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Are there exploitable trends in commodity futures 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 is robust to short-sale constraints, alternative specifications of the moving average lag length, alternative construction of the continuous time-series of futures prices, and impact from data mining. The outperformance of the timing strategy is not driven by the backwardation and contango. It is stronger during recession and can not be explained by macroeconomic variables. Finally, we confirm that the outperformance of the moving average timing strategy in the commodity futures comes from the successful market timing.

1. Introduction

This paper examines the profitability of technical analysis in the commodity futures markets from a new perspective. 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), Lo and Hasanhodzic (2009)). In futures markets, particularly commodity futures markets, technical analysis has been widely used 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), James (1968), Jensen and Benington (1970), and Levy (1971). Recent studies, such as Brock et al. (1992), Lo et al. (2000), Goh et al. (2013), Neely et al. (2014), however, find strong evidence of profitability of technical analysis in stock markets.

Although commodity futures have been traded for more than one hundred years in the US, they are still a relatively unknown asset class (Gorton and Geert Rouwenhorst, 2006). Only a few empirical studies have formally investigated the profitability of technical analysis in commodity futures markets. Early studies such as Houthakker (1961) and Stevenson and Bear (1970) find that technical analysis is profitable, even though other studies such as Praetz (1975) find negative results. Most recently, Szakmary et al. (2010) find that trend-following trading strategies in commodity futures markets are profitable in at least 22 out of 28 markets. Clare et al. (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 et al. (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 individual commodity futures. Han et al. (2013) are the first to apply technical analysis to portfolios of stocks, and find significant and consistent gains

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using a simple moving average timing strategy. One of the reasons for their success is the use of portfolios to reduce the noise and thus increase the signal-to-noise ratio. We extend the analysis to commodity futures markets.

As underscored in the literature (Gorton and Geert Rouwenhorst, 2006, p. 47, Kogan et al., 2009, p. 1345), commodity futures are markedly different from stocks and other conventional assets. Specifically, commodity futures are not claims on long-lived corporations but rather short-maturity claims on real assets, and the underlying commodities often have pronounced seasonality in price levels and volatilities. In addition, commodity futures prices are often backwardated as they decline with time-to-delivery, often mean-reverting, and their price volatility may be often correlated with the degree of backwardation. Hence, what works in the stock markets may not work in the commodity futures markets. This is especially true given the inconclusive evidence on individual commodity futures in the literature. 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. Hence, the behavior of the futures prices, or the dynamics of the futures price trends can be substantially different. Furthermore, volatility of individual commodity futures is often much higher than that of individual stocks, while returns are much lower than those of individual stocks. Therefore, the signal-to-noise ratio is much lower for the commodity futures. Given the relative few number of contracts in cross sections, this really imposes a big question about whether the portfolio approach advocated by Han et al. (2013) can work in the commodity futures markets.

Nevertheless, we find that even with these differences and challenges, the simple moving average timing performs well in futures markets with characteristics-sorted commodity futures portfolios. The basic form of our moving average timing strategy is very simple. On each trading day t, we compare the settlement price with the moving average price. If the settlement price is above the moving average price, we will invest for the next trading day, otherwise we will not invest in the future markets.

This paper makes the following contributions to the literature. First and foremost, extending previous studies, which often examine individual commodity futures contracts, we focus on portfolios of commodity futures sorted on certain characteristics of futures (e.g., volatility, trading volume, open interest, six-month past return, prior-month return, and past 60-month return) and document much stronger evidence for the profitability of technical analysis on commodity futures. Similar to previous studies, 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) 1.28% per annum (0.49) for the lowest volume portfolio, 0.90% per annum (0.34) for the medium volume portfolio, and 3.36% (0.99) 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 0.08, 0.36 versus 0.05, 0.50 versus 0.16, respectively, for the three volume tercile portfolios. Because Sharpe ratios do not measure performance difference intuitively, we employ a related performance measure, Modigliani–Modigliani measure ($M2$), which measures the average return while levering up the volatility to be the same as that of the buy-and-hold strategy. The differences in $M2$ are 3.41%, 5.00%, and 7.28%, respectively, for the three volume sorted tercile portfolios, all of which are statistically significantly positive. Furthermore, the percentage increases in $M2$ are 267.5%, 556.8%, and 216.8%, respectively, for the three volume-sorted portfolios. In other words, if we level up the volatility of the moving average timing strategy to be the same as the volatility of the buy-and-hold strategy, the moving average timing strategy would deliver average returns that are about four times for the lowest volume portfolio, about seven times for the medium volume portfolio, and about three times for the highest volume portfolio, respectively, of those delivered by the buy-and-hold strategy.

Second, we also comprehensively conduct robustness tests in several dimensions and further examine the sources of profitability for moving average timing. We show that the performance gains are generally robust against a number of robustness checks, including the examination of the trading behavior and break-even transaction cost (BETC), subperiod analysis, additional allowance for shorting futures portfolios in implementing the timing strategy, alternative lag window lengths for estimating the moving averages, and alternative construction of the continuous time series of futures prices. We further demonstrate that the superior performance is not due to potential data mining. To understand further the abnormal performance of moving average timing, we examine the relation of the timing performance with backwardation/contango, business cycles, and several macroeconomic variables, respectively. Our results show that the outperformance of moving average timing is not related to backwardation/contango. Similar to Han et al. (2013), Han et al. (forthcoming), and Neely et al. (2014), we find that the moving average timing strategy performs much better than the buy-and-hold strategy during recessions. We further provide evidence that the abnormal performance of the timing strategy is indeed due to successful market timing.

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 backwardation and contango, business cycles, macroeconomic variables, and the Henriksson and Merton (1981) market timing model. Section 7 examines the potential data mining issue. Section 8 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,

Table 1
Summary of individual contracts. This table lists the information about the 35 US commodity futures contracts. We report the symbol, name, start date, price at the start date, end date, price at the end date, and the percentage of price appreciation from the start date to the end date for all contracts.

Symbol	Name	Start Date	Initial Price	End Date	End Price	% Appreciation
C	Corn	02JAN1975	347.00	31DEC2013	422.00	21.61
CC	Cocoa	31DEC1974	1381.00	31DEC2013	2709.00	96.16
KC	Coffee	31DEC1974	59.62	31DEC2013	110.70	85.68
CT	Cotton	31DEC1974	36.80	31DEC2013	84.64	130.00
O	Oats	31DEC1974	166.00	31DEC2013	354.25	113.40
JO	Orange Juice	31DEC1974	50.75	31DEC2013	136.45	168.87
S	Soybean	31DEC1974	697.00	31DEC2013	1312.50	88.31
SM	Soybean Meal	31DEC1974	138.50	31DEC2013	437.70	216.03
BO	Soybean Oil	31DEC1974	36.35	31DEC2013	38.82	6.80
SB	Sugar	31DEC1974	47.20	31DEC2013	16.41	−65.23
W	Wheat	31DEC1974	458.50	31DEC2013	605.25	32.01
VK	White Wheat	16DEC1999	84.00	26JUN2008	103.00	22.62
RR	Rough Rice	06DEC1988	6.78	31DEC2013	15.51	128.76
FC	Feeder Cattle	31DEC1974	30.10	31DEC2013	166.70	453.82
PB	Pork Belly	31DEC1974	61.90	15JUL2011	121.00	95.48
LH	Hogs	01APR1986	43.60	31DEC2013	85.42	95.93
LC	Live Cattle	31DEC1974	39.55	31DEC2013	134.50	240.08
LA	Aluminum	23JUL1997	1643.75	31DEC2013	1761.75	7.18
HG	Copper	06DEC1988	146.89	31DEC2013	344.15	134.29
GC	Gold	02JAN1990	399.60	31DEC2013	1201.90	200.78
LL	Lead	23JUL1997	647.00	31DEC2013	2197.50	239.64
LN	Nickel	23JUL1997	6701.50	31DEC2013	1.38E+04	106.57
PA	Palladium	07JAN1987	119.90	31DEC2013	717.40	498.33
PL	Platinum	01APR1986	404.00	31DEC2013	1371.10	239.38
SI	Silver	02JAN1990	5.15	31DEC2013	19.34	275.51
LT	Tin	23JUL1997	5426.00	31DEC2013	2.23E+04	311.63
LX	Zinc	23JUL1997	1577.00	31DEC2013	2045.00	29.68
CO	Brent Crude Oil	23JUN1988	15.65	31DEC2013	110.80	607.99
CL	Crude Oil	30MAR1983	29.40	31DEC2013	98.42	234.76
QS	Gas Oil	03JUL1989	146.75	31DEC2013	944.25	543.44
HO	Heating Oil	01JUL1986	36.08	31DEC2013	307.72	752.88
NG	Natural Gas	03APR1990	1.64	31DEC2013	4.23	158.72
HU	Unleaded Gasoline	25APR1986	37.80	29DEC2006	154.19	307.91
DA	Milk	11JAN1996	12.18	31DEC2013	18.99	55.91
LB	Lumber	07APR1986	172.50	31DEC2013	360.10	108.75

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 market price, end date, and end market price over the entire sample period for each of the 35 commodity futures contracts.[1] Although almost all the agricultural 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, Heating Oil contracts started to trade on July 1, 1986 with a price of $36.08, but by the end of 2013, the price has gone up to $307.72, an increase of more than 7 times. 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. 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 stock markets. 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 contracts 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 nearby contract (front month contract) up to the expiration. Then we roll our position over to the second nearby 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 nearby 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 two alternative constructions. First, we roll over the contracts 15 days before expiration. Second, 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 et al. (2008), Fuertes et al. (2010), de Groot et al. (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.

[1] The prices reported in Table 1 are unadjusted prices, but the ones we primarily use to analyze the performance of moving average timing strategy are ratio adjusted prices to produce a smooth continuous time series of future prices.

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 et al., 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-sectional 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 daily returns and daily prices for the equal-weighted tercile portfolios.

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 rather than the false jumps induced by adding or dropping one futures from the futures portfolio.

3.2. Moving average (MA) 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. 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 (MA) 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. To statistically compare the performance between the MA timing and buy-and-hold strategies, we construct the difference between the two strategies, which is also a zero-cost spread portfolio that takes a long position in the moving average timing strategy and takes a short position in the buy-and-hold strategy

$$\Delta_{jt} = \tilde{r}_{jt} - r_{jt}. \tag{3}$$

A positive average return of this spread portfolio represents the extra return earned by the MA timing strategy over the buy-and-hold strategy, which can be easily tested statistically.

