Risk-Neutral Skewness and Commodity Futures Pricing *

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Abstract

This paper investigates the predictive content of risk-neutral skewness (RNSK) for the dynamics of commodity futures prices. A trading strategy that buys futures with positive RNSK and sells futures with negative RNSK generates a significant excess return. Unlike traditional commodity risk factors' signals, the positive return generated from the RNSK signal is more pronounced in the contango phase. After controlling traditional commodity risk factors, the RNSK signal exhibits a more stable and prolonged predictive ability. The directional-learning hypothesis explains the RNSK impact when commodity futures show higher idiosyncratic risks and illiquidity (positive RNSK) and overpriced (negative RNSK).

JEL Classifications: C52; C53; G12; G13.

Keywords: Commodity futures; Asset pricing; Skewness; Risk-Neutral; Risk Factors.

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1 Introduction

Assessing the skewness pricing ability in global financial markets becomes increasingly important, and the majority of the studies focus on the global equity market finding negative relation[1]. For example, conditional skewness and realized skewness by (Harvey and Siddique (2000) and Amaya et al. (2015)), expected idiosyncratic skewness proposed by Boyer et al. (2010) and the risk-neutral skewness discussed by (Conrad et al., 2013). Recent studies on risk-neutral skewness indicate a positive relation to subsequent return (Stilger et al. (2017), Chordia et al. (2021), and Gkionis et al. (2021)). Overall, the pricing relation of skewness to returns is mixed.

The commodity literature on this subject is much sparser. Fernandez-Perez et al. (2018) show that commodity returns are strongly negatively related to the realized skewness (the standard Pearson skewness coefficient estimated based on monthly observations with a past 12-month length window of daily excess return). Moreover, they argue that this pricing relation is more in line with the cumulative prospect theory (Barberis and Huang, 2008). A long-short portfolio, buying (selling) the commodities with the lowest (highest) realized skewness, generates an 8.01% annual return.

This paper employs a superior measure of skewness extracted from the futures' options market, namely risk-neutral skewness (RNSK hence after)[2]. We document a positive relation between the RNSK and subsequent futures' returns. Unlike the realized skewness, a backward-looking measure under the physical probability measure, the RNSK is a forward-looking measurement under the risk-neutral probability that focuses on future distribution instead of the past one. Moreover, the options market has been argued to

[1]Earlier studies on skewness explanation via CAPM and conditional skewness effect can be referred to Junkus (1991) and Christie-David and Chaudhry (2001) respectively.

[2]Relevant theoretical details are referred to Kozhan et al. (2013), and Neuberger (2012).

carry more valuable information, which has better forecasting power and reflects the market participants' expectations (see Black (1975), Bates (1991), Jackwerth and Rubinstein (1996) and Bakshi et al. (1997)). In short, prices discovered in the options market may contain information not embedded in the underlying asset's market; hence, the options implied measures (RNSK here) might deliver extra predictive power compared to its counterparty (realized measure with past information)[3].

Although our empirical results also imply a positive relationship between the RNSK and return, different from Stilger et al. (2017) and Gkionis et al. (2021) who argue that the positive pricing relation is due to short-selling constraint and underpricing following the demand-based option pricing framework by Garleanu et al. (2009), the pricing mechanism of the RNSK in the global commodity futures market (where short-selling is allowed) is associated with less liquidity, higher idiosyncratic risk, and overpricing. Furthermore, in general, our findings align with the directional-learning hypothesis framework by Shleifer and Vishny (1997), and Kang and Park (2008).

In particular, informed investors, with private good news on the future underlying movement, choose to purchase more OTM call options (with small cost but leveraged gains) when underlying assets are more pronounced with less liquidity and high idiosyncratic (arbitrage) risk, a more positive RNSK is observed. While informed investors with bad news when underlying assets are overpriced resort to buy more OTM put options to avoid bearing inventory risk from trading futures and to transfer hedging cost to market-makers, a more negative RNSK is observed. Once the positive (negative) information is disseminated to the underlying market, the price will increase (decrease) to correct those beliefs; hence a positive relation is realized.

