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The commodity futures' historical basis in trading strategy and portfolio investment

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ABSTRACT

We propose a new trading strategy named the historical basis strategy and analyze its profitability in both the Chinese and the US commodity futures markets. We also compare the profitability of momentum strategy and carry strategy with that of historical basis strategy. The results indicate that the three strategies are profitable in both markets, especially historical basis strategy performs superior to the momentum strategy and inferior to the carry strategy. We also find that the performance of portfolio investment based on the commodity futures' trading strategies is significantly better than based on the commodity futures themselves, and both of them can achieve diversification benefits in stock-bond-currency portfolios. Furthermore, if energy futures are added to trading strategies and portfolios, their profitability rises significantly while the risks increase.

1. Introduction

The profitability and risk diversification ability of commodity futures in investment have always been the focus of relevant research. In the research of portfolio investment, scholars discussed whether commodity futures can diversify the risks of stocks, bonds and currency in the investment of portfolios, but the conclusions are not consistent. Some scholars believe that the commodity futures can diversify portfolio risks and increase returns (Jensen et al., 2000; Gorton and Rouwenhorst, 2006; Conover et al., 2010; Cheung and Miu, 2010; Daskalaki et al., 2017). The common perception is that the return of commodity futures has negative or small correlation with the return of traditional asset classes, and commodity futures are treated as an alternative asset class. But the others suggest that the benefits ascribed to commodity futures may have been exaggerated (Daskalaki and Skiadopoulos, 2011; Belousova and Dorfleitner, 2012; Bessler and Wolff, 2015; Yan and Garcia, 2017). Furthermore, compared with other commodity futures, energy has its particularity. On the one hand, existing studies have shown that, there is volatility spillover between energy market and the equity markets, and with the development of commodity financialization, the relationship between the energy market and the equity markets has become one of the research focuses (Creti et al., 2013; Lee et al., 2014; Adams and Glück, 2015; Kang et al., 2015; Khalfaoui et al., 2015; Basher and Sadorsky, 2016; Maghyereh et al., 2017; Zhang et al., 2017; Shahzad et al., 2018; Demirer et al., 2020; Hu et al., 2020; Ma et al., 2021). On the other hand, there is a definitive link between the energy futures and the non-energy futures commodity futures (Nazlioglu et al., 2013; Gardebroek and Hernandez, 2013; Charlot and Marimoutou, 2014; Behmiri et al., 2019; Chang et al., 2019; Bonato et al., 2020; Albulescu et al., 2020; Wu et al., 2020). Therefore, the performance of energy commodity futures in trading strategy and portfolio investment is worth to be discussed in detail (Gatfaoui, 2019; Sarwar et al., 2019).

In terms of commodity futures trading strategies, some scholars have proved that the trading strategies applicable in the stock market are also applicable to the commodity futures market. For example, the applicability of momentum (MOM for short) strategies in the commodity futures market has received widespread attention (Shen et al., 2007; Miffre and Rallis, 2007; Asness et al., 2013; Fuertes et al., 2010, 2015). The momentum strategy is buying the commodity futures that outperformed in the recent past and selling the commodity futures that underperformed, and the returns gain from it can interpreted as compensation for bearing risk during times when inventories are low (Miffre and Rallis, 2007; Gorton et al., 2013). The other scholars have explored some unique trading strategies of commodity futures based on the characteristics of commodity futures. The most important and widely accepted one is the term structure strategy, also known as carry

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strategy (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Fuertes et al., 2010, 2015; Gorton et al., 2013; Koijen et al., 2018; Bakshi et al., 2019). The term structure of commodity prices may have been an important driver of realized commodity futures' excess returns, and the strategy based on it is taking long positions in commodities with downward-sloping term structures and short positions in commodities with upward-sloping term structures. In commodity futures related research, the above trading strategy is also called investment style. The style investing in the commodity futures market is that investors use some long/short only strategies or long-short strategies to obtain risk premium or excess return on commodity futures which can be compensation for specific risk factors or a reflection of commodity futures market's anomalies (Ibbotson et al., 2013; Asness et al., 2013; Fernandez-Perez et al., 2019). According to Bakshi et al. (2019), the momentum strategy is related to the aggregate speculative activity, and the carry strategy gains a positive risk premium because of its exposure to innovations in global equity volatility. In addition, Ready et al. (2017) relate commodity returns to the returns of carry trade strategies in foreign exchange markets.

In recent studies on trading strategies, some scholars believe that the combination of multiple trading strategies will yield higher returns. In the stock market, Fitzgibbons et al. (2017) studied the performance of the value and momentum strategies in the stock market, and they believed that the integration (double sorting) of the two strategies can achieve higher returns than mix (sum of the weights is one). Similarly, Israel et al. (2018) reached a conclusion consistent with the former. In terms of the commodity futures markets, Fuertes et al. (2015) sorted commodity futures separately according to their value, momentum, and heterogeneous volatility. Three scores (range from the highest score of N to the lowest score of 1) are assigned to each of the N commodities based on the results of the previous step. Then they build the long-short strategy based on the comprehensive score (sum of the three scores in the previous step) of each commodity futures which can yield more than individual strategies. Bianchi et al. (2015) studied the momentum and reversal strategies in the commodity futures market and believed that the combination of them can achieve higher returns. Fernandez-Perez et al. (2019) used a variety of styles to detect profitability of the equity index futures, interest rate futures, currency futures, fixed income futures and commodity futures in the portfolio investment. They confirmed that the style-integration method's performance is better than that of independent investment style. Inspired by the above research, two approaches will be used when this paper analyze the role of commodity futures in portfolio investment. The one approach is based on the commodity futures themselves. The other one is based on commodity trading strategies.

It is worth noting that, according to the inventory theory and hedging pressure theory, the link between commodity spot price and futures price is not a simple linear relationship which is in terms of interest changes, warehousing costs, and convenience yields or in terms of speculators' hedging pressure (Fama and French, 1987; Basu and Miffre, 2013). The inventory theory and hedging pressure hypothesis explain the link between commodity spot and futures price from different perspectives. According to the inventory theory, the price difference between the two is because the futures contracts have a unique component embedded in them – the convenience yield, which is obtained by the physical holders of commodities, and the convenience yield is negatively correlated with the inventory level. The hedging pressure hypothesis discusses this difference from the perspective of risk premium. Scholars believe that the difference is due to the demand of commodity futures short holders to transfer the price risk. And speculators get a positive risk premium for accepting the price risk that the hedgers are trying to transfer. The trading behavior of market participants will have an impact on inventory levels and hedging pressure, and then change the relationship between commodity spot prices and futures prices, which will release new trading signals to market participants. Furthermore, both the adjustment of commodity inventories and the changes in market hedging pressure will take time. In addition, since the efficient market hypothesis was put forward, scholars have conducted extensive discussions on the informational efficiency of various assets, and believe that it is closely related to whether asset prices can accurately and quickly reflect current market information (Fama, 1970; Kim et al., 2011; Charles et al., 2012; Ortiz-Cruz et al., 2012; Bai et al., 2016; Rösch et al., 2017). Moreover, the information efficiency of the commodity futures market has also been discussed in the existing literature. It can be seen that in different periods, with different investor structures and different types of commodity futures, the information efficiency is different (Kristoufek and Vosvrda, 2013; Chen and Chang, 2015; Fernandez, 2017). This means that commodity futures market information is not always timely and quickly reflected on prices. Therefore, we should not only focus on the corresponding period relationship between commodity spot price and futures price, but also pay attention to their historical relationship. From this point, this paper discusses whether the historical basis (HB for short hereafter) has a stable profitability in commodity trading strategy. In addition to HB strategy, this paper also makes a comparative analysis of the performance of momentum strategy and carry strategy, which are widely recognized trading strategies in commodity futures markets.

The Chinese futures market and the US futures market, the as the world's most important commodity futures trading market, there are many differences between them. In terms of the trading system, the Chinese market has strict restrictions on investors' arbitrage behavior, and there are quantitative restrictions on the trading volume of the nearby contracts. Therefore, it is meaningful to analyze and compare the role of commodity futures in trading strategy and portfolio investment in the two markets. In addition, conducting research in different markets can also ensure the robustness of results.

This study contributes to the literature in several dimensions. Firstly, we introduce a new long-short strategy in the futures markets, which is the HB strategy. Different from the existing researches, which are focused on the analysis of the effect and performance of the basis (difference between the spot price and the futures price in corresponding period) in the research of commodity futures risk premia and trading strategy (Szymanowska et al., 2014; Boons and Prado, 2019; Fernandez-Perez et al., 2019), while we analyze the commodity futures market from the perspective of historical basis which can contain more market information. Whether this trading strategy has good performance in both the Chinese and the US futures market will be tested. Secondly, we compare the role of commodity futures in portfolio construction with different method. Specifically, we still treat stocks, bonds and currency as independent assets to participate in the portfolio, while commodity futures are based on the three trading strategies (the MOM, Carry and HB strategies) when they participate in portfolio construction. Thirdly, we highlight the role of energy futures in commodities strategies and portfolio investment. We analyze whether the energy commodity futures will affect the return and the downside risk of commodity trading strategies and portfolios. In addition, in order to make a better comparative study of the Chinese market and the U.S. market, we chose the same commodity futures in the two markets, which can be divided into three sectors - energy, metal and agricultural futures. Except for the energy futures, all other commodity futures types can be matched one-to-one.

The rest of the paper proceeds as follows. Section 2 presents the methodology are used in this paper. Section 3 outlines the data. Section 4 discusses the main results. Robustness checks in Section 5. Section 6 is the concludes.

2. Methodology

2.1. The strategies

At each month t, futures contracts are sorted separately based on their MOM value, Carry value and HB value. At each month $t + 1$, the

MOM strategy is formed by taking long positions in three commodity futures with highest MOM value in month t while taking short positions in three commodity futures with lowest MOM value in month t. The Carry/HB strategy is formed by taking short positions in three commodity futures with highest Carry/HB value in month t while taking long positions in three commodity futures with lowest Carry/HB value in month t. The futures contracts in each strategy are equally weighted. We calculate the returns as each strategy's gains in month $t+1$. In order to analyze the performance of energy commodity futures in the commodity trading strategies, we analyze the trading strategies including all commodity futures (Strategy I) and the trading strategies including non-energy commodity futures (Strategy II).

The MOM value can be obtained as follows (Asness et al., 2013; Szymanowska et al., 2014)

$$MOM_t^i = \sum\nolimits_{t-11}^{t} \left(R_t^i + 1\right) \tag{1}$$

where MOM_t^i is the momentum of future contract i at time t, R_t^i is the future contract's monthly excess return at time t.

Carry can be defined as the difference between the logarithmic front- and second- nearest futures prices as follows (Fernandez-Perez et al., 2019)

$$Carry_t = ln\left(F_t^i\right) - ln\left(F_t^j\right) \tag{2}$$

where i and j denote the corresponding contract maturity. F_t^i is price of the futures contract i at time t, and F_t^j is price of the futures contract j at time t.

The HB value can be obtained as follows

$$HB_t^i = \sum\nolimits_{t-5}^{t} Basis_t^i \tag{3}$$

where HB_t^i is the HB of future contract i at time t, $Basis_t^i$ is the future contract i's basis at time t. Basis is the contemporaneous difference between future's price and the spot price of their underlying products.