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

$$M2 = Sharpe \times \sigma_b, \tag{4}$$

where *Sharpe* 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,

$$M2 = \mu_t \times \frac{\sigma_b}{\sigma_t}, \tag{5}$$

where μ_t and σ_t are the average excess return and standard deviation of the moving average timing strategy. We further define the difference in $M2$ between the MA timing strategy and buy-and-hold strategy,

$$\Delta(M2) = M2 - \mu_b = \mu_t \times \frac{\sigma_b}{\sigma_t} - \mu_b, \tag{6}$$

where μ_b is the average excess return of the buy-and-hold strategy. A positive $\Delta(M2)$ measures the extra return earned by the MA timing strategy after adjusting for the volatility.[2]

To further appreciate the performance improvement by the MA timing strategy, we report the percentage increase in $M2$, given as

$$\%Inc(M2) = \frac{M2 - \mu_b}{\mu_b} \times 100 = \frac{\Delta(M2)}{\mu_b} \times 100. \tag{7}$$

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

[2] We use GMM approach to assess the statistical significance, similar to Kirby and Ostdiek (2012).

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%[3] 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. 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 et al., 2010). In some contracts the performance improvement is fairly large, but in other contracts the performance deterioration is also rather large. For example, the largest performance improvement is with PB (Pork Belly), average return increased from 0.02% to 12.3%. On the other hand, the largest performance deterioration is with LX (Zinc) futures, average returns reduced from 1.09% to −1.05%. Averaging across the 35 individual contracts yields an average return of only 4.42% and 7.13% per annum, respectively, for the buy-and-hold strategy and the moving average timing strategy. The Sharpe ratio is increased from 0.16 to 0.36.

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.[4] Turning to the statistical significance of the performance improvement, The last three columns of Panel A shows that the average return is improved by 2.03%, 2.68%, and 3.58%, respectively, for the three volatility tercile portfolios, all of which are shown to be statistically positive.[5] Even larger differences are observed for the $M2$ measure: the extra volatility adjusted returns are 3.63%, 5.11%, and 7.13%, respectively, for the three volatility tercile portfolios. Again, all the differences are statistically positive at 1% level. Finally, the last column shows that the relative performance improvement is substantial. For example, the lowest volatility tercile portfolio 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 often 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 average Sharpe ratio of all 35 individual commodity futures with moving average timing (Sharpe ratio is 0.36 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 13.7% per annum, which is much lower than the volatility of all but one commodity future.

Han et al. (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. Zhang (2006) also argues that there is a positive association between asset volatility and price trend. 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 relative 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 0.08 for the lowest ranked tercile, 0.36 versus 0.05 for the second tercile, and 0.50 versus 0.16 for the highest ranked

[3] This is in contrast with the *%Appreciation* of 23.39% reported in Table 1. The difference is likely due to backwardation/contango and the smoothing adjustment.

[4] Other summary statistics not shown in the table suggest that 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.

[5] As we examine the difference, it seems more appropriate to conduct the right-tailed test to test positivity instead of whether or not zero.

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 (*%Inc*(*M*2)) for the buy-and-hold strategy (Panel A) and the MA(5) timing strategy (Panel B). The results are annualized and in percentages. *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	%*Inc*(*M*2)
C	−4.77 (−1.29)	23.1	−0.21	0.07	3.06	4.45* (1.73)	16.1	0.28	0.37	9.57	234.1
CC	4.20 (0.86)	30.5	0.14	0.17	1.91	2.25 (0.65)	21.6	0.10	0.47	7.45	−24.3
KC	6.46 (1.14)	35.2	0.18	0.53	8.74	8.74** (2.14)	25.4	0.34	0.64	16.7	87.4
CT	2.53 (0.64)	24.6	0.10	0.10	2.20	5.09* (1.84)	17.3	0.29	0.52	8.17	186.0
O	−1.86 (−0.39)	29.5	−0.06	−0.01	2.51	9.60*** (2.93)	20.4	0.47	0.58	8.65	845.5
JO	3.54 (0.76)	29.1	0.12	0.83	14.3	9.91*** (2.87)	21.5	0.46	1.63	30.4	278.1
S	2.51 (0.67)	23.4	0.11	−0.12	1.83	4.71* (1.77)	16.6	0.28	0.18	6.22	164.7
SM	7.53* (1.85)	25.5	0.30	0.02	2.14	11.0*** (3.80)	18.1	0.61	0.39	6.34	105.7
BO	−0.79 (−0.20)	25.0	−0.03	0.19	1.36	7.60*** (2.67)	17.8	0.43	0.52	5.40	1,457.0
SB	−2.85 (−0.45)	39.4	−0.07	−0.09	3.65	4.06 (0.92)	27.6	0.15	−0.09	12.7	304.2
W	−5.58 (−1.33)	26.2	−0.21	0.17	2.65	0.51 (0.17)	18.6	0.03	0.31	9.29	112.7
KW	0.55 (0.15)	22.9	0.02	0.22	3.39	9.25*** (3.48)	16.6	0.56	0.72	10.4	2,223.4
RR	−5.50 (−1.16)	23.8	−0.23	0.15	2.32	10.2*** (3.11)	16.3	0.62	0.65	7.86	369.2
FC	3.27 (1.38)	14.8	0.22	−0.09	1.32	6.66*** (4.11)	10.1	0.66	0.37	5.03	197.3
PB	0.02 (0.00)	33.2	0.00	0.06	−0.04	12.3*** (3.19)	23.2	0.53	0.29	3.10	1.13E + 05
LH	1.96 (0.46)	22.6	0.09	−0.07	1.35	5.78** (1.96)	15.5	0.37	0.33	4.92	328.1
LC	4.52* (1.77)	15.9	0.28	−0.06	1.05	6.41*** (3.66)	10.9	0.59	0.27	4.45	106.3
LA	−2.41 (−0.45)	21.6	−0.11	−0.17	2.29	−4.93 (−1.33)	15.1	−0.33	−0.20	8.04	−191.9
HG	9.19* (1.67)	27.5	0.33	−0.03	4.04	3.97 (1.03)	19.2	0.21	0.21	10.8	−38.2
GC	1.27 (0.40)	19.8	0.06	0.01	6.94	1.60 (0.71)	14.1	0.11	0.67	14.8	76.4
LL	11.7 (1.44)	32.9	0.36	−0.04	3.38	9.57* (1.64)	23.6	0.41	0.44	11.1	13.9
LN	12.1 (1.31)	37.5	0.32	0.07	3.37	3.48 (0.54)	25.9	0.13	0.73	10.3	−58.5
PA	9.66 (1.62)	31.3	0.31	0.04	5.81	15.2*** (3.61)	22.1	0.69	0.62	13.4	122.7
PL	5.83 (1.38)	22.2	0.26	−0.31	3.42	5.94** (2.00)	15.6	0.38	0.18	8.23	44.5
SI	2.85 (0.58)	30.6	0.09	−0.33	5.91	3.72 (1.09)	21.2	0.18	0.27	12.1	88.2
LT	12.7* (1.89)	27.3	0.47	0.06	7.19	6.15 (1.33)	18.8	0.33	0.27	12.4	−29.9
LX	1.09 (0.15)	30.1	0.04	−0.09	2.69	−1.05 (−0.20)	20.8	−0.05	0.16	7.94	−239.0
CO	19.4*** (2.88)	34.2	0.57	−0.39	11.8	12.5*** (2.59)	24.4	0.51	−0.91	39.7	−10.1
CL	13.9** (2.14)	36.0	0.39	−0.37	11.2	10.8** (2.35)	25.4	0.43	−0.99	36.9	9.91
QS	16.2*** (2.52)	31.9	0.51	−0.35	11.2	15.1*** (3.21)	23.4	0.65	−0.72	33.8	27.3
HO	17.9*** (2.68)	34.9	0.51	−0.31	10.1	13.9*** (2.88)	25.3	0.55	−0.71	33.3	7.35
NG	−2.28 (−0.22)	51.1	−0.04	0.49	5.50	7.98 (1.04)	37.4	0.21	1.02	18.8	578.3
HU	12.8* (1.69)	34.1	0.37	−0.11	11.5	7.62 (1.41)	24.3	0.31	−1.06	28.8	−16.4
DA	0.94 (0.29)	13.7	0.07	−0.66	12.8	7.16*** (3.31)	9.08	0.79	0.05	27.0	1,044.1

(*continued on next page*)

Table 2 (*continued*)

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	%Inc(M2)
LB	−4.11 (−0.78)	27.7	−0.15	0.12	−0.00	12.3*** (3.29)	19.7	0.63	0.34	3.01	521.8
Average Across All Contracts											
	4.42 (0.74)	28.2	0.16	−0.01	4.94	7.13 (2.04)	20.0	0.36	0.24	13.9	128.3

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(5) price with the current price as the timing signal. If the current price is above the MA(5) 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 daily volatility, daily trading volume, daily 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*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (%*Inc*(*M*2)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	M2	%Inc(M2)
Panel A: Volatility Sorted Portfolios									
Low	1.81 (1.15)	9.91	0.18	3.84*** (3.45)	6.99	0.55	2.03** (1.81)	3.63*** (3.00)	200.5
2	2.93 (1.33)	13.9	0.21	5.61*** (3.64)	9.67	0.58	2.68** (1.70)	5.11*** (2.91)	174.4
High	4.87 (1.57)	19.5	0.25	8.46*** (3.87)	13.7	0.62	3.58** (1.63)	7.13*** (2.95)	146.3
Panel B: Volume Sorted Portfolios									
Low	1.28 (0.49)	16.2	0.08	3.29* (1.81)	11.4	0.29	2.02 (1.09)	3.41** (1.68)	267.5
2	0.90 (0.34)	16.6	0.05	4.15** (2.23)	11.7	0.36	3.25** (1.73)	5.00*** (2.45)	556.8
High	3.36 (0.99)	21.2	0.16	7.44*** (3.15)	14.8	0.50	4.08** (1.69)	7.28*** (2.72)	216.8
Panel C: Open Interest Sorted Portfolios									
Low	1.78 (0.59)	18.9	0.09	5.51*** (2.57)	13.4	0.41	3.73** (1.76)	5.96*** (2.53)	334.9
2	1.03 (0.33)	19.7	0.05	5.37** (2.36)	14.3	0.38	4.35** (2.02)	6.37*** (2.72)	621.3
High	6.66* (1.89)	22.2	0.30	9.46*** (3.77)	15.7	0.60	2.80 (1.12)	6.67*** (2.41)	100.1
Panel D: Momentum Sorted Portfolios									
Low	−1.35 (−0.55)	15.5	−0.09	4.37*** (2.49)	10.9	0.40	5.72*** (3.27)	7.52*** (3.92)	555.4
2	4.58** (2.21)	12.9	0.35	5.32*** (3.62)	9.17	0.58	0.74 (0.51)	2.92** (1.84)	63.8
High	6.34*** (2.44)	16.2	0.39	8.04*** (4.43)	11.3	0.71	1.70 (0.91)	5.19*** (2.50)	81.8
Panel E: Prior-Month Return Sorted Portfolios									
Low	−1.64 (−0.64)	16.2	−0.10	2.42 (1.35)	11.2	0.22	4.06*** (2.18)	5.14*** (2.52)	312.3
2	1.81 (0.87)	13.0	0.14	3.70*** (2.57)	9.02	0.41	1.89* (1.27)	3.52** (2.15)	194.5
High	9.01*** (3.56)	15.9	0.57	10.5*** (5.80)	11.3	0.93	1.46 (0.82)	5.68*** (2.87)	63.1
Panel F: Prior 60-Month Return Sorted Portfolios									
Low	-0.66 (−0.27)	14.2	−0.05	1.73 (1.02)	9.94	0.17	2.39* (1.38)	3.13** (1.65)	476.6
2	3.48 (1.52)	13.4	0.26	6.32*** (4.01)	9.25	0.68	2.84** (1.72)	5.67*** (3.13)	162.8
High	2.83 (0.97)	17.2	0.16	6.43*** (3.20)	11.8	0.55	3.60** (1.69)	6.54*** (2.77)	231.4