[3]The detailed technical comparison discussion between the realized and risk-neutral measurements can be found from Kim and White (2004), Hansis et al. (2010), and Neuberger (2012).

A long-short portfolio sorted on the RNSK outperforms the portfolio sorted on the Pearson skewness yielding a 13.18% annual return that is statistically significant. More importantly, we also find that the Pearson skewness's predictability on return has disappeared after controlling the impact of RNSK. On the contrary, the relation between the RNSK and return remains positive and significant when holding the Pearson skewness.

We find that the RNSK is a relatively longer-lived pricing signal in the commodity futures market, contradicting the short-lived RNSK signal findings in the equity market by Stilger et al. (2017) and Gkionis et al. (2021) who argue that the RNSK pricing ability disappears after the first week or even earlier. In particular, we find that the RNSK signal helps predict futures' return up to 10 weeks after correcting traditional baseline risk factors (market long-only portfolio, term structure, momentum, and hedging pressure). Moreover, return predictability power is robust and even more potent with averaged RNSK signal (up to 30 business days), yielding a 14.6% annual return after correcting the above factors. Finally, our results are robust to another alternative RNSK measurement, different estimation error impacts (i.e., errors caused by truncation, discrete estimation, interpolation, and extrapolation), and additional control variables.

The closest study on how the RNSK predicts return is by Chen et al. (2016) who find a negative relation between the RNSK and TAIFEX futures' index return, which differs from our finding. However, their results focus on one specific market index, and this negative relation is not guaranteed to hold for individual futures' products[4]. Second, the risk-neutral skewness analyzed in their works are grouped based on maturity up to 182 days and all maturity cases, which fits more on the long-run skewness prefer-

[4]For example, crude oil is widely used in many industrial production processes in the global market. Accordingly, its futures contract, WTI crude oil futures, can have very different demand and supply (involving producers, speculators, and many others) structures compared with one specific market index. Therefore, the RNSK pricing relation is worth checking across all commodity products.

ence framework, and a negative relationship between skewness and return is expected. Borochin et al. (2020) reconcile the relationship between the RNSK and return that long-term RNSK negatively predicts the return, while short-term RNSK positively predicts the return.

To sum up, we contribute the global commodity futures literature on the following aspects (1) fill the void of global commodity futures market RNSK pricing test and show that the RNSK positively predict subsequent period futures' return, which is not explained by commodity-specific risk factors (2) the RNSK pricing mechanism is attributed to the directional-learning hypothesis (3) the RNSK has a superior performance compared with the realized skewness (the Pearson skewness), and the pricing ability of the realized skewness disappears after controlling the RNSK (4) the RNSK has a much stable and long-lived predictive power compared with the RNSK findings in the equity market.

2 Background Literature

Over the past two decades, commodity futures pricing has built traditional benchmark factors via a long-short portfolio to capture the evidence of the backwardation and contango. Among them, term structure factor (price difference of the same underlying with different time to maturities, see Koijen et al. (2018), Erb and Harvey (2006), Szymanowska et al. (2014) and Fuertes et al. (2015)), momentum factor (moving average return over a fixed window length, see, Asness et al. (2013b), Erb and Harvey (2006) and Miffre and Rallis (2007)) and hedging pressure (long or net non-commercial short position divided by total non-commercial open interest, see Bessembinder (1992) and Basu and Miffre (2013)) have been tested comprehensively and treated as a baseline model to study in global commodity futures market pricing realm.

Earlier studies about individuals' skewness are from the equity market. Conditional skewness is tested for the equity market under different sorting criteria and sub-sample analysis. They find that conditional skewness can price to some extent but not general for all assets (Harvey and Siddique, 2000). One important reason for this imperfect pricing may be due to the non-ex-ante property of skewness. Boyer et al. (2010) introduce the expected idiosyncratic skewness (estimated by linear forecasting regression on idiosyncratic volatility) and show that it can generate 1% abnormal return monthly. The negative relation between expected idiosyncratic skewness and subsequent return is recorded even after controlling the Fama_French three factors. Their results are also consistent with Amaya et al. (2015) who use a new estimation method with intra-day (high frequency) data to measure realized skewness.