2.2. Portfolio construction methods

For different portfolio construction methods, which are commonly employed by asset managers and analyzed in the literature, we evaluate the returns as yields when commodity futures contracts added to stock-bond-currency portfolios. The five common portfolio construction methods will used in this paper, which is equally-weighted method (EW for short), mean-variance method (MV for short), conditional value-at-risk optimization method (CVaR for short), risk-parity method (RP for short) and mean-absolute deviation method (MAD for short). The MV method (Markowitz, 1952) is a trade-off between portfolio return and portfolio risk, where portfolio risk is represented by variance. For the CVaR method and the MAD method, which is replace the variance in the MV model with conditional value-at-risk value and mean absolute deviation as the risk measurement method of the portfolio, respectively (Konno and Yamazaki, 1991; Rockafellar and Uryasev, 2002). As for the risk parity method, each component of the portfolio contributes equally to the risk of the portfolio (Bessler and Wolff, 2015).

We add commodity futures contracts into portfolio by two approaches. The one is based on commodity futures contracts themselves (Portfolio A), and the other one is through the three trading strategies (Portfolio B). In Portfolio A, stock, bond, currency and commodity futures are weighted according to the portfolio construction method. In Portfolio B, stock, bond, currency and commodity trading strategies are weighted, which means that commodity futures are selected based on trading strategies before portfolio construction, as shown in Eq. (4) and Eq. (5). Further, in order to analyze the performance of energy commodity futures in the portfolio, based on the Portfolio A and Portfolio B, we further analyze the portfolio construction including all commodity futures (Portfolio A1 and Portfolio B1) and the portfolio construction including non-energy commodity futures (Portfolio A2 and Portfolio B2).

Table 1
Description of commodities futures used.

	Asset	Code
Panel A. The Chinese market		
Energy	Fuel oil	FU.SHF
	Thermal coal	ZC.CZC
	Coke	J.DCE
	Coking coal	JM.DCE
Metals	Gold	AU.SHF
	Silver	AG.SHF
	Copper	CU.SHF
Agriculture	Soya-bean oil	Y.DCE
	Corn	C.DCE
	Soya-bean	A.DCE
	Soybean meal	M.DCE
	Cotton	CF.CZC
	Sugar	SR.CZC
Panel B. The US market		
Energy	Fuel oil	CL.NYM
	Thermal coal	NG.NYM
Metals	Gold	GC.CMX
	Silver	SI.CMX
	Copper	HG.CMX
Agriculture	Soya-bean oil	BO.CBT
	Corn	C.CBT
	Soya-bean	S.CBT
	Soybean meal	SM.CBT
	Cotton	CT.NYB
	Sugar	SB.NYB

Notes: This table lists all commodity futures included in the sample sorted by sector information.

$$\Psi = \begin{pmatrix} \psi_1 \\ \vdots \\ \psi_N \end{pmatrix} = \begin{pmatrix} \tau_{1,MOM} & \tau_{1,Carry} & \tau_{1,HB} \\ \tau_{2,MOM} & \tau_{2,Carry} & \tau_{2,HB} \\ \vdots & \vdots & \vdots \\ \tau_{N,MOM} & \tau_{N,Carry} & \tau_{N,HB} \end{pmatrix} \begin{pmatrix} \lambda_{MOM} \\ \lambda_{Carry} \\ \lambda_{HB} \end{pmatrix} \tag{4}$$

$$\lambda_{Stock} + \lambda_{Bond} + \lambda_{Currency} + \lambda_{MOM} + \lambda_{Carry} + \lambda_{HB} \equiv 1 \tag{5}$$

where, ψ_i is the weights of commodity futures i in the portfolio, λ is the weights of assets or trading strategies calculated by various portfolio construction methods. $\tau_{i,j}$ has three values of 0,1 and -1, represent the operations of commodity futures i in various trading strategies, which are not hold, taking long or short position.

3. Data

In the U.S. markets, stocks are represented by the S&P 500 index, bonds by the Barclays US aggregate government bond index and currency by the US Dollar Index.[3] In the Chinese markets, stocks, bonds and currency are represented by the Shanghai composite index, the Chinese government bond index[4] and dollar/RMB exchange rate, respectively.

In the choice of commodity futures, this paper tries to use the futures that can be matched one-to-one in the Chinese and the US markets. Specifically, commodity futures on the US markets include energy (NYMEX crude oil and natural gas), metals (COMEX gold, silver and

[3] The Barclays US Aggregate Bond Index is a broad benchmark index for the U.S. bond market. The index covers all major types of bonds in the U.S. market, including taxable corporate bonds, Treasury bonds, and municipal bonds. The US Dollar Index is used to measure the value of the dollar against a basket of six world currencies - Euro, Swiss Franc, Japanese Yen, Canadian dollar, British pound, and Swedish Krona.

[4] The Chinese government bond index takes all fixed rate treasury bonds listed on Shanghai Stock Exchange as samples and weighted according to the issuance of treasury bonds.

Table 2
Descriptive statistics for commodities futures and capital market index's returns.

	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
Panel A. The Chinese futures market							
Market	−0.5277%	−0.6332%	8.8821%	−7.4858%	3.4342%	0.4314	3.3063
Energy	−0.2409%	1.1128%	24.0981%	−19.3806%	7.4489%	−0.0078	3.4771
Mental	−0.5555%	−0.0162%	9.6740%	−17.8187%	4.3706%	−0.7110	5.3565
Agriculture	−0.5263%	−0.6769%	8.2003%	−8.5404%	3.4474%	0.1122	2.5252
Panel B. The US futures market							
Market	−0.5923%	−0.3223%	10.1103%	−17.0910%	4.4291%	−0.4592	4.2513
Energy	0.6296%	1.0575%	19.4742%	−32.3580%	7.4836%	−0.8979	6.5668
Mental	−0.6383%	−0.7331%	12.1166%	−25.3372%	5.4488%	−0.7137	5.5643
Agriculture	−0.9681%	−0.7216%	11.2218%	−17.7368%	5.7676%	−0.4492	3.2794
Panel C. The capital market							
Chinese stock	−0.9831%	−0.9507%	17.7075%	−26.6819%	6.3035%	−0.2501	5.4091
Chinese bond	−0.6901%	−0.6914%	−0.0501%	−1.3604%	0.2269%	−0.1889	3.9667
Chinese currency	−0.9830%	−1.0693%	2.7023%	−4.4368%	1.0278%	0.6728	5.7641
US stock	−0.0744%	0.4686%	9.2324%	−10.6256%	3.5810%	−0.5027	3.6495
US bond	−0.9136%	−0.9441%	2.1190%	−3.8716%	1.0037%	−0.0273	3.5990
US currency	−0.8375%	−0.8098%	5.0966%	−6.3467%	2.1259%	0.2165	3.4842

Notes: The return for each series is calculated as $R_t = ln\ (P_t/P_{t-1}) - 1$, and P_t is the close price of each series. Summary statistics (monthly mean, median, maximum, minimum, standard deviation, skewness and kurtosis) of the returns are reported. Data obtained from Wind database.

Table 3
Monthly performance of Strategy I.

	MOM	Carry	HB
Panel A. The Chinese market			
Mean	3.4572%	12.906%	7.6945%
Median	4.0908%	11.7769%	7.1199%
Maximum	19.8689%	50.6828%	36.6245%
Minimum	−18.1362%	−1.0328%	−10.8095%
Std.Dev	7.3477%	7.7973%	7.8331%
Sharpe ratio	0.4705	1.6552	0.9823
SR adjusted	0.4466	1.6326	0.9598
Skewness	−0.3364	1.4155	0.7839
Kurtosis	3.4614	7.591	4.8475
MDD mean	21.0085%	21.5255%	21.1415%
Panel B. The US market			
Mean	4.2701%	8.943%	6.3451%
Median	2.5559%	8.078%	5.8985%
Maximum	31.28%	33.6609%	30.7738%
Minimum	−18.2466%	−11.8336%	−8.4636%
Std.Dev	8.3103%	7.4047%	8.0271%
Sharpe ratio	0.5138	1.2077	0.7905
SR adjusted	0.4927	1.1840	0.7685
Skewness	0.8057	0.6564	0.5388
Kurtosis	4.1188	4.4043	3.212
MDD mean	23.3464%	19.8109%	22.7566%

Notes: This table reports the performance of MOM, Carry and HB strategies with total commodity futures. The performance of each strategy is calculated by its monthly excess returns. SR adjusted is the Sharpe ratio adjusted for transaction cost (17.6 basis points). We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u \in \{t-11, t-10, \ldots, t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.
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Table 4
Monthly performance of Strategy II.

	MOM	Carry	HB
Panel A. The Chinese market			
Mean	3.3759%	7.2882%	4.8082%
Median	2.9806%	6.8344%	4.8635%
Maximum	18.7512%	22.6694%	16.0990%
Minimum	−6.7868%	−3.4907%	−4.4378%
Std.Dev	4.8567%	5.0002%	4.5713%
Sharpe ratio	0.6951	1.4576	1.0518
SR adjusted	0.6589	1.4224	1.0133
Skewness	0.4394	0.4072	0.1684
Kurtosis	3.2919	3.2648	2.5064
MDD mean	14.5772%	14.6314%	13.3375%
Panel B. The US market			
Mean	3.5864%	6.7383%	5.3929%
Median	2.1192%	5.4444%	4.6644%
Maximum	27.5861%	33.6609%	30.5004%
Minimum	−12.3798%	−12.6316%	−14.1887%
Std.Dev	7.9224%	7.0422%	7.4258%
Sharpe ratio	0.4527	0.9568	0.7262
SR adjusted	0.4305	0.9319	0.7025
Skewness	1.0840	0.8378	0.5406
Kurtosis	4.3089	5.4684	4.1192
MDD mean	20.5359%	19.2185%	19.9875%

Notes: This table reports the performance of MOM, Carry and HB strategies (exclude energy). The performance of each strategy is calculated by its monthly excess returns. SR adjusted is the Sharpe ratio adjusted for transaction cost (17.6 basis points). We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u \in \{t-11, t-10, \ldots, t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

copper) and agriculture (CBOT soya-bean oil, corn, soya-bean and soybean meal; ICE cotton and sugar). Correspondingly, the Chinese commodity futures are energy (SHF fuel oil; CZC thermal coal; DCE coke and coking coal),[5] metals (SHF gold, silver and copper) and agriculture (DCE soya-bean oil, corn, soya-bean and soybean meal; CZC cotton and sugar). Table 1 lists the commodity futures included in this study by sector. This paper employs continuous commodity futures price series and take the nearest-to-maturity contract as the spot contract, the second nearest-to-maturity contract as the futures contract, same as relevant research (Marshall et al., 2008; Bianchi et al., 2015). Based on the availability of data and in order to ensure that there are enough types of commodity futures to participate in the construction of trading strategy at the beginning of the sample period, the monthly sample data started in January 2010. And the sample ended in December 2019.

Table 2 presents the summary statistics for each market's return. The commodity futures' returns are list by sector. The futures market returns and the returns of various sectors are calculated by the monthly return of the included futures in equally weight. The average return of energy futures is higher than that of metals and agricultural futures, especially

[5] The listing time of the China's crude oil futures is relatively short which was went public on March 26, 2018. On the one hand, it does not meet the requirement of sample length, on the other hand, it is not mature. Therefore, it was not taken into account in our empirical analysis.