tercile, respectively. The increases in average return with or without controlling for the volatility are all statistically positive but one. In addition, the percentage increase in *M*2 is 267.5%, 556.8%, and 216.8%, 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%, 63.8%, and 81.8%, respectively, after controlling for volatility. For prior-month return (Panel E) and prior 60-month return (Panel F) sorted portfolios, the performance improvement is even larger, with $\%Inc(M2)$ of 312.3% and 476.6% for the lowest ranked tercile, 194.4% and 162.8% for the middle tercile, and 63.1% and 231.4% for the highest ranked tercile, respectively.[6]

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 a two-factor model with the market portfolio and S&P commodity index (GSCI), respectively. 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. The GSCI alphas are in general smaller than the Fama–French alphas, suggesting that the GSCI model indeed better captures the relevant risk in commodity futures markets.

5. Robustness

In this section, we examine the robustness of the results in a number of dimensions. We first examine the trading behavior to determine the potential effect of transaction costs on the performance of the moving average timing strategy. We also try to determine whether the timing strategy earns positive returns when it is in the market and earn extra returns relative to the buy-and-hold strategy when it is out of the market. 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. Transaction costs

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 3.94 consecutive holding days on average, while the highest volatility tercile portfolio has an average of 4.11 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), Han et al. (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:

$$\tilde{r}_{jt,L} = \begin{cases} r_{jt}, & \text{if } \ P_{jt-1} > A_{jt-1,L} \ \text{ and } \ P_{jt-2} > A_{jt-2,L}; \\ r_{jt} - \tau, & \text{if } \ P_{jt-1} > A_{jt-1,L} \ \text{ and } \ P_{jt-2} < A_{jt-2,L}; \\ 0, & \text{if } \ P_{jt-1} < A_{jt-1,L} \ \text{ and } \ P_{jt-2} < A_{jt-2,L}; \\ -\tau, & \text{if } \ P_{jt-1} < A_{jt-1,L} \ \text{ and } \ P_{jt-2} > A_{jt-2,L}. \end{cases} \quad (8)$$

Without taking a stand on the level of the appropriate transaction costs, we consider the break-even transaction costs (BETC) 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 11.6 bp, 13.7 bp, and 8.85 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.

Table 5 also reports the turnover rates for the various sorted portfolios. While the portfolios sorted on the prior 60-month returns have the lowest turnover rates (9.60%, 17.5%, and 8.71%), the portfolios sorted on the prior month returns have the highest turnover rates (67.9%, 72.0%, and 67.0%). Volatility sorted portfolios and momentum portfolios have similar turnover rates, and volume and open interest tercile portfolios have even lower turnover rates. It is worth noting that we do not take into consideration of the turnover rates in the calculation of BETC as we use the buy-and-hold strategy of the sorted portfolios as the benchmark. The effect of portfolio turnover would be canceled out even if we consider it.

[6] It is of interest to note that commodity futures do not show short-term or long-term reversal but rather strong momentum. The strong momentum is consistent with the previous literature, such as Miffre and Rallis (2007), Marshall et al. (2008), Fuertes et al. (2010), Clare et al. (2014). Han (2014) shows that moving average timing can be used to enhance the reversal and momentum.

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.

Sorted Portfolios	Buy-and-Hold			MA(5) Timing		
	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*), the break-even transaction costs in basis point (BETC) for the MA(5) timing strategy, and portfolio turnover rate on the six sets of sorted commodity futures portfolios. The sample period is from January 1975 to December 2013.

Rank	Holding Mean	Trading Mean	BETC Mean	Turnover Mean	Holding Mean	Trading Mean	BETC Mean	Turnover Mean	Holding Mean	Trading Mean	BETC Mean	Turnover Mean
	Volatility				Volume				Open Interest			
Low	3.94	12.7	6.34	33.3	4.09	12.7	6.32	13.9	3.98	12.8	11.6	20.7
2	4.04	12.7	8.39	50.5	4.07	12.6	10.2	28.4	4.02	12.6	13.7	38.5
High	4.11	12.4	11.4	32.4	3.98	12.8	12.6	18.7	4.11	12.5	8.85	22.8
	Momentum				Prior-Month Return				Prior 60-Month Return			
Low	3.88	12.7	18.0	30.4	3.90	12.8	12.6	67.9	3.78	12.7	7.45	9.60
2	4.00	12.9	2.27	52.0	3.84	12.9	5.83	72.0	4.24	12.5	9.02	17.5
High	4.14	12.5	5.40	28.8	4.25	12.5	4.62	67.0	3.98	12.6	11.3	8.71

5.2. Performance over holding periods

It is also interesting to analyze performance of the MA timing strategy over the periods when it is in the market versus the periods when it is out of the market. It sheds light on where the superior performance comes from.[7] Table 6 reports the performance decomposition. For each portfolio, we report the average performance gain (δ)[8] when the MA timing strategy is out of the market (Out), which is essentially the negative of the buy-and-hold return, and the average return (*Ret*) when the MA timing strategy is in the market (In) or is holding the positions. Across the board, both δ and *Ret* are statistically positive, which suggests that the MA timing strategy on average is successful. It knows when to get out and when to get in so that it generates gains when in the market or avoids losses when out of the market. In general, performance gains generated from stepping outside the markets are lower than returns generated from holding the positions. This is because most sorted portfolios yield positive (or close to zero) average returns during the sample period. The second column for each In or Out case in Table 6 reports the slope coefficient of regressing either the performance gain (δ) when the MA timing strategy is out of the market or *Ret* when the MA timing strategy is in the market on the number of consecutive days in either case. All the slope coefficients are statistically significant and positive, suggesting that the longer the MA timing strategy is in one position (either in or out of the market), the higher the performance gains or average returns it generates. Again, it provides evidence for the successful timing ability of the strategy.

5.3. Subperiod analysis

In this subsection, we divide the whole sample period into three subperiods roughly corresponding to the last three decades and examine the performance of the MA timing strategy in each

[7] We thank one of the referees for suggesting this point.
[8] The average performance gain δ is larger than the average return of Δ reported in Table 3 as Δ is averaged over the entire sample period, whereas δ is over the periods when the strategy is out of the market.

Table 6

Performance over holding periods. The table reports the performance of the MA(5) timing strategy on various sorted commodity futures portfolios over different holding periods. δ under *Out* is the return difference between the MA timing and the buy-and-hold strategy, or the negative of the average return of the underlying portfolio as the MA timing strategy is out of the market, while *Ret* under *In* is the average return of the MA timing strategy, which is also the average return of the buy-and-hold strategy as the MA timing strategy is in the market. The *Slope* column represents the slope coefficient of regressing either the average return difference (δ) when the MA timing strategy is out of the market or the average return (*Ret*) when the MA timing strategy is in the market to the number of consecutive holding days. The significance of δ is from the right-tailed test, $H_0: \delta = 0, H_1: \delta > 0$, and similarly for *Ret*. 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	Out		In		Out		In		Out		In	
	δ	Slope	Ret	Slope	δ	Slope	Ret	Slope	δ	Slope	Ret	Slope
	Volatility				Volume				Open Interest			
Low	4.18**	11.8***	7.46***	12.1***	4.17	23.7***	6.37**	16.3***	7.59**	23.9***	10.8***	20.0***
	(1.81)	(25.1)	(3.45)	(25.6)	(1.09)	(24.6)	(1.81)	(21.1)	(1.76)	(22.8)	(2.57)	(20.5)
2	5.55**	18.9***	10.8***	15.5***	6.68**	20.5***	8.09***	17.1***	8.90**	21.2***	10.5***	19.4***
	(1.70)	(27.2)	(3.64)	(24.8)	(1.73)	(24.5)	(2.23)	(22.5)	(2.02)	(22.0)	(2.36)	(21.0)
High	7.43**	27.7***	16.3***	19.6***	8.41**	29.5***	14.4***	22.5***	5.86	31.9***	18.1***	21.3***
	(1.63)	(28.2)	(3.87)	(22.6)	(1.69)	(25.9)	(3.15)	(23.7)	(1.12)	(24.7)	(3.77)	(20.9)
	Momentum				Prior-Month Return				Prior 60-Month Return			
Low	11.4***	18.7***	8.81***	16.7***	8.09***	20.2***	4.86*	18.7***	4.81*	18.3***	3.44	17.4***
	(3.27)	(26.8)	(2.49)	(23.2)	(2.18)	(26.8)	(1.35)	(22.8)	(1.38)	(23.1)	(1.02)	(23.4)
2	1.54	16.5***	10.2***	14.4***	3.87*	17.4***	7.25***	15.8***	5.92**	15.5***	12.1***	13.7***
	(0.51)	(24.3)	(3.62)	(24.0)	(1.27)	(26.4)	(2.57)	(24.6)	(1.72)	(22.3)	(4.01)	(22.8)
High	3.62	20.9***	15.2***	18.0***	3.18	22.9***	19.3***	17.4***	7.41**	22.5***	12.5***	20.1***
	(0.91)	(24.9)	(4.43)	(24.7)	(0.82)	(26.1)	(5.81)	(25.2)	(1.69)	(24.3)	(3.20)	(22.4)