Different from the above studies, ex-ante (risk-neutral) skewness measure is introduced and obtained in two different ways, see Bali and Murray (2013) and Conrad et al. (2013). Both of them find the same negative pricing relationships between the RNSK and expected return. However, Stilger et al. (2017) and Gkionis et al. (2021), on the contrary, find positive-return relation in the global equity market. The above opposite sign finding difference may be due to signal fading caused by moving average treatment as the RNSK is argued by mainly capturing short-term arbitrage. More recently, Borochin et al. (2020) has documented that the RNSK positively (negatively) predicts return in a short (long) run, reconciling the mixing pricing return relation sign in equity's market.

While in the global commodity futures market, so far, the latest research on skewness is by Fernandez-Perez et al. (2018) who estimate the realized skewness and show its non-trivial effect on pricing asset's return. Their empirical results demonstrate that after controlling the traditional baseline risk factors, buying (selling) the lowest (highest) quantile realized Pearson skewness assets generate 8.01% annual return.

Unlike the futures index study on the RNSK by Chen et al. (2016), Triantafyllou et al. (2015) pay more attention to the grain commodity market. Rather than predicting the return, they estimate the risk-neutral skewness following Bakshi et al. (2003) and find that it helps improve forecast variance. Therefore, this paper has no similar study that mainly focuses on the risk-neutral skewness pricing ability in the global commodity futures market.

3 Pricing Mechanism of RNSK

Under the realized skewness measurement, the positively skewed assets are argued to be more preferred by investors. This is because investors either show lottery-like behavior (Mitton and Vorkink, 2007) or evaluate such assets under a particular value function (convex in loss and concave in gain) under the cumulative prospect theory (Tversky and Kahneman (1992) and Barberis and Huang (2008)). In both cases, those assets are overpriced, subsequently generating negative returns, indicating a negative relationship between skewness and return. Fernandez-Perez et al. (2018) empirically confirm this negative relation between commodity futures return and skewness under the cumulative prospect theory. However, none of the above fits our findings as options market trading impact is not considered.

In fact, the RNSK pricing process generally fits informed trading behavior theories (Easley et al. (1998), Bollen and Whaley (2004) and Kang and Park (2008)). In particular, investors with private information about future underlying movement can choose one of the markets (futures and options) or even both to exploit the high return (Easley et al., 1998). With negative news about future returns, hedgers and speculators can buy more

OTM put options (no obligation to pay back with an upfront cost), driving RNSK to a relatively smaller value. On the contrary, to exploit the perceived potential positive price change, they can resort to the options market by buying more OTM call options, leading to a larger RNSK value. In this sense, without bearing more costs on trading underlying futures, utilizing the options market can help avoid tail risk and amplify potential gains.

Under the directional-learning hypothesis by Kang and Park (2008), we argue that investors with positive information on the underlying future movement will resort to the options market to buy more OTM call options when underlying assets exhibit less liquidity and high idiosyncratic risk. When futures contracts' liquidity is dry, getting the best trade price is more challenging given a wider bid-ask spread market. Trading activity via arbitrage, hedging, and speculation might be inaccurate for futures contracts with high idiosyncratic risk. Under this case, margin (collateral) requirement occurred intraday with mark-to-market increased loss can force liquidation before convergence happens (Shleifer and Vishny (1997) and Liu and Longstaff (2004)). Investors will choose to purchase more OTM call options given all the associated risks above, driving RNSK to be more positive. Once the information is diffused to the underlying market, those assets will adjust their price to correct this belief.

Similarly, investors, equipped with the directional-learning hypothesis and informed by negative future underlying movement, will resort to buying more OTM put options when underlying assets are perceived to be overpriced. We argue that investors have transferred risks (managing underlying inventory and hedging cost) to market-makers who consequentially require a premium on selling those OTM put options, yielding a more negative RNSK in the end. Again, when information moves to the underlying market, the underlying price will react to correct this difference, generating a negative return.

The above is also, to some extent, compatible with the demand-based option pricing framework of Garleanu et al. (2009), although their short-selling constraints argument does not exist here.