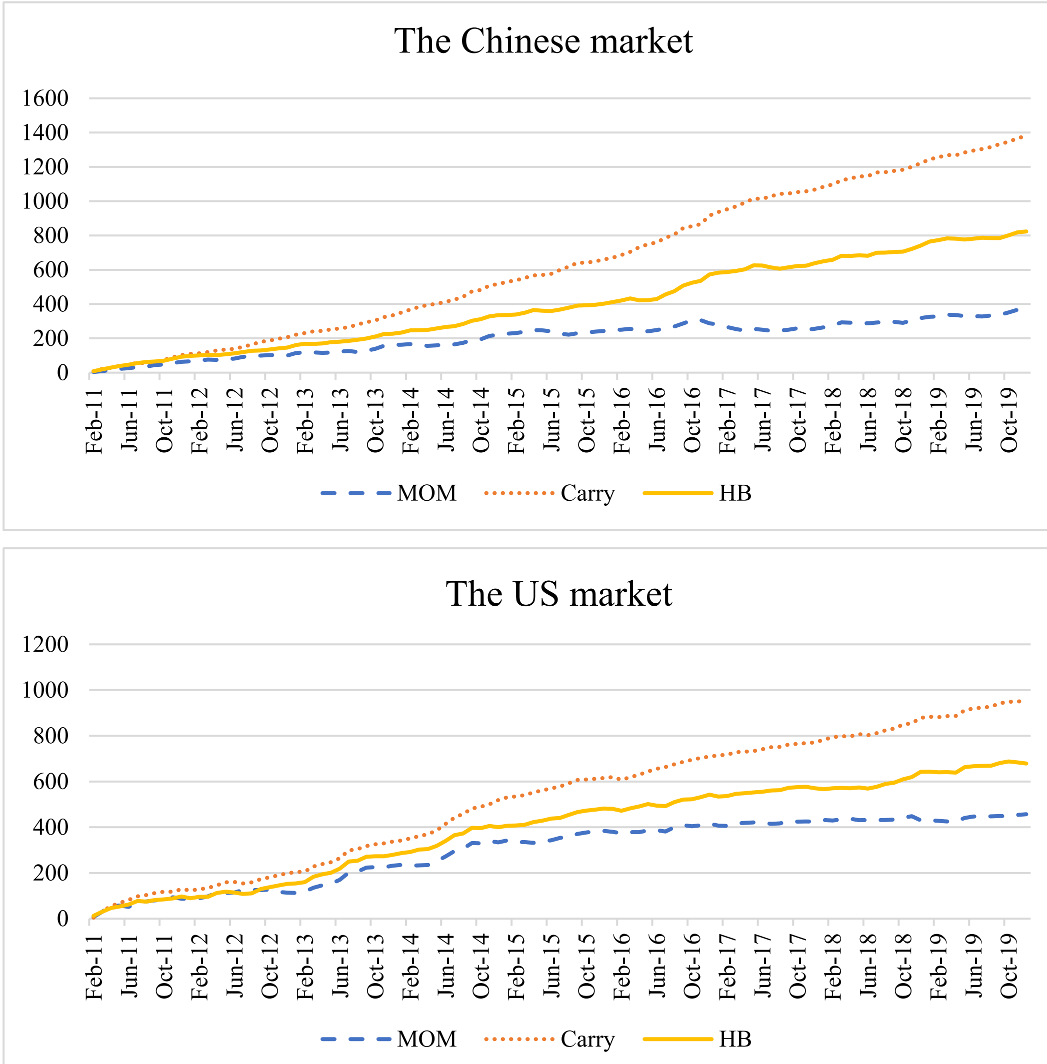

Fig. 1. Cumulative monthly returns (%).

the U.S. market. Moreover, the standard deviation of the energy commodity futures' return is significantly higher than that of other kinds of futures.

4. Results

We compute all strategies and portfolios with monthly rebalancing.

4.1. Benefits of strategies in commodity futures market

Table 3 and Table 4 are report the performance of the Strategy I and the Strategy II. Fig. 1 shows the monthly cumulative returns of the Strategy I. In addition, the performance of long-only strategies and short-only strategies are listed in Appendix A and Appendix B.

First of all, in terms of the performance of each trading strategy, whether energy futures are included or not, the Carry strategy is the best followed by the HB strategy in both markets. Compared with the other two trading strategies, the MOM strategy's performance is not good. And the results can also be intuitively seen in the Fig. 1. In addition, the HB strategy has a good performance in both markets (Strategy I & Strategy II). On the one hand, this reflects the applicability of this trading strategy in the commodity futures market. On the other hand, it shows that commodity futures market information is not always timely and quickly reflected on prices, which means that the imperfection of the commodity futures market makes trading strategy based on commodity futures' historical basis profitable.

Secondly, comparing the performance of Strategy II, the performance of Strategy I are better in the all markets. In other words, energy futures can enhance the performance of trading strategies. This conclusion is consistent with the results of Table 2, the return of energy commodity futures is higher than other types of commodity futures. In addition, the MDD value of each strategy has been reduced, after excluding energy futures.

In order to be able to better understand about the HB strategy, Table 5 shows the different sectors' HB values (equal weighted in the same sector). Compared with metal and agricultural futures, whether in the Chinese market or the US market, energy futures have the lowest HB, which means that the difference between its futures prices and spot prices is the most significant from a historical perspective. In addition, in

[2] Marshall et al. (2012) estimate, depending on different dollar value trade size buckets, half spreads between 3.1 and 4.4 basis points. According to Yang et al. (2018), the transaction costs in the Chinese futures market is from 0.3%% to 1.7%%. Sakkas and Tessaromatis (2020) assume the half-spread is 4.4 basis points, and the monthly transaction costs for long-short commodity strategy is $2 \times 4.4 \times 2 = 17.6$ basis points. In this paper, we follow set the transaction costs as 17.6 basis points for long-short commodity strategy.

Table 5
Descriptive statistics for HB.

	Energy	Mental	Agriculture
Panel A. The Chinese futures market			
Mean	−6.5281%	−2.4137%	−2.7839%
Median	−12.0339%	−3.1398%	−4.9703%
Maximum	60.8837%	8.0786%	14.4987%
Minimum	−38.7884%	−9.0118%	−18.3885%
Std.Dev	19.3898%	3.7468%	9.9187%
Skewness	1.0362	1.0343	−0.0126
Kurtosis	4.0141	3.6478	1.6072
Panel B. The US futures market			
Mean	−11.7842%	−1.5560%	−0.3387%
Median	−11.7447%	−1.2538%	−3.5259%
Maximum	11.1037%	1.0869%	31.7575%
Minimum	−37.9624%	−4.5159%	−19.4235%
Std.Dev	11.5090%	1.5066%	12.7995%
Skewness	−0.1656	−0.2670	0.6337
Kurtosis	2.7045	2.0318	2.6610

Notes: This table reports the summary statistics of commodity futures' HB value (logarithmic and dimensionless) and sorted by sector information.

Table 6
Correlations of traditional asset classes.

	Stock	Bond	Currency
Panel A. The Chinese market			
Stock	1.0000 –		
Bond	−0.0456 (0.6222)	1.0000 –	
Currency	−0.2077* (0.0234)	0.1577 (0.0868)	1.0000 –
Panel B. The US market			
Stock	1.0000 –		
Bond	−0.1803* (0.0497)	1.0000 –	
Currency	−0.4449* (0.0000)	0.0115 (0.9010)	1.0000 –

Notes: This table reports the Pearson correlations and *p*-values (in parentheses). * Denotes statistical significance at the 5% level or better.

Table 7
Correlations of Strategy I with traditional asset classes.

	MOM	Carry	HB
Panel A. The Chinese market			
Chinese stock	0.1611 (0.0974)	0.0090 (0.9266)	0.0703 (0.4719)
Chinese bond	0.3351* (0.0004)	−0.0268 (0.7840)	0.0478 (0.6246)
Chinese currency	−0.0832 (0.3940)	0.1174 (0.2283)	0.0612 (0.5310)
Panel B. The US market			
US stock	0.0374 (0.7023)	−0.2130* (0.0276)	−0.1978* (0.0411)
US bond	−0.0265 (0.7865)	−0.0067 (0.9454)	−0.0998 (0.3063)
US currency	0.0105 (0.9149)	−0.0167 (0.8642)	−0.0060 (0.9514)

Notes: This table reports the Pearson correlations and p-values (in parentheses). * Denotes statistical significance at the 5% level or better.

order to further verify the applicability of the trading strategy, the results of the sub-sample analysis are listed in Appendix C and the descriptive statistics of the trading strategy with different holding periods are listed in Appendix D and Appendix E. It can be seen that the profitability of HB strategy is robust. Appendix F and Appendix G show the frequency of each commodity futures in trading strategies. The results of Strategy I show that J.DCE, C.DCE and SR.CZ appear more frequently in the Chinese market, while the U.S. market is concentrated in NG.NYM, C.CBT and SB.NYB. The results of Strategy II show that C. DCE and SR.CZ appear more frequently in the Chinese market, while the U.S. market is concentrated in C.CBT and SB.NYB. In general, among non-energy futures, corn and sugar appear frequently in both markets.

Table 8
Correlations of Strategy II with traditional asset classes.

	MOM	Carry	HB
Panel A. The Chinese market			
Chinese stock	0.0118 (0.9044)	−0.0402 (0.6807)	0.0230 (0.8143)
Chinese bond	0.1651 (0.0893)	0.1956* (0.0435)	0.0888 (0.3629)
Chinese currency	−0.2807* (0.0034)	−0.0887 (0.3634)	−0.3011* (0.0016)
Panel B. The US market			
US stock	−0.0830 (0.3953)	−0.0426 (0.6632)	−0.0381 (0.6966)
US bond	−0.0123 (0.8998)	−0.1694 (0.0812)	−0.1815 (0.0613)
US currency	−0.0728 (0.4560)	0.0271 (0.7818)	−0.0168 (0.8633)

Notes: This table reports the Pearson correlations and p-values (in parentheses). * Denotes statistical significance at the 5% level or better.

Table 9
Descriptive statistics for benchmark portfolio.

	The Chinese market	The US market
Return	−0.8854%	−0.6085%
Std.Dev	2.0573%	1.0713%
Downside volatility	48.9358%	32.4682%
Sharpe ratio	−2.1569	−2.7665
Sortino ratio	−0.0907	−0.0913
MDD mean	14.6089%	6.0468%

Notes: This table reports the performance of benchmark portfolio. In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The MDD value is calculated based on the previous 12 months of each benchmark portfolio's returns. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u \in \{t-11, t-10, \dots, t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

4.2. Diversification benefits

In this part, we will test the role of commodity futures in portfolio investment. In the construction of the US market's portfolio, the assets used are the S&P 500 index, the Barclays US aggregate government bond index, the US Dollar Index, and the commodity futures in the US market. In the construction of the Chinese market's portfolio, the assets used are the Shanghai composite index, the Chinese government bond index, dollar/RMB exchange rate, and the commodity futures in the Chinese market. The correlations of traditional asset classes are shown in Table 6. Table 7 and Table 8 report the correlations of each strategy with traditional asset classes, and most of the correlations are insignificant. Among them, there is a significant negative correlation between some strategies and traditional assets, such as Carry and HB strategies with the US stock in Table 7, MOM and HB strategies with the Chinese currency in Table 8. These results imply that trading strategies have the ability to diversify the traditional assets' risks. However, the MOM strategy in Table 7 and the Carry strategy in Table 8 are positively correlated with the Chinese bond.

For the convenience of comparative analysis, this paper takes the equally weighted portfolio of stocks, bonds and currency as the benchmark portfolio, and the descriptive statistics of its returns are listed in

Table 10
Monthly performance of Portfolio A1.