of the subperiods. Results are reported in Table 7. To save space, Table 7 only reports results for volatility sorted portfolios, but Fig. 1 plots the results for all the sorted portfolios. Panel A reports the performance in the first subperiod from January 2, 1975 to December 31, 1989, Panel B reports the performance from January 2, 1990 to December 31, 1999, and Panel C reports the performance from January 2, 2000 to December 31, 2013. In each subperiod, the buy-and-hold strategy yields quite different performance. For example, the three tercile volatility portfolios yield 1.05%, 0.79%, and 2.07%, respectively, in the first subperiod, yield −2.78%, 2.58%, and 5.15% in the second subperiod, and yield 5.86%, 5.41%, and 7.61% 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 MA timing strategy delivers an average return of 5.31%, 3.05%, and 7.31%, respectively, for the three tercile portfolios. Although the average return difference is only significant for the lowest volatility tercile likely due to higher volatility for the other two terciles, the difference in *M*2 measure is all positively significant at 6.39%, 3.54%, and 8.41%, respectively. Superior performance of the MA timing strategy is a bit weaker in the second subperiod when only the highest volatility tercile portfolio experiences significantly positive outperformance in *M*2 measure from MA timing, even though the percentage increase is over 100%.[9] However, it becomes strong again in the third subperiod when two of the higher volatility tercile portfolios experience large and significantly positive increase in *M*2 measure.

Fig. 1 plots the annualized average returns of the buy-and-hold and the leveraged average returns (*M*2) of the MA timing strategies in each of the subperiods for all the six tercile portfolios. It can be seen that in all cases the MA timing strategy performs better than the buy-and-hold strategy in all three subperiods, and the performance improvements are rather large.

5.4. With shorting

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

$$\tilde{r}_{jt,L} = \begin{cases} r_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L}; \\ -r_{jt}, & \text{otherwise.} \end{cases} \tag{9}$$

The results are reported in Table 8. We report the MA timing performance of using the same six sorted tercile portfolios.

The results are similar to but a little stronger than the results of no short reported in 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, respectively. However, the MA timing strategy with short generates much higher volatility, the same as that of the buy-and-hold strategy. As a result, the Sharpe ratios of the MA timing strategy with short are only slightly higher than those of the MA timing strategy without short (0.59 versus 0.55, 0.60 versus 0.58, and 0.62 versus 0.62), and the percentage increases in *M*2 are actually lower due to higher volatilities.

The results from other sorted tercile 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, and as a result, the percentage increases in *M*2 are higher, 555.4% versus 845.7% and 312.3% versus 494.1%.

5.5. Alternative moving average lag length

In this subsection, we analyze the performance of using different moving average window lengths. Fig. 2 compares the performance (annualized average returns) of the buy-and-hold strategy to the annualized average returns (*M*2) of the MA timing strategy after levering up the volatility, using various moving average window lengths. The various lag lengths plotted are 3-day,

[9] We do not report performance increase in *M*2 when the average return is negative as *M*2 is not well defined in this case.

Table 7

Subperiod performance. We compare the performance of buy-and-hold strategy with the MA(5) timing strategy in the last three decades. Results reported in the table are for volatility sorted tercile portfolios. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (*%Inc*(*M*2)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	*M*2	*%Inc*(*M*2)
Panel A: January 2, 1975 to December 29, 1989									
Low	1.05	10.9	0.10	5.31***	7.77	0.68	4.26**	6.39***	611.4
	(0.37)			(2.64)			(2.16)	(3.00)	
2	0.79	13.6	0.06	3.05	9.59	0.32	2.26	3.54*	448.2
	(0.22)			(1.23)			(0.90)	(1.29)	
High	2.07	20.1	0.10	7.31**	14.0	0.52	5.24	8.41**	406.4
	(0.40)			(2.02)			(1.41)	(2.05)	
Panel B: January 2, 1990 to December 31, 1999									
Low	−2.78	7.34	−0.38	−0.67	5.17	−0.13	2.11		
	(−1.20)			(−0.41)			(1.28)		
2	2.58	10.4	0.25	4.05*	7.40	0.55	1.48	3.14	121.9
	(0.78)			(1.74)			(0.64)	(1.25)	
High	5.15	16.7	0.31	8.26**	12.4	0.66	3.11	5.95*	115.5
	(0.98)			(2.11)			(0.89)	(1.58)	
Panel C: January 3, 2000 to December 31, 2013									
Low	5.86**	10.4	0.56	5.49***	7.23	0.76	−0.36	2.03	34.7
	(2.13)			(2.87)			(−0.18)	(0.93)	
2	5.41	16.0	0.34	9.38***	11.1	0.85	3.97	8.17***	151.2
	(1.28)			(3.21)			(1.30)	(2.36)	
High	7.61	20.6	0.37	9.79***	14.2	0.69	2.18	6.55*	86.1
	(1.40)			(2.60)			(0.55)	(1.51)	

10-day, 20-day, and 50-day. In each case, results on all six sets of sorted portfolios are plotted. Across the board, the performance of the MA timing strategy is much higher than that of the buy-and-hold, and the performance improvement is often rather large. With longer lag lengths, the performance is only slightly lower.

5.6. 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 two alternative constructions. In Panel I, the rollover occurs 15 days before the expiration. In Panel II, prices are not adjusted during the rollover.[10] 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. Nevertheless, in all cases the moving average timing strategy performs much better than the buy-and-hold strategy. For example, in Panel II 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 2.90% (0.29), 2.91% (0.22), and −0.76% (-0.04), respectively, for the three volatility portfolios. The performance increase is 110.7%, 96.4%, and 911.6%, respectively.

6. Source of abnormal performance

In this section, we explore the source of abnormal performance generated by moving average timing. We examine whether the outperformance of moving average timing is driven by backwardation and contango, whether the performance displays any cyclic patterns, whether it depends on some macroeconomic variables, and whether outperformance is due to the market timing.

6.1. Backwardation and contango

Commodity futures are either in normal backwardation or contango. Backwardation occurs when the futures price rises as the maturity approaches. This is because the hedgers (producers and consumers of the underlying commodity) are net short, and therefore the futures price has to rise as maturity approaches to entice speculators to open long positions. Contango occurs when the future price falls as the maturity approaches. This is because the hedgers are net long, and thus the futures price has to fall as maturity approaches to entice speculators to open short positions (Keynes, 1930; Miffre, 2000).

It is possible that the MA timing strategy profits by taking advantage of backwardation/contango. Presumably, the MA timing strategy will take a long position of the commodities that are in backwardation and get out or take a short position when the commodities are in contango, although it is less likely given the short moving average windows we consider. Another possibility is that the price difference when rolling the futures contributes to the superior performance of the MA timing strategy. This is again less likely given that the continuous time-series of futures prices we use are smoothed out to eliminate the impact of price difference. In addition, in one of the robustness tests above, we use the time-series of future prices without adjustment, which does include the impact of backwardation and contango, but the results are not very different.

Nevertheless in this subsection we examine further whether the superior performance of the MA timing strategy is related to backwardation/contango. To measure whether a commodity futures is in backwardation or contango, we calculate roll-returns for every commodity futures each month. The roll-return is calculated as

$$RR_t = \frac{P_{Nearest,t}}{P_{Distant,t}} - 1.$$

[10] Another alternative construction using differences instead ratios to construct the continuous time-series yields stronger outperformance for the MA timing strategy as the performance of the buy-and-hold strategy is rather poor.

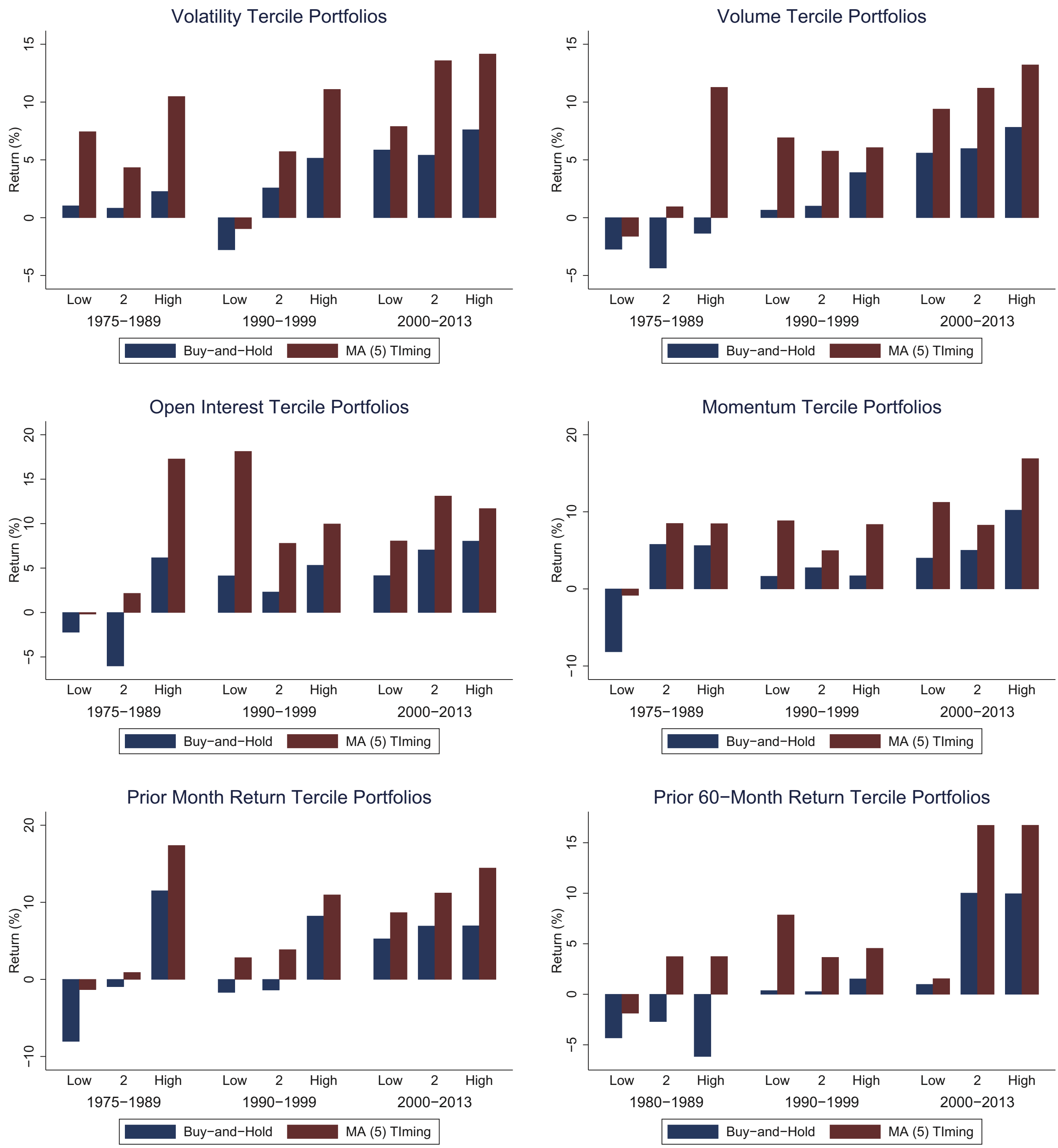

Fig. 1. MA timing performance in subperiods. This figure plots the annualized average returns of the buy-and-hold strategy and the annualized levered average returns ($M2$) of the MA(5) timing strategies over roughly each of the past three decades. The first period is from January 2, 1975 to December 29, 1989, the second is from January 2, 1990 to December 31, 1999, and the last is from January 3, 2000 to December 31, 2013.