Collectively, we document a positive relation between the RNSK and return under the informed trading behavior framework. When underlying assets become illiquid and less prone to arbitrage (speculate), informed investors will purchase more OTM call options to maximize their profits, associated with a more positive RNSK. As that information is distributed to the underlying market, the price will increase to correct those beliefs implied from the options market. When underlying assets are learned to be overpriced, to exploit the benefit of the potential price drop, informed investors will choose the options market to buy more OTM put options rather than to sell futures contracts to avoid potential risk. After the information moves to the underlying market, the price of those assets will reflect accordingly, yielding a negative return. Therefore, we argue that RNSK is a positive signal for the underlying futures market price move in all scenarios.

4 Data and Methodology

4.1 Data

Daily settlement futures price, trading volume, and open interest data from 10/10/2007 to 01/03/2016 are collected from DataStream: agriculture sector (Cocoa, Coffee C, Corn, Cotton NO.2, Frozen Concentrated Orange Juice, Oats, Rough Rice, Soybean Meal, Soybean Oil, Soybeans, Sugar NO.11, Wheat), the energy sector (RBOB gasoline, Heating Oil NO.2, Light Sweet Crude Oil, Natural Gas), livestock (Feeder Cattle, Lean Hogs, Live Cattle), metal (Gold and Silver)[5]. Returns are calculated as the log difference in prices with the same contract. Consistent with the literature, we focus on the nearest-to-maturity contract and roll to the second nearest-to-maturity contract one week before the nearest-to-maturity contract expires. Options data are obtained from DataStream with daily strikes, traded volumes, maturities, contract prices (both call and put options) for each specific product. Futures' only aggregated long and short open interest data are downloaded from Commodity Futures Trading Commission website in weekly frequency[6]. In addition, equity market-related data (Fama_French five factors) are downloaded from the Fama_French data library website. Both commodity (GSCI) and equity (CRSP) market index prices are collected from the datastream and CRSP research databases, respectively. Eventually, we convert all daily data into weekly data using each Tuesday's daily observation.

4.2 Methodology

To comprehensively address the pricing ability test on RNSK, we first illustrate how we build the RNSK in an unbiased manner below and then discuss other commodity risk factors used in the control test. Like others in the literature, we consider portfolio long-short construction to build the final risk factor by cross-sectional ranking and sorting method. A full description of the factors used in this paper can be found in the table 1.

[Insert Table 1 around here]

[5] We exclude palladium and platinum for the consideration of estimation bias due to limited amount of OTM options data available.

[6] CFTC requires future trading participators to identify their types (hedgers, speculators, not reportable...).

4.2.1 RNSK

Bakshi et al. (2003) show that volatility, skewness, and kurtosis can be mimicked via quadratic, cubic, and quartic pay-off structures by using daily observation cross over options data with different strike prices for the same underlying, denoted this measure as BKM. Since BKM estimators are weighted by the underlying's squared or cubed strike price, it might cause estimation bias, especially during the illiquid period in which the call options part will deteriorate, and the put options part will be overstated. Put options price increases rapidly when market exception falls in downside way, resulting in more negative value in estimation (Kozhan et al. (2013), and Leontsinis and Alexander (2017)). To account for the jump, discrete, and downside risks (errors) under the BKM method, Kozhan et al. (2013) present a new estimation measure. We leverage this measure (denoted as RNSK) in the global commodity futures market to reduce estimation error, such as jump risk (contract rollover) and discrete risk (commodity futures are less liquid compared with the equity and rates, hence fewer options contracts to estimate RNSK)[7].

$$v_{t,T}^{L} = 2\sum_{K_i \le F_{t,T}} \frac{P_{t,T}\left(K_i\right)}{B_{t,T}K_i^2}\Delta I\left(K_i\right) + 2\sum_{K_i > F_{t,T}} \frac{C_{t,T}\left(K_i\right)}{B_{t,T}K_i^2}\Delta I\left(K_i\right) \tag{1}$$

$$v_{t,T}^{E} = 2\sum_{K_i \le F_{t,T}} \frac{P_{t,T}\left(K_i\right)}{B_{t,T}K_iF_{t,T}}\Delta I\left(K_i\right) + 2\sum_{K_i > F_{t,T}} \frac{C_{t,T}\left(K_i\right)}{B_{t,T}K_iF_{t,T}}\Delta I\left(K_i\right) \tag{2}$$

