	-2.98	-0.10***	0.06**	-2.45	-0.10***	0.08***
	(-0.42)	(-4.92)	(1.70)	(-1.04)	(-5.77)	(2.35)	(-0.75)	(-5.54)	(2.58)
2	-5.22*	-0.11***	0.09**	-1.61	-0.11***	0.06*	-2.15	-0.11***	0.08**
	(-1.69)	(-4.40)	(2.52)	(-0.51)	(-4.99)	(1.87)	(-0.65)	(-5.02)	(2.38)
High	-3.86	-0.13***	0.09**	-4.43	-0.11***	0.09**	-1.96	-0.08***	0.05
	(-1.02)	(-4.53)	(2.12)	(-1.15)	(-3.97)	(2.44)	(-0.54)	(-3.29)	(1.59)
	Momentum			**Prior-Month Return**			**Prior 60-Month Return**		
Low	0.66	-0.12***	0.06*	-0.20	-0.12***	0.05*	2.23	-0.07***	0.01
	(0.21)	(-4.76)	(1.70)	(-0.07)	(-5.71)	(1.82)	(0.84)	(-3.96)	(0.25)
2	-5.55**	-0.11***	0.07***	-4.25	-0.12***	0.07**	-2.89	-0.13***	0.07***
	(-2.33)	(-5.91)	(2.87)	(-1.59)	(-5.43)	(2.43)	(-1.20)	(-7.55)	(2.74)
High	-3.90	-0.10***	0.07**	-4.45	-0.10***	0.07**	-6.10*	-0.16***	0.11***
	(-1.45)	(-5.32)	(2.48)	(-1.63)	(-5.03)	(2.38)	(-1.67)	(-5.88)	(2.69)