We download from Bloomberg the historical settlement prices for all futures contracts from 1975 to 2013. Each month, we use the daily settlement prices of the nearest contract as $P_{Nearest,t}$, and we use the daily settlement prices of a contract that matures in the same month as the nearest contract but matures in the next year as $P_{distant,t}$.[11] We calculate the roll-returns each trading day and take the average over the trading days in a month as the monthly measure of the roll-returns. A positive roll-return RR_t indicates that the futures is in backwardation, as the futures price on the nearest contract exceeds the futures price on the distant contract. Conversely, a negative roll-return suggests that the market is in contango.

Each month, we calculate the average roll-returns of the sorted portfolios averaging across the commodities in the portfolio and report them in Panel A of Table 10. Interestingly, tercile portfolios sorted by volatility, trading volume, and open interest have negative roll-returns on average, suggesting that the commodity futures in these portfolios are more likely in contango. In contrast, roll-returns increase monotonically across the terciles for momentum tercile portfolios, and tercile portfolios sorted by both prior returns. In addition, all three highest ranked portfolios have positive RR_t, suggesting that they are in backwardation. These results are

[11] If there is no such contract, we use the most distant contract available.

Table 8
MA Timing with shorting. We calculate the MA(5) 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 report the average return (*Avg Ret*), standard deviation (*Std Dev*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (*%Inc*(*M2*)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	*M2*	*%Inc*(*M2*)
Panel A: Volatility Sorted Portfolios									
Low	1.81	9.91	0.18	5.87***	9.90	0.59	4.06**	3.37*	170.9
	(1.15)			(3.72)			(1.81)	(1.47)	
2	2.93	13.9	0.21	8.29***	13.8	0.60	5.36**	5.00*	130.1
	(1.33)			(3.75)			(1.70)	(1.53)	
High	4.87	19.5	0.25	12.0***	19.4	0.62	7.16**	6.96*	137.2
	(1.57)			(3.88)			(1.63)	(1.49)	
Panel B: Volume Sorted Portfolios									
Low	1.28	16.2	0.08	5.31**	16.2	0.33	4.03	4.03	316.0
	(0.49)			(2.05)			(1.09)	(1.08)	
2	0.90	16.6	0.05	7.40***	16.6	0.45	6.51**	6.51**	724.6
	(0.34)			(2.80)			(1.73)	(1.73)	
High	3.36	21.2	0.16	11.5***	21.2	0.54	8.16**	8.16**	243.1
	(0.99)			(3.41)			(1.69)	(1.66)	
Panel C: Open Interest Sorted Portfolios									
Low	1.78	18.9	0.09	9.24***	18.9	0.49	7.46**	7.46**	419.2
	(0.59)			(3.07)			(1.76)	(1.72)	
2	1.03	19.7	0.05	9.72***	19.7	0.49	8.69**	8.70**	848.5
	(0.33)			(3.10)			(2.02)	(2.01)	
High	6.66*	22.2	0.30	12.3***	22.2	0.55	5.60	5.60	84.0
	(1.89)			(3.47)			(1.12)	(1.11)	
Panel D: Momentum Sorted Portfolios									
Low	−1.35	15.5	−0.09	10.1***	15.4	0.65	11.4***	11.5***	845.7
	(−0.55)			(4.07)			(3.27)	(3.24)	
2	4.58**	12.9	0.35	6.06***	12.9	0.47	1.48	1.48	32.3
	(2.21)			(2.92)			(0.51)	(0.51)	
High	6.34***	16.2	0.39	9.74***	16.2	0.60	3.41	3.41	53.8
	(2.44)			(3.75)			(0.91)	(0.90)	
Panel E: Prior-Month Return Sorted Portfolios									
Low	−1.64	16.2	−0.10	6.48***	16.2	0.40	8.12***	8.12**	494.1
	(−0.64)			(2.51)			(2.18)	(2.16)	
2	1.81	13.0	0.14	5.59***	13.0	0.43	3.78*	3.78*	209.0
	(0.87)			(2.70)			(1.27)	(1.26)	
High	9.01***	15.9	0.57	11.9***	15.9	0.75	2.92	2.92	32.4
	(3.56)			(4.71)			(0.82)	(0.81)	
Panel F: Prior 60-Month Return Sorted Portfolios									
Low	−0.66	14.2	−0.05	4.12*	14.2	0.29	4.78*	4.78*	726.7
	(−0.27)			(1.70)			(1.38)	(1.36)	
2	3.48	13.4	0.26	9.16***	13.4	0.68	5.67**	5.68**	163.2
	(1.52)			(4.01)			(1.72)	(1.72)	
High	2.83	17.2	0.16	10.0***	17.2	0.58	7.20**	7.21**	255.1
	(0.97)			(3.43)			(1.69)	(1.68)	

consistent with the prior literature on momentum such as Miffre and Rallis (2007) and Erb and Harvey (2006).

Panel A of Table 10 also reports the average ranking of roll-returns for each sorted portfolio. To derive that, we first sort commodities into three tercile each month and then average the ranking across the commodities in the portfolio. Across the board, all tercile portfolios regardless of how they are ranked have roughly the same average ranking of roll-return, which is also the middle ranking (rank 2), suggesting that there is no systematic large difference in backwardation or contango across the tercile portfolios. For the past return sorted portfolios such as momentum, there are patterns of monotonic increasing in ranking of roll-returns, consistent with those of the roll-returns. However, the differences are not big.[12]

Panel B of Table 10 reports the results of applying the MA timing on the tercile portfolios sorted by the roll-returns. Similarly to other sorted portfolios, we observe significant performance increase over the buy-and-hold strategy. For the buy-and-hold strategy, commodities that are in backwardation (the highest ranked portfolio) do deliver significantly higher returns than the commodities that are in contango (the lowest ranked portfolio). Similar pattern is observed in the MA timing strategy, but the performance increase relative to the buy-and-hold strategy does not follow a similar pattern, suggesting that the outperformance is not related to backwardation/contango. In deed, the percentage increase in *M2* is the highest for commodities in contango because of the poor performance of the buy-and-hold strategy, and is the lowest for commodities in backwardation because of better performance of the buy-and-hold strategy.

6.2. Business cycle

Han et al. (2013) find that moving average timing performs much better in stock markets during recessions than during expansions relative to a buy-and-hold strategy. Han et al. (forthcoming) also show that a trend factor constructed based on moving

[12] These difference could explain the large return differences between the highest ranked and lowest ranked tercile portfolios seen in Table 3.

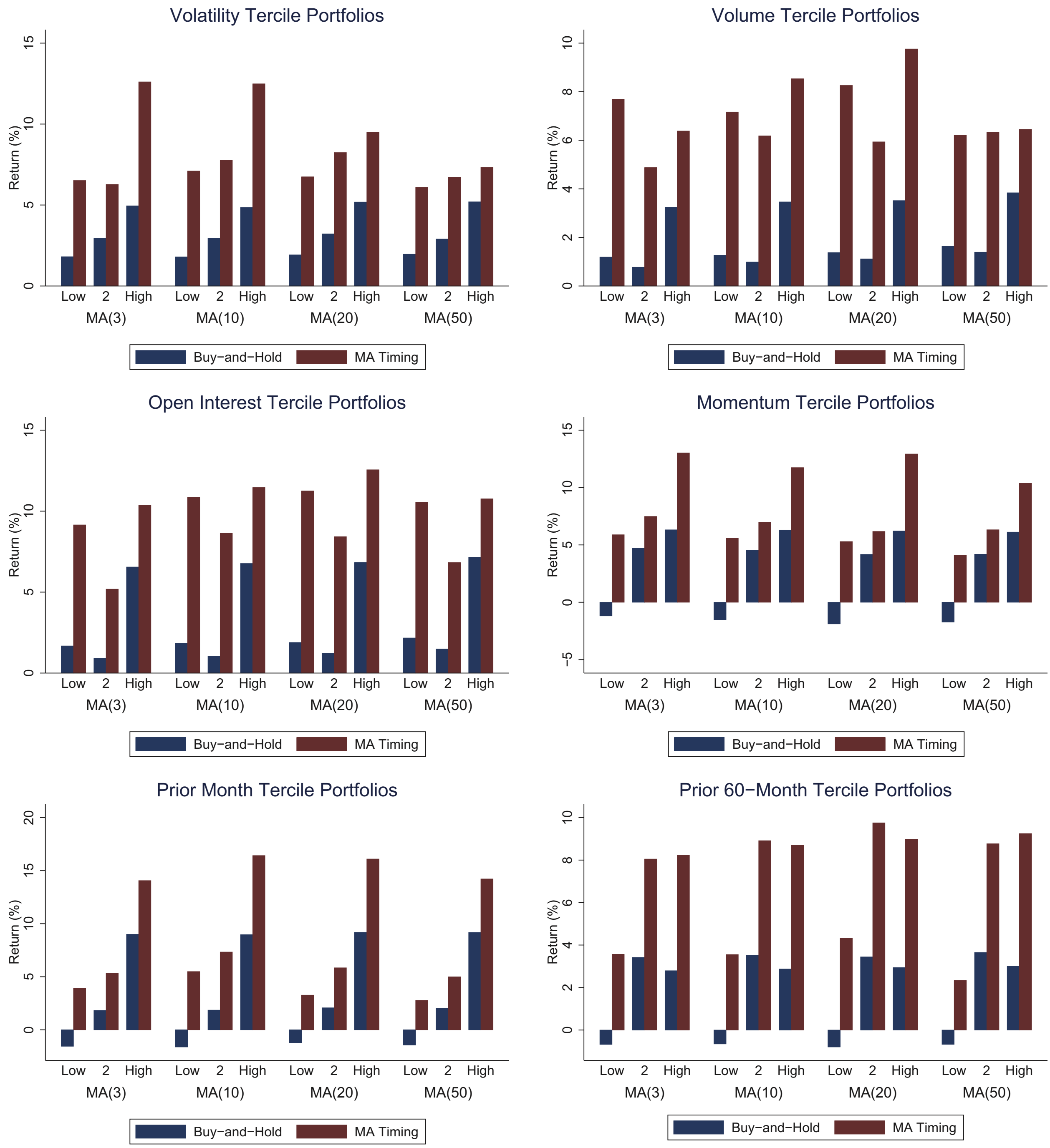

Fig. 2. MA timing performance using alternative lag length. This figure plots the annualized average returns of the buy-and-hold strategy and the annualized levered average returns ($M2$) of the MA timing strategies using alternative lag lengths including 3-day, 10-day, 20-day, and 50-day.