Where, $B_{t,T}$ is the present value of a bond at time t with time-to-maturity (T-t) given the expired data is unit, $P_{t,T}$ and $C_{t,T}$ are put and call options market price at time t with time-to-maturity (T-t), K_i is the strike price level for underlying at value index i, i

[7] For comparison, BKM sorted long-short portfolio (risk factor) is also reported in some tables and figures.

stands for the different strikes listed for given futures contract on time t.

$$\Delta I\left(K_i\right)=\left\{\begin{array}{ll}\frac{K_{i+1}-K_{i-1}}{2}, & \text{for } 0 \leq i \leq N(\text{with } K_{-1} \equiv 2K_0-K_1, K_{N+1}=2K_N-K_{N-1}) \\ 0, & \text{Otherwise}\end{array}\right\}$$

$$RNSK_{t,T} \equiv 3\frac{v_{t,T}^{E}-v_{t,T}^{L}}{\left(v_{t,T}^{L}\right)^{\frac{3}{2}}} \tag{3}$$

Where, $RNSK_{t,T}$ is the RNSK at time t with the expiration time T.

In practice, we first filter out all ITM options contracts and leave only OTM options, and further remove contracts with the number of OTM call and put option price data less than 4[8]. Trapezoidal approximation (Dennis and Mayhew (2002) and Conrad et al. (2013)) is implemented to calculate of equations (1) and (2) in discrete case. Finally, those options that have only one week left to maturities will also be excluded as the trading behavior on these options will distort the fair values of options themselves to some extent.

We first compute the implied volatility via the Black model using the bisection method for each contract with all daily data information. To solve the sparse strike price data problem and truncation error, we further construct a refined implied volatility interval via natural cubic spline interpolation on strike level (Jiang and Tian (2005), Jiang and Tian (2007) and Carr and Wu (2008)). The fitted interval is scaled by two standard deviations of underlying price to guarantee the minimum effect from truncation error (Jiang and Tian, 2005). We use the linear interpolation method to account for the implied volatility smile effect or skew effect for any data points beyond the current truncated extreme strike price range[9]. Finally, we convert all fitted implied volatility data from the above-refined

[8]The number of call and put options is required to be equal to estimate the RNSK.

[9]We also consider flat extrapolation (extreme value on two sides will be used for points outside strike price range without linear fitting) and no extrapolation (only consider data interpolation within a strike

interval back to obtain call and put market price via Black model to have an adequate number of the options price and strike to compute the RNSK.

After the estimation procedure, following the literature, 30 days constant maturity series RNSK for each underlying product is constructed via interpolation. Suppose there is a contract with exact time-to-maturity equal to 30, the corresponding RNSK value is used directly; otherwise, Hermite cubic spline is used to interpolate constant maturity RNSK. The Hermite cubic spline method is argued to account for calendar arbitrage issue and non-linear trend for long-maturity data fitting and provides excellent shape-preserving merit (Leontsinis and Alexander, 2017)[10].

4.2.2 Commodity Market Variables

We follow the commodity market characteristics studied in the literature and compute the commodity-specific risk factors in the following ways.

The *term structure* factor portfolio is constructed using the basis signal. The basis is defined as the price differential between two consecutive futures contracts on the same underlying product. Following Koijen et al. (2018), to make the signal more informative to sort a cross-section of commodities, we employ the scaled basis measure below,

$$TS_{i,t} = \frac{log(F_{i,t}^{T_1}/F_{i,t}^{T_2})}{T_2 - T_1} \tag{4}$$

where $F_{i,t}^{T_1}$ and $F_{i,t}^{T_2}$ is the futures price for front and second month contract with maturity T_1 and T_2 separately. The subscript i is index for product and t is index for time. A positive (negative) basis signals a backwardated (contangoed) market and as such predicts

range), results are similar not reported here.

[10] For robustness, we also apply linearly interpolate to estimate the constant time-to-maturity RNSK, since results are similar to Hermite cubic spline, so not reported.

that commodity futures prices will subsequently rise (fall).