	EW	MV	CVaR	Risk Parity	MAD
Panel A. The Chinese market					
Return	−0.7250%	0.9851%	1.5363%	−0.0425%	1.0955%
Std.Dev	2.8771%	4.4186%	5.0697%	1.3516%	3.7405%
Downside volatility	47.2665%	36.3542%	37.3498%	46.1233%	36.4745%
Sharpe ratio	−1.5497	−0.5810	−0.4803	−3.1117	−0.7498
Sortino ratio	−0.0883	−0.0706	−0.0652	−0.0912	−0.0769
MDD mean	4.7374%	7.9993%	9.5440%	0.2528%	6.5767%
Panel B. The US market					
Return	−0.5989%	1.1478%	1.1042%	−0.0451%	1.2645%
Std.Dev	3.4516%	7.3816%	5.9673%	2.5748%	6.7495%
Downside volatility	36.5073%	37.1124%	35.4744%	34.7672%	35.5341%
Sharpe ratio	−0.8522	−0.1711	−0.2763	−1.1612	−0.2090
Sortino ratio	−0.0811	−0.0340	−0.0465	−0.0860	−0.0397
MDD mean	9.2343%	20.8976%	15.7903%	0.4964%	19.5219%

Notes: This table reports the performance of portfolios based on assets (with total commodity futures). In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Table 11
Monthly performance of Portfolio B1.

	EW	MV	CVaR	Risk Parity	MAD
Panel A. The Chinese market					
Return	3.6854%	8.3165%	8.4546%	0.1399%	8.3980%
Std.Dev	3.5409%	6.6525%	6.7024%	1.4225%	6.7667%
Downside volatility	13.6927%	5.3405%	5.3427%	29.0445%	5.3819%
Sharpe ratio	0.0360	0.7152	0.7185	−1.9114	0.7214
Sortino ratio	0.0093	0.8909	0.9014	−0.0936	0.9070
MDD mean	9.7606%	18.6536%	18.7741%	0.6604%	18.9141%
Panel B. The US market					
Return	3.1015%	4.9375%	4.2316%	0.1271%	6.3010%
Std.Dev	3.3670%	4.8073%	4.4106%	1.3780%	6.8019%
Downside volatility	8.6893%	5.6661%	8.1845%	17.0714%	5.7334%
Sharpe ratio	0.2438	0.5526	0.4206	−1.1018	0.6713
Sortino ratio	0.0945	0.4688	0.2267	−0.0889	0.7965
MDD mean	8.9594%	12.4289%	11.6688%	0.5947%	18.1133%

Notes: This table reports the performance of portfolios based on MOM, Carry and HB strategies (with total commodity futures). In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Table 9.

Both Tables 10 and 12 are returns of Portfolio A1 and Portfolio A2 which are constructed based on the commodity futures themselves, while Tables 11 and 13 are returns of Portfolio B1 and Portfolio B2 which are based on the trading strategies. Among them, Table 10 and Table 11 are the results of portfolio construction including all commodity futures, while Table 12 and Table 13 are the results of portfolio construction including non-energy commodity futures.

Firstly, compared with the performance of the benchmark portfolio, whether it is the Chinese market or the US market, the profitability of each portfolio has increased significantly after include the commodity futures. That means, the diversification benefits can be obtained.

Secondly, comparing the performance of the portfolio based on commodity futures themselves with the portfolio based on the trading

Table 12
Monthly performance of Portfolio A2.

	EW	MV	CVaR	Risk Parity	MAD
Panel A. The Chinese market					
Return	−0.6178%	1.0087%	0.7135%	−0.0563%	0.8917%
Std.Dev	2.3716%	4.4951%	4.5882%	1.4597%	4.4153%
Downside volatility	46.2209%	36.3037%	38.0720%	46.2299%	36.6417%
Sharpe ratio	−1.7583	−0.5658	−0.5859	−2.8911	−0.5925
Sortino ratio	−0.0902	−0.0701	−0.0706	−0.0913	−0.0714
MDD mean	4.4355%	9.7419%	9.6712%	0.3367%	9.2988%
Panel B. The US market					
Return	−0.7954%	0.9998%	0.5118%	−0.0668%	0.8019%
Std.Dev	3.5817%	10.2559%	5.5216%	2.7753%	5.1037%
Downside volatility	38.1299%	47.2709%	38.6674%	36.4726%	36.9128%
Sharpe ratio	−0.8797	−0.1322	−0.4094	−1.1375	−0.4341
Sortino ratio	−0.0826	−0.0287	−0.0585	−0.0866	−0.0600
MDD mean	9.7682%	24.5983%	16.2315%	0.6384%	14.1130%

Notes: This table reports the performance of portfolios based on assets (exclude energy futures). In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Table 13
Monthly performance of Portfolio B2.

	EW	MV	CVaR	Risk Parity	MAD
Panel A. The Chinese market					
Return	2.3211%	5.4916%	5.6775%	0.1003%	5.1542%
Std.Dev	2.4251%	4.3902%	4.4660%	1.2101%	4.3822%
Downside volatility	18.2977%	8.6805%	8.7976%	31.0503%	8.7373%
Sharpe ratio	−0.5103	0.4403	0.4446	−2.4434	0.4349
Sortino ratio	−0.0676	0.2227	0.2257	−0.0952	0.2181
MDD mean	6.8079%	12.4742%	12.6525%	0.5319%	12.5120%
Panel B. The US market					
Return	2.5168%	5.1434%	5.0033%	0.0825%	4.1849%
Std.Dev	3.2511%	5.8798%	5.5652%	1.3432%	5.3951%
Downside volatility	10.4850%	7.1412%	7.1304%	19.5662%	7.3244%
Sharpe ratio	0.0725	0.4868	0.4633	−1.3298	0.4462
Sortino ratio	0.0225	0.4008	0.3616	−0.0913	0.3287
MDD mean	8.0508%	14.2675%	13.4404%	0.5706%	13.0134%

Notes: This table reports the performance of portfolios based on MOM, Carry and HB strategies (exclude energy futures). In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Table 14
Out-of-sample performance of Portfolio B1.

	The Chinese market				The US market			
	12 months	24 months	36 months	48 months	12 months	24 months	36 months	48 months
Panel A. MV								
Return	6.2766%	6.5377%	6.5481%	6.0849%	4.2642%	4.1631%	4.1046%	3.6764%
Std.Dev	3.8508%	4.1292%	4.1988%	4.1158%	3.1441%	3.1722%	3.1961%	2.9348%
Downside volatility	7.4016%	5.8364%	5.9436%	5.6815%	6.6598%	7.0620%	6.8431%	6.3812%
Sharpe ratio	0.9961	1.0711	1.0152	0.9020	1.0111	0.9089	0.8861	0.7535
Sortino ratio	0.3724	0.5163	0.5152	0.4825	0.3068	0.2655	0.2646	0.2246
MDD mean	10.8996%	11.6292%	11.6871%	11.5498%	8.9029%	8.8400%	9.1324%	8.5414%
Panel B. CVaR								
Return	6.4822%	8.4119%	8.8892%	8.7711%	4.4813%	5.3571%	5.5322%	5.4444%
Std.Dev	1.8076%	3.8631%	4.3186%	4.6831%	2.0515%	3.7114%	4.4930%	4.8152%
Downside volatility	6.0912%	6.4366%	4.5659%	1.9915%	7.7672%	6.8052%	4.4505%	4.8358%
Sharpe ratio	1.1048	2.3090	3.8922	5.5890	0.9702	1.3927	1.7129	2.2001
Sortino ratio	0.4856	0.7593	1.1834	2.7254	0.2910	0.4510	0.7276	0.6619
MDD mean	11.9104%	17.2651%	19.1082%	19.2172%	9.6259%	12.7796%	13.8652%	14.2801%
Panel C. MAD								
Return	6.3385%	8.4130%	9.1014%	8.7102%	4.2575%	5.2748%	5.7365%	5.7509%
Std.Dev	3.0875%	4.8797%	5.3802%	5.3473%	2.4913%	3.4706%	3.9982%	4.1728%
Downside volatility	7.5984%	6.6633%	5.0851%	2.4413%	6.9507%	6.6772%	5.2466%	5.3567%
Sharpe ratio	1.0261	2.2673	4.1040	5.1700	0.9910	1.4383	1.8350	1.9937
Sortino ratio	0.3710	0.7337	1.1042	2.1983	0.2930	0.4473	0.6562	0.6548
MDD mean	11.2098%	16.8555%	19.2442%	18.9468%	9.0536%	12.5065%	14.0985%	14.4859%
Panel D. Risk Parity								
Return	0.1674%	0.1440%	0.1385%	0.1486%	0.1302%	0.1230%	0.1267%	0.1312%
Std.Dev	0.6394%	0.6382%	0.6318%	0.6641%	0.5280%	0.5719%	0.6095%	0.6272%
Downside volatility	2.0181%	1.6747%	1.6505%	1.0936%	1.9386%	1.8199%	1.6685%	1.4779%
Sharpe ratio	−18.2498	−33.9006	−42.5202	−87.7518	−20.0025	−25.1884	−29.2406	−40.4043
Sortino ratio	−1.6613	−2.0184	−2.0282	−2.9215	−1.0786	−1.1898	−1.2988	−1.4292
MDD mean	0.2160%	0.2221%	0.2245%	0.2388%	0.1827%	0.2099%	0.2214%	0.2347%

Notes: This table reports the performance of portfolios based on MOM, Carry and HB strategies (with total commodity futures), which are adjusted monthly. In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u \in \{t-11, t-10, \dots, t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

strategies, it can be seen that the latter has better performance in both markets, whether the energy futures are included or not. This means that the portfolio construction method based on the commodity futures trading strategy can obtain more diversification benefits than the former.

Thirdly, the portfolios which include energy futures have better profitability in both markets. That is, when energy futures participate in portfolio construction, it will improve the diversification benefits. In the portfolio based on strategies, the downside risk of the portfolio return decreases after energy is excluded (MDD values are decrease). But in the portfolio based on commodity futures themselves, the situation becomes the opposite.

In the study of Bessler and Wolff's (2015), analyzed the in-sample and out-of-sample portfolio effects resulting from adding commodities to a stock-bond portfolio. And their empirical results suggest that the out-of-sample benefits of commodities are much lower than in-sample. In Table 14 and Table 15, we conduct out-of-sample analysis, which is based on a 12/24/36/48-month estimation window and monthly rebalancing, to test the profitability of Portfolio B1 and Portfolio B2. The results show that the profitability of portfolio construction based on trading strategy is still robust in out-of-sample test. Appendix H and Appendix I show the portfolio components' weight in portfolios. The results of MV, CVaR and MAD methods show that: (1) Among the Portfolio B1, the Carry strategy has a high weight in both markets, and the HB strategy has a high weight in the Chinese market; (2) Among the Portfolio B2, both markets are concentrated in Carry and MOM strategies. The results of RP method show that both markets are concentrated in bond and currency.

5. Robustness tests

In this section, this paper will do some tests to verify the robustness of the HB' profitability in the commodity futures trading strategy and the portfolio investment.

In the first robustness test, this article will verify whether the return of HB strategy will be explained by that of the MOM and the Carry strategies. If it cannot be fully explained, it means that the potential risks covered by the HB strategy and the other two types of trading strategies are different. The following regression can be used:

$$R_t^{HB} = \alpha + \beta_1 R_t^{MOM} + \beta_2 R_t^{Carry} + \varepsilon_t \tag{6}$$

where, R_t^{MOM}, R_t^{MOM} and R_t^{Carry} are the returns of the HB, MOM and Carry strategies at time t, respectively. The α is the intercept of regression and ε_t is the residual term.

Table 16 shows the regression results. It can be seen that the value of the intercept in each equation is significantly different from zero. In other words, the returns obtained based on the HB strategy cannot be fully explained by the returns obtained based on the MOM and the Carry strategies. Therefore, the HB strategy can be used as an independent trading strategy in the commodity futures market, same as the MOM and Carry strategies.

The second robustness test is the White (2000) Reality Check (RC). The passive long-only benchmark which is equally weights all commodities over the sample period (Table 17). The test results of data snooping test show that the performance of trading strategy is not due to luck or random noise in the data (Table 18).

In the third robustness test, this article will change the calculation method of HB from 6-months accumulated values to 12-months, and

Table 15
Out-of-sample performance of Portfolio B2.