average signals in stock markets performs better during recessions. Table 11 reports separately the performance of the moving average timing strategy in expansions (Panel A) and recessions (Panel B) as determined by the NBER. Not surprisingly, the buy-and-hold strategy on the volatility sorted commodity portfolios performs better during 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.[13] 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 is only 43.3% and 73.1%, respectively, for the medium and high volatility tercile portfolios during expansions, but is 187.9% and 184.9%, respectively, during recessions.

[13] Results reported in the table are for the volatility sorted portfolios, other characteristics sorted portfolios generate similar results.

Table 9
Alternative construction of rollover returns. This table reports the performance of the MA(5) timing using alternatively constructed futures returns. Panel I uses the futures returns adjusted by cumulative ratios of the front-month contracts and the second nearest-to-maturity contracts. The rollover occurs on the 15th of the month before expiration. Panel II uses the unadjusted futures returns with the rollover occurring on the expiration day. We use the MA(5) timing with no short. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (*%Inc*(*M*2)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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 15th

Rank	Buy-and-Hold			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	*M*2	*%Inc*(*M*2)
Panel A: Volatility Sorted Portfolios									
Low	2.61*	9.85	0.26	4.86***	6.90	0.70	2.26**	4.33***	166.3
	(1.66)			(4.42)			(2.01)	(3.54)	
2	3.71*	13.8	0.27	6.32***	9.66	0.65	2.61**	5.34***	143.8
	(1.68)			(4.10)			(1.65)	(3.05)	
High	4.80	19.5	0.25	8.67***	13.7	0.63	3.86**	7.51***	156.4
	(1.55)			(3.96)			(1.75)	(3.13)	
Panel B: Momentum Sorted Portfolios									
Low	−1.11	15.4	−0.07	4.89***	10.9	0.45	6.00***	8.00***	720.2
	(−0.45)			(2.79)			(3.45)	(4.19)	
2	5.34***	12.9	0.41	6.73***	9.10	0.74	1.39	4.19***	78.4
	(2.58)			(4.61)			(0.95)	(2.63)	
High	6.47***	16.3	0.40	8.40***	11.2	0.75	1.93	5.72***	88.4
	(2.47)			(4.66)			(1.02)	(2.70)	
Panel C: Prior-Month Return Sorted Portfolios									
Low	−0.87	16.2	−0.05	2.48	11.1	0.22	3.35**	4.47***	514.6
	(−0.34)			(1.40)			(1.79)	(2.20)	
2	2.92	13.2	0.22	4.31***	9.27	0.47	1.39	3.23**	110.3
	(1.39)			(2.92)			(0.93)	(1.97)	
High	8.53***	15.7	0.54	10.7***	11.2	0.96	2.20	6.51***	76.3
	(3.40)			(6.00)			(1.25)	(3.32)	
Panel D: Prior 60-Month Return Sorted Portfolios									
Low	1.74	14.3	0.12	3.76**	10.1	0.37	2.03	3.57**	205.9
	(0.71)			(2.18)			(1.18)	(1.89)	
2	3.19	13.3	0.24	5.47***	9.24	0.59	2.28*	4.72***	148.0
	(1.40)			(3.47)			(1.39)	(2.62)	
High	2.50	16.9	0.15	6.40***	11.6	0.55	3.90**	6.84***	273.2
	(0.87)			(3.25)			(1.86)	(2.96)	

Panel II: Construction without Adjustment

Rank	Buy-and-Hold			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	*M*2	*%Inc*(*M*2)
Panel A: Volatility Sorted Portfolios									
Low	2.90*	9.89	0.29	4.37***	7.08	0.62	1.47*	3.21***	110.7
	(1.84)			(3.87)			(1.34)	(2.71)	
2	2.91	13.4	0.22	4.08***	9.55	0.43	1.17	2.81**	96.4
	(1.36)			(2.68)			(0.78)	(1.72)	
High	−0.76	18.4	−0.04	4.35**	13.0	0.33	5.11***	6.89***	911.6
	(−0.26)			(2.09)			(2.47)	(3.12)	
Panel B: Momentum Sorted Portfolios									
Low	2.32	14.9	0.16	4.35***	10.6	0.41	2.03	3.79**	163.7
	(0.97)			(2.56)			(1.21)	(2.04)	
2	2.37	12.6	0.19	3.55***	8.99	0.39	1.18	2.62**	110.8
	(1.17)			(2.46)			(0.83)	(1.68)	
High	−1.34	15.9	−0.08	2.02	11.0	0.18	3.37**	4.26**	317.3
	(−0.53)			(1.15)			(1.84)	(2.13)	
Panel C: Prior-Month Return Sorted Portfolios									
Low	2.68	15.7	0.17	3.70**	11.2	0.33	1.02	2.49*	93.1
	(1.07)			(2.06)			(0.58)	(1.32)	
2	2.04	12.6	0.16	3.73***	9.03	0.41	1.69	3.15**	154.5
	(1.02)			(2.59)			(1.21)	(2.10)	
High	−1.28	15.3	−0.08	4.39***	10.8	0.41	5.67***	7.50***	586.1
	(−0.53)			(2.55)			(3.28)	(3.91)	
Panel D: Prior 60-Month Return Sorted Portfolios									
Low	7.34***	13.5	0.54	8.30***	9.77	0.85	0.95	4.16***	56.6
	(3.18)			(4.97)			(0.60)	(2.40)	
2	1.34	12.7	0.11	4.01***	9.02	0.44	2.66**	4.30***	320.4
	(0.62)			(2.60)			(1.75)	(2.58)	
High	−5.34*	17.2	−0.31	0.95	12.1	0.08	6.29***	6.68***	125.2
	(−1.82)			(0.46)			(3.02)	(2.96)	

Table 10
Effects of backwardation and contango. The table reports the effects of backwardation and contango on the performance of the MA timing strategies. Panel A reports the distributions of roll return and roll tercile rank among various characteristics-sorted portfolios. Panel B compares the performance of the buy-and-hold strategy and the MA timing strategy on portfolios sorted on the roll returns. 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 A: Roll Return and Rank Distribution

Rank	Roll Ret(%)	Roll Rank	Roll Ret(%)	Roll Rank	Roll Ret(%)	Roll Rank
	Volatility		Volume		Open Interest	
Low	−0.71***	2.03***	−2.68***	1.91***	−1.73**	1.99***
	(−6.08)	(233.4)	(−4.35)	(35.3)	(−2.57)	(37.1)
2	−1.46***	1.99***	−2.12***	1.88***	−1.81***	1.91***
	(−13.4)	(263.6)	(−4.05)	(47.8)	(−3.47)	(48.6)
High	−0.82***	2.01***	−1.76***	1.99***	−2.21***	1.97***
	(−7.42)	(318.9)	(−3.15)	(71.2)	(−3.05)	(55.9)
High-Low	−0.11	-0.02	0.92	0.08	−0.48	−0.02
	(−0.74)	(−1.23)	(1.22)	(1.20)	(−0.59)	(−0.23)
	Momentum		Prior-Month Return		Prior 60-Month Return	
Low	−3.76***	1.79***	−1.79***	1.95***	−3.33***	1.84***
	(−11.0)	(85.1)	(−5.39)	(137.4)	(−7.05)	(61.0)
2	−1.28***	1.99***	−1.13***	2.01***	−1.01**	2.01***
	(−3.14)	(111.0)	(−2.94)	(133.1)	(−2.19)	(89.7)
High	1.97***	2.24***	0.05	2.08***	0.71	2.16***
	(4.06)	(108.7)	(0.12)	(138.7)	(1.44)	(70.9)
High-Low	5.73***	0.45***	1.84***	0.13***	4.03***	0.32***
	(10.5)	(12.0)	(5.38)	(5.38)	(5.99)	(5.87)

Panel B: Roll Return Sorted Portfolios

Rank	Buy-and-Hold			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	*M*2	%*Inc*(*M*2)
Low	0.84	15.9	0.05	3.59**	11.1	0.32	2.74*	4.27***	506.1
	(0.33)			(2.02)			(1.52)	(2.19)	
2	3.98	15.6	0.25	7.05***	10.9	0.65	3.07**	6.15***	154.5
	(1.60)			(4.06)			(1.72)	(3.16)	
High	4.94*	16.5	0.30	7.54***	11.7	0.65	2.60*	5.71***	115.6
	(1.88)			(4.06)			(1.40)	(2.81)	

Table 11
Business cycles. This table contrasts the performance improvement of the MA(5) timing strategy over 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*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (%*Inc*(*M*2)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	*M*2	%*Inc*(*M*2)
Panel A: Expansion									
Low	4.08***	9.36	0.44	4.75***	6.76	0.70	0.67	2.51**	61.4
	(2.54)			(4.11)			(0.61)	(2.08)	
2	5.28**	12.9	0.41	5.38***	9.15	0.59	0.10	2.28*	43.3
	(2.39)			(3.43)			(0.07)	(1.36)	
High	7.19**	18.0	0.40	8.85***	12.8	0.69	1.66	5.26***	73.1
	(2.33)			(4.04)			(0.77)	(2.20)	
Panel B: Recession									
Low	−12.9**	12.8	−1.00	−2.07	8.33	−0.25	10.8***		
	(−2.30)			(−0.57)			(2.53)		
2	−12.3	19.1	−0.64	7.10	12.5	0.57	19.4***	23.1***	187.9
	(−1.48)			(1.30)			(3.11)	(3.20)	
High	−10.1	27.1	−0.37	5.89	18.6	0.32	16.0*	18.7**	184.9
	(−0.86)			(0.73)			(1.86)	(2.02)	

6.3. Macroeconomic variables

From the above discussion, it is clear that the recession dummy can explain part of the abnormal performance of the moving average timing, but this dummy variable may proxy for other macroeconomic variables. Hong and Yogo (2009) show that the short rate and the yield spread predict commodity returns. A high yield spread, which tends to coincide with recessions, predicts low commodity returns. In particular, Energy returns are more sensitive to the yield spread and Agriculture and Metals are more responsive to the short rate. Prokopczuk and Symeonidis (2013) find that while the volatility of CPI index impacts the volatility of most commodities, volatility of Industrial Production impacts Livestocks return volatility, and money supply $M2$ volatility affects Agricultural futures' return volatility.