	The Chinese market				The US market			
	12 months	24 months	36 months	48 months	12 months	24 months	36 months	48 months
Panel A. MV								
Return	4.5900%	4.6573%	4.6086%	4.1218%	3.9159%	4.0043%	4.0005%	3.7670%
Std.Dev	8.6551%	3.2020%	3.2557%	3.0552%	3.3173%	3.3969%	3.2899%	3.1833%
Downside volatility	4.2700%	3.5768%	3.3589%	3.6607%	3.3237%	2.8873%	1.7388%	1.7630%
Sharpe ratio	0.5265	0.5326	0.4933	0.3680	1.0931	1.0723	1.2389	1.1335
Sortino ratio	0.2506	0.3167	0.3342	0.2126	0.5099	0.5944	0.9815	0.8642
MDD mean	3.0580%	8.9903%	9.0554%	8.7240%	9.2770%	9.3273%	9.4085%	9.1078%
Panel B. CVaR								
Return	5.6454%	5.3137%	5.6504%	5.7443%	4.0876%	4.6118%	4.6202%	5.0919%
Std.Dev	1.2065%	2.8824%	3.2865%	3.7532%	2.8120%	3.6114%	4.3636%	5.2710%
Downside volatility	4.8749%	1.8559%	1.5139%	0.8952%	3.7172%	1.8691%	1.5172%	0.9379%
Sharpe ratio	1.5420	1.3627	2.2542	3.5203	1.0612	1.4828	1.6923	2.3258
Sortino ratio	0.4750	0.9641	1.4296	2.6819	0.5021	1.2431	1.5333	3.0370
MDD mean	9.6173%	11.7777%	12.8043%	13.4559%	9.8027%	11.5646%	11.9264%	13.7443%
Panel C. MAD								
Return	4.5814%	5.3636%	5.7966%	5.8433%	3.9755%	4.5944%	5.0511%	5.3286%
Std.Dev	2.4298%	3.3072%	3.6273%	3.7739%	2.6799%	3.4247%	3.8318%	4.0831%
Downside volatility	4.5016%	2.0987%	1.3026%	0.4082%	3.3693%	2.1813%	0.6241%	0.8549%
Sharpe ratio	0.5167	1.3881	2.2685	3.6797	1.1280	1.5303	1.8345	2.1669
Sortino ratio	0.2358	0.8764	1.7737	6.1234	0.5207	1.0572	4.4177	3.6090
MDD mean	8.7538%	11.7883%	12.9068%	13.3460%	9.6197%	11.6806%	12.9506%	13.6981%
Panel D. Risk Parity								
Return	0.1395%	0.1196%	0.1018%	0.1234%	0.1087%	0.0905%	0.0882%	0.0933%
Std.Dev	0.5823%	0.5760%	0.5368%	0.5867%	0.5461%	0.5547%	0.5510%	0.5641%
Downside volatility	2.1580%	2.1478%	1.9996%	0.8849%	1.5755%	1.7456%	1.5995%	1.1852%
Sharpe ratio	−21.8178	−37.1429	−46.0408	−95.9836	−18.5228	−27.2790	−35.1970	−54.7652
Sortino ratio	−1.5665	−1.5852	−1.6926	−3.6390	−1.3408	−1.2591	−1.3789	−1.8140
MDD mean	0.2018%	0.2088%	0.2009%	0.2216%	0.2004%	0.2057%	0.2068%	0.2202%

Notes: This table reports the monthly performance of portfolios based on MOM, Carry and HB strategies (exclude energy), which are adjusted monthly. In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Table 16
Time series regressions of trading strategies.

			The Chinese market	The US market
α			−1.7963*	−1.1545*
			(−1.8716)	(−1.6656)
β1			0.4682***	0.2450***
			(7.0299)	(3.9181)
β2			0.6100***	0.7216***
			(9.7199)	(10.2821)
Adjusted R-squared			0.5881	0.6801
Residuals' diagnostic	LM Test:	F-statistic	1.0509	0.4228
		P-value	0.3923	0.8318
	ARCH Test:	F-statistic	0.6501	0.4821
		P-value	0.6621	0.7889

Notes: This table reports the regression results of HB strategy's returns on carry strategy and MOM strategy's returns. Below each coefficient the corresponding t-statistic is reported in parentheses, and ***, **, and * are represent significant at the 1%, 5%, and 10%, respectively.

verify its performance in the trading strategy and portfolio investment. In this case, the calculation of HB* can be expressed as follows:

$$HB_t^* = \sum\nolimits_{t-11}^{t} Basis_t \tag{7}$$

Table 19 shows the performance of HB* strategy. It can be seen that HB* strategy can obtain significant returns, and its performance is better than of the MOM strategy which is same as the HB strategy. Table 20 shows the results of portfolio construction based on the MOM, the Carry and the HB* strategies. Compared with the performance of benchmark portfolio, Sharpe ratios have increased significantly, and MAD/CVaR method performs better than other methods. The empirical results in this part are consistent with those in Section 4.

Table 17
Performance of passive long benchmark.

	The Chinese market	The US market
Mean	−0.5277%	−0.5923%
Median	−0.6332%	−0.3223%
Maximum	8.8821%	10.1103%
Minimum	−7.4858%	−17.0910%
Std.Dev	3.4342%	4.4291%
Sharpe ratio	−0.1537	−0.1337
Skewness	0.4314	−0.4592
Kurtosis	3.3063	4.2513
MDD mean	9.2220%	11.7674%

In short, the profitability of trading strategy and portfolio investment based on the historical basis are robust.

6. Conclusion

This paper studies the profitability of some trading strategies in the commodity futures markets in the Chinese and the US market, as well as the diversification benefits of commodity futures in stock-bond-currency portfolios.

Firstly, this paper proposes a new commodity futures trading strategy - HB trading strategy, which is based on the historical basis of the commodity futures. The results show that HB strategy is applicable and

Table 18
Data-snooping test for strategy superiority versus passive long benchmark.

Bootstrap dependence	Reality Check Consistent *p*-values		
	MOM	Carry	HB
Panel A: The Chinese market			
q = 0.05	0.0000	0.0000	0.0000
q = 0.10	0.0000	0.0000	0.0000
q = 0.15	0.0000	0.0000	0.0000
Panel B: The US market			
q = 0.05	0.0000	0.0000	0.0000
q = 0.10	0.0000	0.0000	0.0000
q = 0.15	0.0000	0.0000	0.0000

Notes: This table reports the result of data-snooping test. The p-values for superior performance. The parameter q is the geometric distribution that determines the block-length in the bootstrap samples, where the expected block length is given by 1/q.

Table 19
Monthly performance of HB* strategy.

	The Chinese market	The US market
Mean	6.1233%	6.3092%
Median	5.9823%	4.4855%
Maximum	36.6245%	30.7738%
Minimum	−14.4023%	−8.7116%
Std.Dev	7.4730%	7.5833%
Sharpe ratio	0.8194	0.8320
SR adjusted	0.7958	0.8088
Skewness	0.6151	0.7735
Kurtosis	5.0189	3.5501
MDD mean	21.1415%	21.5681%

Notes: This table reports the performance of HB* strategy with total commodity futures. The performance of each strategy is calculated by its monthly excess returns. SR adjusted is the Sharpe ratio adjusted for transaction cost (17.6 basis points). We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Table 20
Monthly performance of portfolio based on MOM, Carry and HB* strategies.

	EW	MV	CVaR	Risk Parity	MAD
Panel A. The Chinese market					
Return	3.2966%	8.0437%	8.0761%	0.1215%	8.9887%
Std.Dev	3.5152%	6.5315%	6.7073%	1.4190%	6.6808%
Downside volatility	16.0960%	5.8407%	6.1012%	30.0783%	6.0662%
Sharpe ratio	−0.0744	0.6867	0.6934	−1.9942	0.6930
Sortino ratio	−0.0162	0.7679	0.7622	−0.0941	0.7632
MDD mean	9.4766%	18.4081%	18.8637%	0.6365%	18.7920%
Panel B. The US market					
Return	3.0370%	4.9461%	3.7994%	0.1262%	3.7209%
Std.Dev	3.2962%	4.8150%	3.6338%	1.3759%	3.8922%
Downside volatility	16.6151%	5.6737%	7.1844%	17.0736%	6.5482%
Sharpe ratio	−0.1581	0.5535	0.3687	−1.1075	0.4264
Sortino ratio	−0.0314	0.4697	0.1865	−0.0892	0.2535
MDD mean	8.6792%	12.4378%	9.1539%	0.5877%	9.9137%

Notes: This table reports the performance of portfolios based on MOM, Carry and HB* strategies (with all commodity futures). In the calculation of the Sharpe ratios and the Sortino ratios, the China's 10-year Treasury bond monthly yield and the U.S. 10-year Treasury bond monthly yield are used as the risk-free interest rates for the Chinese market and the U.S. market, respectively. The result of MV method is the maximum Sharpe ratio point on the effective front. The result of the CVaR/MAD method is the optimal risk/return ratio on the effective front. We define the drawdowns D_t as the percentage drop in each portfolio's monthly returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

robust in commodity futures market. Secondly, when discussing the diversification benefits of commodity futures, this paper uses five common portfolio construction methods, and comparatively analyzes the profitability of portfolio investment based on the commodity futures themselves and based on the commodity futures trading strategies. We confirm that the commodity futures can achieve diversification benefits, and the performance of portfolio investment based on trading strategies is better. Thirdly, this paper empirically analyzes the role of energy futures in commodity futures trading strategies and portfolio investment. The results confirm that when energy futures are taken into account, trading strategies and portfolios' profitability and downside risk will be significantly impacted. Finally, this paper comparatively analyzes the performance of the above studies in the Chinese market and the US market, confirming that although there are some differences between them, the above conclusions are applicable in both markets.

Moreover, our research has several practical implications. First of all, when investors apply commodity trading strategies, the HB strategy can be a good choice. Secondly, when the commodity futures are included in the portfolio, the portfolio construction method based on trading strategy can be considered. Finally, the use of energy futures needs to be very careful in the actual investment and risk management.