We construct the volatility series following Prokopczuk and Symeonidis (2013), and also include the short (real) rate, the yield spread (defined as the difference between AAA bond yield and the

Table 12
Effect of business cycle and macroeconomic variables. This table reports the results of regressing the return difference (Δ) between the MA(5) timing and the buy-and-hold strategies on recession dummy, CPI volatility, money supply *M*2 volatility, industrial production volatility, yield spread, default spread, and interest rate. 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 2013.

	Low Volatility			Mid Volatility			High Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.67	10.5	−0.63	0.10	−0.58	5.80	1.66	1.61	−14.8
	(0.61)	(1.58)	(−0.07)	(0.07)	(−0.06)	(0.41)	(0.76)	(0.12)	(−0.80)
Recession	10.1**	11.9***	12.8**	19.3***	19.6***	23.6***	14.4	16.2*	15.2
	(2.30)	(2.79)	(2.41)	(2.76)	(2.89)	(2.72)	(1.60)	(1.87)	(1.49)
Vol (CPI)		−0.87	−0.43		−0.37	−0.41		−1.68	−1.10
		(−1.09)	(−0.45)		(−0.33)	(−0.30)		(−1.04)	(−0.58)
Vol (M2)		−0.22	0.08		0.27	0.15		0.46	1.25
		(−0.47)	(0.16)		(0.42)	(0.21)		(0.52)	(1.27)
Vol(IP)		−0.93	−0.53		0.20	0.49		1.86	1.97
		(−0.71)	(−0.34)		(0.10)	(0.20)		(0.70)	(0.65)
Yield Spread			−0.38			−2.58			0.14
			(−0.09)			(−0.45)			(0.02)
Default Spread			−0.11			−0.05			−0.15
			(−0.62)			(−0.21)			(−0.41)
Short Rate			0.46*			−0.17			0.65
			(1.93)			(−0.49)			(1.31)
$\bar{R}^2$ (%)	0.1	0.1	0.1	0.2	0.1	0.1	0.0	0.0	0.0

short rate), and the default spread (defined as the yield difference between BAA and AAA bonds). We regress the return difference (spread portfolio) on the recession dummy and the macroeconomic variables. The results for volatility sorted portfolios are reported in Table 12, others are qualitatively similar. First, the recession dummy is positive and significant either alone or with other variables for all but the highest volatility portfolio for which the recession dummy is significant only in the presence of the three volatility series. In fact, most of the variables are insignificant with the highest volatility portfolio, which is likely due to its very high volatility. The significantly positive coefficient on the recession dummy confirms the results in Table 11 that the moving average timing performs much better in recession compared to the buy-and-hold strategy. When initially adding the three volatility series and subsequently adding the two yield spreads and the short interest rate, the recession dummy remains significant and its coefficient becomes larger. However, all the other variables are insignificant, suggesting that the performance increase of the MA timing strategy over the buy-and-hold strategy cannot be explained by the volatility series and the various yields.

6.4. 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 alphas 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):

$$\Delta_{jt} = \alpha_j + \beta_{j,mkt} r_{mkt,t} + \gamma_{j,mkt} r_{mkt,t} I_{r_{mkt}>0} + \epsilon_{jt}, \qquad j = 1, 2, 3 \quad (10)$$

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. Data mining issue

Unlike in the stock markets where thousands of stocks are traded and can be used to form various portfolios, there are much fewer number of commodities that are traded in the futures markets, and in this paper we use at most 35 commodities to form portfolios. This could potentially lead to the concern that the superior performance of the MA timing strategy could be due to the influence of a limited number of commodities since unlike the stock markets for which a portfolio can alleviate the undue influence of outliers. Our extensive robustness tests above should alleviate the concern to some extent. In this section, we attempt to further address the potential issue of data mining. We first examine the composition of commodities in the tercile portfolios and try to find any systematic patterns. We then run simulations on randomly sorted portfolios for which the performance does not depend on the composition of the commodities.

Table 15 lists the distributions of commodities in each of the three terciles for all the six sorts. Except for volume and open interest sorted portfolios, all other tercile portfolios have similar

Table 13
Risk adjusted abnormal returns of the spread portfolios. The table reports the risk-adjusted abnormal returns of the spread portfolio (Δ) between the MA(5) 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		
	α (%)	β_{mkt}	β_{smb}	β_{hml}	α (%)	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)
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 (Δ) between the MA(5) 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	α (%)	β_{mkt}	γ_{mkt}	α (%)	β_{mkt}	γ_{mkt}	α (%)	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)

Table 15
Portfolio composition distribution. This table reports for each commodity the percentage of months over the entire sample period when the commodity is in one of the tercile portfolios for all the six sets of tercile portfolios. The sample period is from January 1975 to December 2013.

Symbol	Volatility			Volume			Open Interest			Momentum			Prior-Month Ret			Prior 60-Month Ret		
	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High
C	48.5	36.3	15.2		27.3	72.7		29.2	70.8	35.3	39.0	25.8	30.8	39.2	30.0	52.2	42.6	5.15
CC	10.7	34.2	55.1	28.3	71.7		30.0	58.9	11.1	37.9	24.2	37.9	36.2	28.3	35.5	47.5	23.3	29.2
KC	15.8	28.5	55.7	11.2	88.1	0.70	13.8	71.5	14.6	36.4	24.7	38.8	39.4	23.9	36.8	37.8	17.9	44.2
CT	32.3	45.5	22.2	28.5	70.7	0.76	27.3	57.7	15.0	32.7	34.6	32.7	31.5	33.4	35.1	33.6	29.7	36.8
O	14.6	42.1	43.3	92.9	7.08		93.1	6.65	0.26	39.3	27.8	32.8	38.1	30.4	31.5	49.3	35.2	15.5
JO	27.1	32.9	40.0	84.5	15.5		58.5	41.5		34.4	30.1	35.5	36.2	30.4	33.4	35.5	27.5	37.0
S	40.4	42.3	17.3	1.95	36.0	62.0	6.79	41.0	52.2	25.3	44.4	30.3	25.3	45.4	29.3	20.6	66.4	13.0
SM	27.8	45.7	26.5	1.19	50.6	48.2	0.26	58.8	40.9	23.8	39.6	36.6	27.8	39.2	33.0	18.4	36.8	44.9
BO	30.1	44.2	25.6	0.67	50.0	49.3	2.14	42.1	55.7	31.8	39.6	28.6	31.7	39.2	29.1	25.7	57.4	16.9
SB	7.91	22.6	69.4	6.51	32.5	61.0		3.56	96.4	42.9	20.3	36.8	39.0	24.2	36.8	29.2	34.1	36.8
W	19.4	55.8	24.8	29.5	24.3	46.3	28.0	22.3	49.7	41.2	34.3	24.5	33.3	37.1	29.6	52.8	39.1	8.11
KW	48.7	35.3	16.0	7.46	91.2	1.32	3.51	84.2	12.3	27.5	46.3	26.2	27.4	44.5	28.1	23.0	54.2	22.8
RR	42.5	40.8	16.7	100.0			100.0			40.3	38.2	21.5	36.4	33.3	30.3	56.9	36.0	7.11
FC	83.1	15.4	1.50	83.7	16.3		88.7	11.3		20.8	47.4	31.8	21.4	43.9	34.7	19.9	56.9	23.3
PB	10.6	19.7	69.7	84.5	14.7	0.78	98.6	1.38		35.2	25.2	39.6	38.7	23.1	38.2	46.6	26.2	27.2
LH	42.6	43.5	13.8	12.2	86.1	1.70	27.7	61.3	10.9	31.0	29.8	39.3	32.9	28.4	38.7	43.0	34.6	22.4
LC	76.3	20.1	3.63		84.2	15.8		42.1	57.9	20.1	50.4	29.4	22.5	45.2	32.3	23.5	35.5	40.9
LA	63.5	27.9	8.63	4.81	81.7	13.5	1.94	81.6	16.5	28.8	56.0	15.2	27.6	52.6	19.9	41.6	58.4	
HG	25.6	46.2	28.2	7.61	80.6	11.8		77.1	22.9	27.6	34.7	37.8	29.1	38.8	32.1	8.33	48.8	42.9
GC	67.9	20.1	12.0	9.62	12.4	78.0	5.24	15.4	79.4	26.9	48.8	24.3	25.3	45.9	28.8	38.3	33.7	28.0
LL	20.9	36.7	42.3	75.0	25.0		98.0	1.98		27.4	35.8	36.8	32.0	28.9	39.2	14.0	22.1	64.0
LN	1.52	40.6	57.9	75.0	25.0		95.0	5.00		35.6	25.7	38.7	37.2	25.5	37.2	13.1	10.2	76.6
PA	24.8	32.0	43.2	98.3	1.71		81.8	18.2		33.1	23.9	42.9	29.9	34.1	36.0	26.1	25.0	48.9
PL	47.4	38.4	14.1	67.9	32.1		54.2	44.7	1.19	22.1	47.5	30.4	26.3	41.7	32.0	30.1	33.8	36.0
SI	23.7	35.9	40.4	9.35	38.4	52.3	8.30	39.7	52.0	32.8	40.1	27.1	34.3	32.2	33.5	34.9	28.5	36.6
LT	40.1	36.5	23.4	99.0	0.96		100.0			20.9	39.8	39.3	24.5	40.3	35.2		36.5	63.5
LX	34.0	33.5	32.5	6.73	91.3	1.92	58.0	40.0	2.00	37.7	37.7	24.6	34.2	34.2	31.6	44.5	25.5	29.9
CO	11.8	40.8	47.4			100.0		3.16	96.8	22.3	25.0	52.7	26.6	31.1	42.3	3.25	19.9	76.8
CL	12.2	36.9	50.9	3.15	5.73	91.1	2.44	4.88	92.7	28.5	23.2	48.3	33.0	25.6	41.4	10.1	18.5	71.4
QS	20.4	42.5	37.1		37.6	62.4	0.91	53.4	45.7	27.5	24.7	47.7	27.1	33.9	39.0	7.30	33.5	59.2
HO	11.2	31.5	57.3	4.89	14.7	80.4	8.51	72.3	19.1	26.3	30.0	43.7	29.6	29.6	40.9	9.67	23.0	67.3
NG	3.51	11.2	85.3	7.04	7.75	85.2	11.0	36.0	53.0	47.5	16.2	36.3	43.8	18.7	37.5	38.4	11.2	50.4
HU	4.92	33.6	61.5		47.3	52.7	4.76	81.0	14.3	29.7	30.1	40.2	35.7	25.8	38.5	10.3	26.5	63.2
DA	85.6	10.7	3.72	92.3	7.69		92.3	7.69		31.2	41.3	27.4	21.2	50.0	28.8	65.6	33.1	1.30
LB	18.9	39.6	41.4	98.3	1.72		100.0			39.9	30.1	30.1	36.6	31.7	31.7	56.6	24.6	18.8

Table 16
Randomly sorted portfolios. This table reports the average performance of the MA(5) timing strategy on randomly sorted tercile portfolios over 1000 simulations. For each simulation, we randomly assign the commodities into one of the three tercile portfolios and then apply the MA(5) timing strategy on the tercile portfolios. Panel A uses all the commodities, whereas Panel B excludes BO, KW, PB, and DA, commodities that generate huge performance gains in Table 2∗∗∗ (Super performers). We report the average return (*Avg Ret*), standard deviation (*Std Dev*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (*%Inc*(*M*2)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	M2	%*Inc*(*M*2)
Panel A: Randomly Sorted Portfolios									
Low	3.10∗∗∗	14.45	0.21∗∗∗	5.55∗∗∗	10.11	0.55∗∗∗	2.45∗∗∗	4.82∗∗∗	155.5
	(71.6)		(71.6)	(152.2)		(157.0)	(69.2)	(114.4)	
2	3.06∗∗∗	14.45	0.21∗∗∗	5.52∗∗∗	10.11	0.55∗∗∗	2.46∗∗∗	4.82∗∗∗	157.5
	(69.9)		(69.9)	(146.6)		(150.6)	(69.3)	(113.6)	
High	3.08∗∗∗	14.44	0.21∗∗∗	5.48∗∗∗	10.08	0.54∗∗∗	2.40∗∗∗	4.77∗∗∗	154.9
	(73.6)		(73.5)	(146.2)		(155.8)	(66.3)	(117.6)	
Panel B: Randomly Sorted Portfolios Excluding Super Performers									
Low	3.61∗∗∗	15.12	0.24∗∗∗	5.72∗∗∗	10.47	0.54∗∗∗	2.11∗∗∗	4.63∗∗∗	128.3
	(79.1)		(79.1)	(129.7)		(149.6)	(50.5)	(100.9)	
2	3.73∗∗∗	15.11	0.25∗∗∗	5.82∗∗∗	10.50	0.55∗∗∗	2.09∗∗∗	4.61∗∗∗	123.6
	(78.4)		(78.3)	(131.2)		(146.8)	(51.6)	(100.8)	
High	3.63∗∗∗	15.13	0.24∗∗∗	5.80∗∗∗	10.52	0.55∗∗∗	2.16∗∗∗	4.70∗∗∗	129.5
	(76.6)		(76.8)	(131.8)		(146.1)	(52.7)	(106.9)	

share of almost all commodities. In other words, almost all commodities have roughly similar chance falling in any of the three tercile portfolios, and not a single commodity stays in one tercile all the time. For volume and open interest sorted portfolios, there are indeed a few commodities that tend to stay in a particular tercile. This is not surprising given that trading volume and open interest tend to be stable over time. However, the performance of the MA timing strategy on these two sets of tercile portfolios does not differ substantially from that on the other four sets of tercile portfolios.

To further alleviate the concern, we conduct simulation analysis next. We first sort the commodities randomly into three terciles and construct three tercile portfolios, and then we apply the same MA timing strategy to the randomly sorted tercile portfolios.

Table 17
Subperiod performance of randomly sorted portfolios. This table reports the average performance of the MA(5) timing strategy on randomly sorted tercile portfolios over 1000 simulations over the last three decades. For each simulation, we randomly assign the commodities into one of the three tercile portfolios and then apply the MA(5) timing strategy on the tercile portfolios. We report the average return (*Avg Ret*), standard deviation (*Std Dev*), and Sharpe ratio (*Sharpe*) for the buy-and-hold strategy and MA timing strategy, respectively. We also report the difference between the two strategies for the average return and M2 measure, and the percentage increase in the M2 measure (%*Inc*(*M*2)). The significance of the differences is from the right-tailed test, $H_0 : \Delta = 0, H_1 : \Delta > 0$, where Δ is difference in either the average return or the M2 measure. 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			MA(5) Timing			Difference (Δ)		
	Avg Ret	Std Dev	Sharpe	Avg Ret	Std Dev	Sharpe	Avg Ret	M2	%*Inc*(*M*2)
Panel A: January 2, 1975 to December 29, 1989									
Low	1.12∗∗∗	15.4	0.07∗∗∗	4.56∗∗∗	10.8	0.42∗∗∗	3.45∗∗∗	5.39∗∗∗	481.2
	(13.5)		(13.5)	(68.1)		(69.2)	(53.7)	(70.8)	
2	0.97∗∗∗	15.4	0.06∗∗∗	4.49∗∗∗	10.7	0.42∗∗∗	3.52∗∗∗	5.44∗∗∗	560.8
	(12.1)		(12.1)	(67.4)		(68.6)	(52.9)	(68.4)	
High	0.98∗∗∗	15.4	0.06∗∗∗	4.35∗∗∗	10.7	0.41∗∗∗	3.37∗∗∗	5.26∗∗∗	536.7
	(12.2)		(12.1)	(66.2)		(67.8)	(53.5)	(72.1)	
Panel B: January 2, 1990 to December 31, 1999									
Low	1.60∗∗∗	11.2	0.14∗∗∗	3.60∗∗∗	8.17	0.44∗∗∗	2.00∗∗∗	3.34∗∗∗	208.8
	(21.8)		(21.7)	(57.8)		(58.5)	(35.7)	(50.6)	
2	1.63∗∗∗	11.3	0.14∗∗∗	3.62∗∗∗	8.17	0.44∗∗∗	1.99∗∗∗	3.34∗∗∗	204.9
	(22.3)		(22.4)	(57.9)		(58.7)	(35.8)	(51.2)	
High	1.60∗∗∗	11.3	0.14∗∗∗	3.53∗∗∗	8.15	0.43∗∗∗	1.93∗∗∗	3.27∗∗∗	204.4
	(21.9)		(21.7)	(56.1)		(57.1)	(33.4)	(48.6)	
Panel C: January 3, 2000 to December 31, 2013									
Low	6.24∗∗∗	15.4	0.41∗∗∗	7.96∗∗∗	10.6	0.75∗∗∗	1.72∗∗∗	5.30∗∗∗	84.9
	(103.8)		(103.5)	(139.9)		(144.6)	(32.0)	(78.7)	
2	6.27∗∗∗	15.4	0.41∗∗∗	7.95∗∗∗	10.6	0.75∗∗∗	1.68∗∗∗	5.23∗∗∗	83.4
	(100.9)		(100.5)	(139.5)		(144.2)	(30.8)	(76.7)	
High	6.34∗∗∗	15.4	0.41∗∗∗	8.04∗∗∗	10.6	0.76∗∗∗	1.70∗∗∗	5.34∗∗∗	84.2
	(107.8)		(107.4)	(136.2)		(144.6)	(30.7)	(78.8)	

We repeat this analysis 1,000 times to report the average in Panel A of Table 16. Because of the random sorting procedure and the large number of simulations, the performance of the buy-and-hold strategy is very similar across the three tercile portfolios, so is the performance of the MA timing strategy. But the MA timing strategy performs much better. The Sharp ratios increase from 0.21 for the buy-and-hold strategy to 0.55 for the MA timing strategy. The performance increase in *M*2 is highly significant and is about 155% over that of the buy-and-hold.

Panel B shows the results of a similar simulation except that a few commodities are excluded. The excluded commodities are referred to as super performers; they are BO, KW, PB, and DA, all of which deliver much higher performance under MA timing (see Table 2). Panel B shows that even excluding these super performers, the performance of the MA timing strategy as well as the buy-and-hold does not change much. Both Sharpe ratios and performance increase in *M*2 are very similar to those in Panel A.

Table 17 also reports the performance over the three subperiods. It is clear that the buy-and-hold strategy performs the worst in the first subperiod, and improves somewhat in the second subperiod, but performs substantially better in the third subperiod. The average returns (Sharpe ratios) are around 1.0% (0.06), 1.6% (0.14), and 6.27% (0.41), respectively for the three subperiods. On the other hand, the MA timing strategy performs well in the first two subperiods, but performs the best in the last subperiod in terms of absolute performance. The average returns (Sharpe ratios) are around 4.5% (0.42), 3.6% (0.44), and 8.0% (0.75), respectively for the three subperiods. In terms of relative performance improvement, the first subperiod is the best with more than 500% improvement, whereas the third subperiod improves the least because the much higher performance of the buy-and-hold.

8. 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.

For the source of abnormal performance of the moving average timing, we find that the outperformance of the moving average timing is unlikely to be related to backwardation and contango, the outperformance is much higher in recessions and can not be explained by the macroeconomic variables. However, even though the abnormal returns after being 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.

To alleviate the concern related to the data mining issue, we further provide detailed examination of the composition of commodities in the tercile portfolios and conduct simulation analysis. The results provide evidence against the impact from data mining.

Finally, future research is called for to examine the profitability of the moving average timing on international commodity futures markets, which not only is interesting and important by itself, but also serves as an alternative to mitigate the data-mining concern.

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