Acknowledgements

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Appendix A. Monthly performance of long/short-only Strategy I

	MOM		Carry		HB	
	Long-only	Short-only	Long-only	Short-only	Long-only	Short-only
Panel A. The Chinese market						
Mean	−2.8287%	0.6285%	5.0699%	−7.8361%	2.8073%	−4.8873%
Median	−2.9791%	0.8063%	4.3583%	−7.3741%	2.2625%	−5.1388%
Maximum	9.8750%	19.2454%	25.2634%	5.8862%	22.4528%	11.9010%
Minimum	−16.6445%	−25.4471%	−5.1994%	−31.0170%	−8.3792%	−23.5854%
Std.Dev	5.3229%	6.1052%	5.3512%	6.1057%	5.1077%	6.0856%
Sharpe ratio	−0.5314	0.1029	0.9474	−1.2834	0.5496	−0.8031
Skewness	−0.0247	−0.6015	1.2568	−0.6844	0.7014	−0.1968
Kurtosis	2.7079	5.8829	5.5643	4.1371	4.3327	4.1443
MDD mean	14.8479%	17.4591%	16.3885%	16.1623%	15.0646%	16.7532%
Panel B. The US market						
Mean	−3.2245%	1.0455%	3.4868%	−5.4562%	2.0574%	−4.2877%

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	MOM		Carry		HB	
	Long-only	Short-only	Long-only	Short-only	Long-only	Short-only
Median	−1.3342%	1.2758%	3.7422%	−4.0736%	1.5560%	−3.0975%
Maximum	11.5529%	12.0608%	16.1723%	12.0809%	16.1723%	12.8968%
Minimum	−30.0043%	−18.4798%	−11.9820%	−30.0043%	−9.7579%	−30.0043%
Std.Dev	7.6959%	5.6421%	4.8826%	7.6172%	5.1567%	7.9171%
Sharpe ratio	−0.4190	0.1853	0.7141	−0.7163	0.3990	−0.5416
Skewness	−1.0518	−0.8073	−0.1509	−0.9267	0.0200	−0.7580
Kurtosis	4.1672	4.3646	3.5258	3.7488	3.0557	3.7435
MDD mean	18.3621%	15.6653%	15.3666%	16.9809%	15.0530%	17.4168%

Notes: This table reports the performance of long-only strategies and short-only strategies with total commodity futures. The performance of each strategy is calculated by its monthly excess returns. We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u \in \{t-11, t-10, \ldots, t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Appendix B. Monthly performance of long/short-only Strategy II

	MOM		Carry		HB	
	Long-only	Short-only	Long-only	Short-only	Long-only	Short-only
Panel A. The Chinese market						
Mean	−2.5857%	0.7902%	2.7003%	−4.5879%	1.5396%	−3.2686%
Median	−1.9622%	0.4154%	2.6350%	−4.5546%	1.5411%	−2.8638%
Maximum	7.0617%	11.5069%	10.7903%	5.5167%	10.8056%	6.7272%
Minimum	−14.6537%	−8.6935%	−8.6619%	−18.1162%	−8.6619%	−16.1706%
Std.Dev	4.2418%	3.9736%	3.6716%	4.3971%	3.7637%	4.4062%
Sharpe ratio	−0.6096	0.1989	0.7354	−1.0434	0.4091	−0.7418
Skewness	−0.4203	0.1777	−0.2735	−0.2065	−0.1094	−0.2115
Kurtosis	2.9984	2.9609	3.5077	2.9749	3.0921	2.9156
MDD mean	11.0508%	10.6798%	14.5044%	11.9249%	13.5775%	12.9555%
Panel B. The US market						
Mean	−3.1977%	0.3887%	1.8937%	−4.8446%	1.3298%	−4.0631%
Median	−1.5305%	0.8423%	1.6187%	−3.5664%	1.0991%	−2.5321%
Maximum	11.5529%	10.7387%	13.2322%	12.0809%	12.1625%	12.8968%
Minimum	−30.0043%	−23.5959%	−20.8329%	−30.0043%	−21.6213%	−30.0043%
Std.Dev	7.7149%	5.4527%	5.0799%	7.5782%	4.9847%	7.6672%
Sharpe ratio	−0.4145	0.0713	0.3728	−0.6393	0.2668	−0.5299
Skewness	−0.9898	−1.1433	−0.8640	−0.9476	−0.9593	−0.8029
Kurtosis	4.1681	6.0150	5.9402	3.9403	7.2341	3.9829
MDD mean	18.5650%	13.6961%	14.5005%	13.7784%	13.7723%	13.9539%

Notes: This table reports the performance of long-only strategies and short-only strategies (exclude energy). The performance of each strategy is calculated by its monthly excess returns. We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u \in \{t-11, t-10, \ldots, t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Appendix C. Monthly performance of trading strategy in sub-samples

	The Chinese market			The US market		
	MOM	Carry	HB	MOM	Carry	HB
Panel A. Strategy I						
2010/01–2012/12	4.3290	8.9800	6.3576	4.9387	8.6290	6.6097
2013/01–2014/12	5.0687	12.9421	7.8869	9.1803	13.3492	10.3396
2015/01–2016/12	2.7830	16.6392	9.8637	3.3895	7.9155	5.9247
2017/01–2019/12	2.2753	12.9014	6.9743	1.1565	6.8911	3.7934
Panel B. Strategy II						
2010/01–2012/12	4.3051	7.3821	5.5373	4.1734	6.5803	5.2937
2013/01–2014/12	4.4380	8.7212	6.1034	8.0420	11.6876	10.4949
2015/01–2016/12	3.6649	8.6975	5.2928	1.5377	5.4127	3.5352
2017/01–2019/12	1.8816	5.3332	3.1559	1.6069	4.4233	3.2935

Notes: This table reports the average monthly excess returns of MOM, Carry and HB strategies in sub-samples.

Appendix D. Monthly performance of Strategy I with different holding period

	The Chinese market			The US market		
	MOM	Carry	HB	MOM	Carry	HB
Panel A. Holding for 3 months						
Mean	3.2224%	12.9673%	7.8610%	4.3657%	9.7900%	6.8236%
Median	5.6112%	11.6600%	5.9749%	3.2618%	9.6169%	5.8622%

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	The Chinese market			The US market		
	MOM	Carry	HB	MOM	Carry	HB
Maximum	31.4334%	46.9906%	52.4186%	32.3014%	33.6469%	32.9434%
Minimum	−25.2556%	−19.5575%	−19.0714%	−25.7048%	−17.8113%	−16.4667%
Std.Dev	10.5882%	10.5411%	11.6955%	10.8460%	10.3811%	10.4801%
Sharpe ratio	0.3043	1.2302	0.6721	0.4025	0.9431	0.6511
SR adjusted	0.2877	1.2135	0.6571	0.3863	0.9261	0.6343
Skewness	−0.2919	0.5485	1.0118	0.3958	0.0000	0.1223
Kurtosis	2.9023	4.4520	5.3845	3.1230	2.8881	2.3411
MDD mean	26.6983%	27.7501%	28.5886%	26.8691%	26.2627%	25.7783%
Panel B. Holding for 6 months						
Mean	3.1660%	12.6714%	8.0750%	5.0534%	10.7773%	9.0930%
Median	3.0646%	9.9444%	7.9761%	3.0786%	11.4946%	8.4341%
Maximum	27.1601%	53.1637%	67.4811%	37.0796%	37.7787%	48.4744%
Minimum	−29.1250%	−18.3891%	−16.1612%	−18.2314%	−15.5476%	−18.2314%
Std.Dev	10.9742%	12.8509%	12.6940%	11.7836%	10.9866%	13.0345%
Sharpe ratio	0.2885	0.9860	0.6361	0.4289	0.9810	0.6976
SR adjusted	0.2725	0.9723	0.6223	0.4139	0.9649	0.6841
Skewness	−0.1732	0.8426	1.5424	0.4940	−0.2548	0.3905
Kurtosis	2.9419	4.6710	7.9816	2.7681	2.8714	3.2032
MDD mean	25.9653%	32.0192%	28.3470%	27.8335%	27.3575%	29.4314%
Panel C. Holding for 12 months						
Mean	−1.3162%	14.4476%	10.7116%	4.8476%	16.1684%	17.1075%
Median	−1.7164%	13.1036%	8.9849%	5.1251%	15.7348%	16.9245%
Maximum	27.3566%	56.6461%	62.3840%	37.8069%	45.4457%	49.8813%
Minimum	−33.1605%	−13.4518%	−27.6174%	−34.9002%	−17.3681%	−11.3887%
Std.Dev	13.1217%	14.8274%	15.5397%	13.2604%	12.1463%	14.6195%
Sharpe ratio	−0.1003	0.9744	0.6893	0.3656	1.3311	1.1702
SR adjusted	−0.1137	0.9625	0.6780	0.3523	1.3166	1.1581
Skewness	0.0679	0.8014	0.5701	−0.0496	−0.2432	0.1621
Kurtosis	2.5505	3.7923	3.6114	3.2387	3.0926	2.4217
MDD mean	25.7276%	33.7482%	33.6841%	28.1943%	28.6054%	26.5920%

Notes: This table reports the performance of MOM, Carry and HB strategies with total commodity futures. The performance of each strategy is calculated by its monthly excess returns. SR adjusted is the Sharpe ratio adjusted for transaction cost (17.6 basis points). We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\dots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Appendix E. Monthly performance of Strategy II with different holding period

	The Chinese market			The US market		
	MOM	Carry	HB	MOM	Carry	HB
Panel A. Holding for 3 months						
Mean	3.2224%	12.9673%	7.8610%	4.3657%	9.7900%	6.8236%
Median	5.6112%	11.6600%	5.9749%	3.2618%	9.6169%	5.8622%
Maximum	31.4334%	46.9906%	52.4186%	32.3014%	33.6469%	32.9434%
Minimum	−25.2556%	−19.5575%	−19.0714%	−25.7048%	−17.8113%	−16.4667%
Std.Dev	10.5882%	10.5411%	11.6955%	10.8460%	10.3811%	10.4801%
Sharpe ratio	0.3043	1.2302	0.6721	0.4025	0.9431	0.6511
SR adjusted	0.2877	1.2135	0.6571	0.3863	0.9261	0.6343
Skewness	−0.2919	0.5485	1.0118	0.3958	0.0000	0.1223
Kurtosis	2.9023	4.4520	5.3845	3.1230	2.8881	2.3411
MDD mean	18.8247%	19.2142%	17.5430%	27.3703%	25.3456%	24.2662%
Panel B. Holding for 6 months						
Mean	3.9268%	6.3307%	5.4539%	4.4040%	8.0946%	7.6970%
Median	3.4472%	6.2346%	5.8444%	4.2345%	8.3827%	8.4678%
Maximum	30.8129%	32.2043%	21.7103%	40.2395%	31.4466%	48.7985%
Minimum	−14.2400%	−16.0505%	−14.3160%	−19.5530%	−25.9836%	−22.3134%
Std.Dev	9.0375%	8.7944%	8.4563%	11.7461%	10.6800%	13.1106%
Sharpe ratio	0.4345	0.7199	0.6449	0.3749	0.7579	0.5871
SR adjusted	0.4150	0.6998	0.6241	0.3599	0.7414	0.5737
Skewness	0.5205	0.0933	−0.1736	0.2628	−0.3247	0.3780
Kurtosis	3.2838	2.8102	2.2794	3.0991	3.2879	3.5087
MDD mean	19.7326%	22.4277%	16.6666%	27.0425%	27.2862%	29.4371%
Panel C. Holding for 12 months						
Mean	2.9049%	8.8038%	8.2710%	4.1909%	11.6107%	12.0950%
Median	2.4117%	7.3065%	9.5278%	2.8822%	11.4678%	11.8225%
Maximum	26.7474%	35.0902%	38.0924%	38.9266%	51.6364%	42.3914%
Minimum	−22.3444%	−19.1258%	−23.5672%	−33.1517%	−14.3198%	−13.9998%
Std.Dev	12.3037%	11.9905%	12.8846%	13.1172%	13.8472%	12.8546%
Sharpe ratio	0.2361	0.7342	0.6419	0.3195	0.8385	0.9409

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	The Chinese market			The US market		
	MOM	Carry	HB	MOM	Carry	HB
SR adjusted	0.2218	0.7196	0.6283	0.3061	0.8258	0.9272
Skewness	0.0412	0.0110	−0.3394	0.0071	0.5354	0.1913
Kurtosis	2.0091	2.3500	2.5258	3.1591	3.4316	2.3533
MDD mean	22.4480%	30.7537%	24.7506%	30.4733%	30.0050%	26.5824%

Notes: This table reports the performance of MOM, Carry and HB strategies (exclude energy). The performance of each strategy is calculated by its monthly excess returns. SR adjusted is the Sharpe ratio adjusted for transaction cost (17.6 basis points). We define the drawdowns D_t as the percentage drop in each strategy's monthly excess returns from the t to $t-11$, and the Maxdrawdown (MDD) as $MDD = max_{u\in\{t-11,t-10,\ldots,t\}} D_u$. The MDD mean refers to the mean of the MDD values in the whole sample.

Appendix F. The frequency of each commodity futures in Strategy I

	MOM			Carry			HB		
	Long-only	Short-only	Long-short	Long-only	Short-only	Long-short	Long-only	Short-only	Long-short
Panel A. The Chinese market									
FU.SHF	9.88%	4.63%	7.25%	15.25%	8.47%	**11.86%**	15.93%	2.95%	9.44%
ZC.CZC	5.56%	10.49%	8.02%	2.82%	10.73%	6.78%	1.77%	11.80%	6.78%
J.DCE	12.04%	7.72%	**9.88%**	11.86%	9.60%	**10.73%**	12.39%	10.91%	**11.65%**
JM.DCE	7.72%	8.33%	8.02%	7.91%	9.60%	8.76%	5.60%	10.91%	8.26%
AU.SHF	1.85%	2.47%	2.16%	2.82%	3.95%	3.39%	0.59%	1.47%	1.03%
AG.SHF	4.94%	2.47%	3.70%	2.26%	0.57%	1.41%	3.54%	2.06%	2.80%
CU.SHF	2.78%	10.49%	6.64%	0.00%	5.08%	2.54%	0.00%	5.60%	2.80%
Y.DCE	8.02%	1.23%	4.63%	11.02%	3.67%	7.34%	8.85%	0.89%	4.87%
C.DCE	14.51%	7.72%	**11.11%**	10.17%	9.04%	9.60%	12.09%	10.62%	**11.36%**
CF.CZC	7.72%	11.73%	9.72%	9.32%	9.32%	9.32%	11.80%	11.50%	**11.65%**
A.DCE	14.51%	1.54%	8.02%	13.84%	2.82%	8.33%	15.93%	1.47%	8.70%
SR.CZ	8.33%	15.12%	**11.73%**	7.06%	13.28%	**10.17%**	7.67%	13.27%	10.47%
CM.DCE	2.16%	16.05%	9.10%	5.65%	13.84%	9.75%	3.83%	16.52%	10.18%
Panel B. The US market									
CL.NYM	10.49%	6.17%	8.33%	9.60%	8.19%	8.90%	11.21%	7.37%	9.29%
NG.NYM	20.68%	4.32%	**12.50%**	19.21%	5.37%	**12.29%**	21.24%	5.31%	**13.27%**
GC.CMX	3.70%	3.09%	3.40%	0.85%	9.89%	5.37%	0.00%	9.14%	4.57%
SI.CMX	4.32%	7.10%	5.71%	1.41%	5.37%	3.39%	0.30%	4.42%	2.36%
HG.CMX	2.16%	8.95%	5.56%	1.41%	10.45%	5.93%	0.00%	10.62%	5.31%
BO.CBT	5.25%	3.09%	4.17%	8.47%	1.13%	4.80%	9.14%	0.00%	4.57%
C.CBT	19.75%	8.02%	**13.89%**	24.29%	5.08%	**14.69%**	24.48%	7.96%	**16.22%**
CT.NYB	5.56%	16.36%	10.96%	8.47%	15.54%	12.01%	5.90%	14.75%	10.32%
S.CBT	5.25%	12.65%	8.95%	5.08%	11.58%	8.33%	5.60%	13.86%	9.73%
SB.NYB	17.59%	12.65%	**15.12%**	16.95%	11.58%	**14.27%**	19.17%	9.14%	**14.16%**
SM.CBT	5.25%	17.59%	11.42%	4.24%	15.82%	10.03%	2.95%	17.40%	10.18%

Note: The data in bold is the three commodity futures with the highest frequency in each strategy.

Appendix G. The frequency of each commodity futures in Strategy II

	MOM			Carry			HB		
	Long-only	Short-only	Long-short	Long-only	Short-only	Long-short	Long-only	Short-only	Long-short
Panel A. The Chinese market									
AU.SHF	4.32%	5.25%	4.78%	6.50%	8.76%	7.63%	5.60%	5.01%	5.31%
AG.SHF	10.19%	5.25%	7.72%	6.78%	3.39%	5.08%	9.73%	5.31%	7.52%
CU.SHF	3.70%	18.52%	11.11%	0.57%	15.25%	7.91%	0.30%	17.70%	9.00%
Y.DCE	17.59%	3.40%	10.49%	17.51%	6.78%	12.15%	18.29%	3.54%	10.91%
C.DCE	18.83%	9.26%	**14.04%**	15.54%	11.86%	**13.70%**	14.45%	12.68%	**13.57%**
CF.CZC	10.80%	12.96%	11.88%	14.97%	11.86%	**13.42%**	14.16%	12.68%	**13.42%**
A.DCE	19.44%	2.16%	10.80%	20.62%	5.37%	12.99%	21.24%	3.54%	12.39%
SR.CZ	10.80%	19.14%	**14.97%**	9.89%	17.80%	**13.84%**	11.21%	17.99%	**14.60%**
CM.DCE	4.32%	24.07%	**14.20%**	7.63%	18.93%	13.28%	5.01%	21.53%	13.27%
Panel B. The US market									
GC.CMX	6.17%	3.09%	4.63%	1.69%	13.56%	7.63%	0.59%	13.57%	7.08%
SI.CMX	6.79%	8.64%	7.72%	4.24%	10.17%	7.20%	2.06%	7.67%	4.87%
HG.CMX	7.72%	11.42%	9.57%	3.39%	13.56%	8.47%	3.83%	12.68%	8.26%
BO.CBT	13.89%	3.40%	8.64%	16.38%	1.69%	9.04%	20.65%	0.30%	10.47%
C.CBT	21.91%	8.02%	**14.97%**	25.14%	5.08%	**15.11%**	24.48%	8.26%	**16.37%**
CT.NYB	7.41%	19.44%	13.43%	11.02%	16.38%	**13.70%**	7.96%	16.22%	12.09%
S.CBT	7.72%	12.96%	10.34%	12.71%	11.58%	12.15%	12.68%	13.86%	**13.27%**
SB.NYB	19.44%	13.27%	**16.36%**	17.80%	11.58%	**14.69%**	20.94%	9.14%	**15.04%**
SM.CBT	8.95%	19.75%	**14.35%**	7.63%	16.38%	12.01%	6.78%	18.29%	12.54%

Note: The data in bold is the three commodity futures with the highest frequency in each strategy.

Appendix H. Portfolio weights Portfolio B1

	The Chinese market				The US market			
	12 months	24 months	36 months	48 months	12 months	24 months	36 months	48 months
Panel A. MV								
Bond	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Stock	0.1306	0.1218	0.1404	0.1680	**0.2923**	**0.3137**	**0.2939**	0.2792
Currency	0.1176	0.1343	0.1563	0.1871	0.0912	0.0769	0.0895	0.1071
Carry	**0.2778**	**0.3168**	**0.3275**	**0.3448**	**0.2664**	**0.2957**	**0.2681**	**0.2320**
MOM	0.1600	0.0980	0.0845	0.0963	0.2535	0.2279	0.2521	**0.3017**
HB	**0.3139**	**0.3291**	**0.2912**	**0.2038**	0.0966	0.0858	0.0964	0.0801
Panel B. CVaR								
Bond	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000	0.0000
Stock	0.1112	0.0225	0.0185	0.0136	**0.2701**	0.2164	0.1930	0.1931
Currency	0.1473	0.0391	0.0057	0.0021	0.0844	0.0237	0.0145	0.0059
Carry	**0.3423**	0.3787	**0.4088**	**0.4057**	**0.2808**	**0.3567**	**0.3840**	**0.4283**
MOM	0.0850	0.1683	0.1797	0.2044	0.2508	**0.3126**	**0.3334**	**0.2860**
HB	**0.3143**	**0.3915**	**0.3872**	**0.3741**	0.1124	0.0905	0.0750	0.0867
Panel C. MAD								
Bond	0.0000	0.0000	0.0000	0.0000	0.0008	0.0000	0.0000	0.0000
Stock	0.1326	0.0308	0.0087	0.0175	**0.2831**	0.2207	0.1799	0.1762
Currency	0.1021	0.0377	0.0000	0.0000	0.0992	0.0220	0.0065	0.0011
Carry	**0.2886**	**0.3740**	**0.4075**	**0.3939**	**0.2596**	**0.3713**	**0.4253**	**0.4765**
MOM	0.1679	0.1506	0.1676	0.1854	0.2555	**0.2949**	**0.2945**	**0.2868**
HB	**0.3089**	**0.4069**	**0.4162**	**0.4032**	0.1019	0.0910	0.0938	0.0594
Panel D. Risk Parity								
Bond	**0.2968**	**0.2911**	**0.3343**	**0.3211**	**0.3320**	**0.3540**	**0.3856**	**0.3948**
Stock	0.1368	0.1142	0.1012	0.0944	0.2192	0.2119	0.2069	0.2026
Currency	**0.3649**	**0.4062**	**0.3867**	**0.4037**	**0.2478**	**0.2395**	**0.2146**	**0.2052**
Carry	0.0717	0.0674	0.0652	0.0681	0.0676	0.0666	0.0679	0.0706
MOM	0.0674	0.0621	0.0582	0.0582	0.0681	0.0641	0.0617	0.0624
HB	0.0623	0.0589	0.0543	0.0546	0.0653	0.0639	0.0632	0.0644

Note: The data in bold is the two components with highest weight in each portfolio.

Appendix I. Portfolio weights of Portfolio B2

	The Chinese market				The US market			
	12 months	24 months	36 months	48 months	12 months	24 months	36 months	48 months
Panel A. MV								
Bond	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Stock	0.0937	0.0830	0.0926	0.1108	0.1919	0.2048	0.1969	0.1521
Currency	0.1078	0.1231	0.1433	0.1715	0.0693	0.0331	0.0386	0.0462
Carry	**0.2752**	**0.2848**	**0.2665**	**0.2671**	**0.3007**	**0.3197**	**0.2999**	**0.2593**
MOM	0.2401	**0.2577**	**0.2616**	**0.2632**	**0.3402**	**0.3370**	**0.3626**	**0.4339**
HB	**0.2831**	0.2515	0.2360	0.1874	0.0979	0.1054	0.1021	0.1086
Panel B. CVaR								
Bond	0.0000	0.0000	0.0000	0.0000	0.0025	0.0000	0.0000	0.0000
Stock	0.0982	0.0301	0.0262	0.0205	0.1754	0.1561	0.1585	0.1037
Currency	0.0224	0.0379	0.0000	0.0021	0.0649	0.0185	0.0132	0.0008
Carry	**0.3172**	**0.3238**	**0.3722**	**0.3943**	**0.2758**	**0.3571**	**0.4498**	**0.4671**
MOM	0.1970	**0.3476**	**0.4091**	**0.3526**	**0.3592**	**0.3298**	**0.3037**	**0.3434**
HB	**0.3652**	0.2606	0.1924	0.2305	0.1223	0.1386	0.0748	0.0850
Panel C. MAD								
Bond	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Stock	0.0935	0.0329	0.0059	0.0057	0.1937	0.1533	0.1145	0.0899
Currency	0.1098	0.0264	0.0000	0.0010	0.0618	0.0115	0.0000	0.0000
Carry	**0.2659**	**0.3241**	**0.3824**	**0.4203**	**0.3014**	**0.3525**	**0.4420**	**0.5196**
MOM	0.2405	**0.3446**	**0.4184**	**0.3947**	**0.3425**	**0.3639**	**0.3413**	**0.3086**
HB	**0.2903**	0.2720	0.1933	0.1784	0.1006	0.1187	0.1021	0.0819
Panel D. Risk Parity								
Bond	**0.2414**	**0.2028**	**0.2482**	**0.2013**	**0.3541**	**0.3855**	**0.4247**	**0.4306**
Stock	0.1346	0.1239	0.1079	0.1090	0.1922	0.1806	0.1758	0.1792
Currency	**0.3618**	**0.4283**	**0.4279**	**0.4602**	**0.2197**	**0.2203**	**0.1989**	**0.1866**
Carry	0.0818	0.0781	0.0711	0.0764	0.0781	0.0709	0.0688	0.0714
MOM	0.0950	0.0875	0.0730	0.0759	0.0848	0.0758	0.0675	0.0667
HB	0.0854	0.0794	0.0719	0.0773	0.0711	0.0669	0.0642	0.0655

Note: The data in bold is the two components with highest weight in each portfolio.

Appendix J. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105780.

References

Adams, Z., Glück, T., 2015. Financialization in commodity markets: a passing trend or the new normal? J. Bank. Financ. 60, 93–111.
Albulescu, C.T., Tiwari, A.K., Ji, Q., 2020. Copula-based local dependence between energy, agriculture and metal commodity markets. Energy 202, 117762.
Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. J. Financ. 68 (3), 929–985.
Bai, J., Philippon, T., Savov, A., 2016. Have financial markets become more informative? J. Financ. Econ. 122 (3), 625–654.
Bakshi, G., Gao, X., Rossi, A.G., 2019. Understanding the sources of risk underlying the cross section of commodity returns. Manag. Sci. 65 (2), 619–641.
Basher, S.A., Sadorsky, P., 2016. Hedging emerging market stock prices with oil, gold, VIX, and bonds: a comparison between DCC, ADCC and GO-GARCH. Energy Econ. 54, 235–247.
Basu, D., Miffre, J., 2013. Capturing the risk premium of commodity futures: the role of hedging pressure. J. Bank. Financ. 37, 2652–2664.
Behmiri, N.B., Manera, M., Nicolini, M., 2019. Understanding dynamic conditional correlations between oil, natural gas and non-energy commodities futures markets. Energy J. 40 (2).
Belousova, J., Dorfleitner, G., 2012. On the diversification benefits of commodities from the perspective of euro investors. J. Bank. Financ. 36 (9), 2455–2472.
Bessler, W., Wolff, D., 2015. Do commodities add value in multi-asset portfolios? An out-of-sample analysis for different investment strategies. J. Bank. Financ. 60, 1–20.
Bianchi, R.J., Drew, M.E., Fan, J.H., 2015. Combining momentum with reversal in commodity futures. J. Bank. Financ. 59, 423–444.
Bonato, M., Gupta, R., Lau, C.K.M., Wang, S., 2020. Moments-based spillovers across gold and oil markets. Energy Econ. 89, 104799.
Boons, M., Prado, M.P., 2019. Basis-Momentum. J. Financ. 74 (1), 239–279.
Chang, C.L., Liu, C.P., McAleer, M., 2019. Volatility spillovers for spot, futures, and ETF prices in agriculture and energy. Energy Econ. 81, 779–792.
Charles, A., Olivier, D., Kim, Jae-Hoon, 2012. Exchange-rate return predictability and the adaptive markets hypothesis: evidence from major foreign exchange rates. J. Int. Money Financ. 31, 1607–1626.
Charlot, P., Marimoutou, V., 2014. On the relationship between the prices of oil and the precious metals: revisiting with a multivariate regime-switching decision tree. Energy Econ. 44, 456–467.
Chen, Y.L., Chang, Y.K., 2015. Investor structure and the informational efficiency of commodity futures prices. Int. Rev. Financ. Anal. 42, 358–367.
Cheung, C.S., Miu, P., 2010. Diversification benefits of commodity futures. J. Int. Financ. Mark. Inst. Money 20 (5), 451–474.
Conover, C.M., Jensen, G.R., Johnson, R.R., Mercer, J.M., 2010. Is now the time to add commodities to your portfolio? J. Invest. 19, 10–19.
Creti, A., Joëts, M., Mignon, V., 2013. On the links between stock and commodity markets' volatility. Energy Econ. 37, 16–28.
Daskalaki, C., Skiadopoulos, G., 2011. Should investors include commodities in their portfolios after all? New evidence. J. Bank. Financ. 35, 2606–2626.
Daskalaki, C., Skiadopoulos, G., Topaloglou, N., 2017. Diversification benefits of commodities: a stochastic dominance efficiency approach. J. Empir. Financ. 44, 250–269.
Demirer, R., Ferrer, R., Shahzad, S.J.H., 2020. Oil price shocks, global financial markets and their connectedness. Energy Econ. 88, 104771.
Erb, C.B., Harvey, C.R., 2006. The strategic and tactical value of commodity futures. Financ. Anal. J. 62, 69–97.
Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Financ. 25 (2), 383–417.
Fama, E.F., French, K.R., 1987. Commodity futures prices: some evidence on forecast power, premiums, and the theory of storage. J. Bus. 60, 55–73.
Fernandez, V., 2017. A historical perspective of the informational content of commodity futures. Res. Policy 51, 135–150.
Fernandez-Perez, A., Fuertes, A.M., Miffre, J., 2019. A comprehensive appraisal of style-integration methods. J. Bank. Financ. 105, 134–150.
Fitzgibbons, S., Friedman, J., Pomorski, L., Serban, L., 2017. Long-only style investing: don't just mix, integrate. J. Invest. 26 (4), 153–164.
Fuertes, A.M., Miffre, J., Rallis, G., 2010. Tactical allocation in commodity futures markets: combining momentum and term structure signals. J. Bank. Financ. 34 (10), 2530–2548.
Fuertes, A.M., Miffre, J., Fernández-Pérez, A., 2015. Commodity strategies based on momentum, term structure and idiosyncratic volatility. J. Futur. Mark. 35 (3), 274–297.
Gardebroek, C., Hernandez, M.A., 2013. Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. Energy Econ. 40, 119–129.
Gatfaoui, H., 2019. Diversifying portfolios of U.S. stocks with crude oil and natural gas: a regime-dependent optimization with several risk measures. Energy Econ. 80, 132–152.
Gorton, G.B., Rouwenhorst, K.G., 2006. Facts and fantasies about commodity futures. Financ. Anal. J. 62, 47–68.
Gorton, G.B., Hayashi, F., Rouwenhorst, K.G., 2013. The fundamentals of commodity futures returns. Rev. Fin. 17 (1), 35–105.
Hu, M., Zhang, D., Ji, Q., Wei, L., 2020. Macro factors and the realized volatility of commodities: a dynamic network analysis. Res. Policy 68, 101813.
Ibbotson, R.G., Chen, Z., Kim, D., Wendy, Y.H., 2013. Liquidity as an investment style. Financ. Anal. J. 69 (3), 30–44.
Israel, R., Jiang, S., Ross, A., 2018. Craftsmanship alpha: an application to style investing. J. Portfolio Manag. 43, 23–39.
Jensen, G.R., Johnson, R.R., Mercer, J.M., 2000. Efficient use of commodity futures in diversified portfolios. J. Futur. Mark. 20, 489–506.
Kang, W., Ratti, R.A., Yoon, K.H., 2015. The impact of oil price shocks on the stock market return and volatility relationship. J. Int. Financ. Mark. Inst. Money 34, 41–54.
Khalfaoui, R., Boutahar, M., Boubaker, H., 2015. Analyzing volatility spillovers and hedging between oil and stock markets: evidence from wavelet analysis. Energy Econ. 49, 540–549.
Kim, J.H., Shamsuddin, A., Lim, K.P., 2011. Stock return predictability and the adaptive markets hypothesis: evidence from century-long U.S. data. J. Empir. Financ. 18 (5), 868–879.
Koijen, R.S.J., Moskowitz, T.J., Pedersen, L.H., Vrugt, E.B., 2018. Carry. J. Financ. Econ. 127, 197–225.
Konno, H., Yamazaki, H., 1991. Mean-absolute deviation portfolio optimization model and its application to Tokyo stock market. Manag. Sci. 37, 519–531.
Kristoufek, L., Vosvrda, M., 2013. Commodity futures and market efficiency. Energy Econ. 42, 50–57.
Lee, Y., Huang, Y., Wu, C., 2014. Dynamic correlations and volatility spillovers between crude oil and stock index returns: the implications for optimal portfolio construction. Int. J. Energy Econ. Policy 4 (3), 327–336.
Ma, Y.R., Ji, Q., Wu, F., Pan, J., 2021. Financialization, idiosyncratic information and commodity co-movements. Energy Econ. 94, 105083.
Maghyereh, A., Awartani, B., Tziogkidis, P., 2017. Volatility spillovers and cross-hedging between gold, oil and equities: evidence from the Gulf cooperation council countries. Energy Econ. 68, 440–453.
Markowitz, H., 1952. Portfolio selection. J. Financ. 7 (1), 77–91.
Marshall, B.R., Cahan, R.H., Cahan, J.M., 2008. Can commodity futures be profitably traded with quantitative market timing strategies? J. Bank. Financ. 32 (9), 1810–1819.
Marshall, B.R., Nguyen, N.H., Visaltanachoti, N., 2012. Commodity liquidity measurement and transaction costs. Rev. Financ. Stud. 25 (2), 599–638.
Miffre, J., Rallis, G., 2007. Momentum strategies in commodity futures markets. J. Bank. Financ. 31 (6), 1863–1886.
Nazlioglu, S., Erdem, C., Soytas, U., 2013. Volatility spillover between oil and agricultural commodity markets. Energy Econ. 36, 658–665.
Ortiz-Cruz, A., Rodriguez, E., Ibarra-Valdez, C., Alvarez-Ramirez, C., 2012. Efficiency of crude oil markets: evidences from informational entropy analysis. Energy Policy 41, 365–373.
Ready, R., Roussanov, N., Ward, C., 2017. Commodity trade and the carry trade: a tale of two countries. J. Financ. 72 (6), 2629–2684.
Rockafellar, R.T., Uryasev, S., 2002. Conditional value-at-risk for general loss distributions. J. Bank. Financ. 26 (7), 1443–1471.
Rösch, D.M., Subrahmanyam, A., van Dijk, M.A., 2017. The dynamics of market efficiency. Rev. Financ. Stud. 30 (4), 1151–1187.
Sakkas, A., Tessaromatis, N., 2020. Factor based commodity investing. J. Bank. Financ. 115, 1–19.
Sarwar, S., Shahbaz, M., Anwar, A., Tiwari, A.K., 2019. The importance of oil assets for portfolio optimization: the analysis of firm level stocks. Energy Econ. 78, 217–234.
Shahzad, S.J., Mensi, W., Hammoudeh, S., Rehman, M.U., Al-Yahyaee, K., 2018. Extreme dependence and risk spillovers between oil and Islamic stock markets. Emerg. Mark. Rev. 34, 42–63.
Shen, Q., Szakmary, A.C., Sharma, S.C., 2007. An examination of momentum strategy in commodity future markets. J. Futur. Mark. 27 (3), 227–256.
Szymanowska, M., De Roon, F.A., Nijman, T., Van der Goorbergh, R., 2014. An anatomy of commodity futures risk premia. J. Financ. 69, 453–482.
White, H., 2000. A reality check for data snooping. Econometrica 68 (5), 1097–1126.
Wu, F., Zhao, W.L., Ji, Q., Zhang, D., 2020. Dependency, centrality and dynamic networks for international commodity futures prices. Int. Rev. Econ. Financ. 67, 118–132.
Yan, L., Garcia, P., 2017. Portfolio investment: are commodities useful? J. Commod. Mark. 8, 43–55.
Yang, Y., Göncü, A., Pantelous, A.A., 2018. Momentum and reversal strategies in Chinese commodity futures markets. Int. Rev. Financ. Anal. 60, 177–196.
Zhang, Y.J., Chevallier, J., Guesmi, K., 2017. "De-financialization" of commodities? Evidence from stock, crude oil and natural gas markets. Energy Econ. 68, 228–239.