The *hedging pressure* factor portfolio is based on a variable that signals the direction of trade of commodity trading participators (Basu and Miffre, 2013). We measure the hedging pressure by speculators' long positions only (also documented as large non-commercial traders by CFTC)[11]. The general formula is formatted as follows:

$$HP_{i,t} = \frac{\#long\ speculation\ positions_{i,t}}{total\ \#speculation\ positions_{i,t}} \tag{5}$$

Where $HP_{i,t}$ is represented by large non-commercial traders (speculators) hedging pressure for particular futures product i at time t[12].

The *momentum* signal is the average commodity futures return over a past window. As in Asness et al. (2013a), Szymanowska et al. (2014) and Miffre and Rallis (2007), we adopt a 12-month (52 weeks in our paper) window period. Formally,

$$MoM_{i,t} = \frac{\sum_{j=t-1}^{j=t-52} r_{i,j}}{52} \tag{6}$$

where $r_{i,t} = lnF^{T_1}(i,t) - lnF^{T_1}(i,t-1)$ is the (log) return of the nearest-to-maturity commodity futures product i on week t.

The *realized skewness* signal is the "*Pearson's moment coefficient of skewness of each commodity at month-end t using the daily return history in the preceding 12-month window*" proposed in (Fernandez-Perez et al., 2018). To be consistent with their measure, we also use daily return data over the past 12-month to estimate the Pearson skewness

[11]Long only hedger's position (large commercial traders) is also computed and tested, showing similar results to speculators' results, therefore not reported in this paper.

[12]We do aware of the net hedging pressure measurement in recent literature, see (Szymanowska et al. (2014), De Roon et al. (2000), Basu and Miffre (2013) and Bessembinder (1992)), robustness check on net position for both hedgers and speculators are conducted with similar results to long only one, no reported.

coefficient. After daily estimation, we use Tuesday's daily estimator as a weekly result for analysis.

$$SK_{i,t} = \frac{\left[\frac{1}{D}\sum_{d=1}^{D}\left(r_{i,d,t} - \hat{\mu}_{i,t}\right)^3\right]}{\hat{\sigma}_{i,t}^3} \tag{7}$$

Where, $r_{i,d,t}$ is the daily return for i^{th} commodity asset with d spanning from 1 to 252 (D=252) at time t. $\hat{\mu}_{i,t}$ is the standard mean estimation, and $\hat{\sigma}_{i,t}$ is the standard error with scaling factor $\sqrt{1/(D-1)}$[13].

4.2.3 Risk Factor Portfolio Construction

The weekly time-series of long-short portfolio returns (represented by TS, HP, MoM, SK, and RNSK in this following content) are obtained by buying and selling quantile group assets simultaneously. In particular, commodity assets at the end of each week are grouped according to the latest signal observations and held until the end of next week when new factor observations become available. Then, the portfolio weekly rebalance procedure continues until the end of the data sample. The ranking period is the most recent 52-week window for MoM and SK signals, while TS, HP, and RNSK use the latest signals. In particular, we denote L and S as the commodities included in the long and short portfolios. HP, TS, MoM, and RNSK factors are constructed as high(L)-minus-low(S) portfolios, while only SK is created as low(L)-minus-high(S) portfolios. This follows from the wisdom that a high value of hedgers' hedging pressure, basis, momentum, and risk-neutral skewness predict an increase in subsequent commodity futures prices. In contrast, a high value of realized skewness indicates a decrease in consequent commodity futures

[13] We also estimate a quantile-based skewness following (Green and Hwang, 2012) with past one-year daily observations. This new measure implies the same negative skewness-return relationship but with a trivial return. Again, this again points out that our option-based skewness is distinct mainly due to risk-neutral property and no historical data inclusion.

prices instead (Bakshi et al. (2019), Bessembinder (1992), Basu and Miffre (2013), Miffre and Rallis (2007), Stilger et al. (2017), Amaya et al. (2015) and Fernandez-Perez et al. (2018)). Hereafter, the notation HML denotes the corresponding long-short portfolio. Descriptive statistics for all five factor portfolios are reported in Table 3.

5 Empirical Results

5.1 Summary Statistics for Return and Commodity Risk Factors

Summary statistics of rolling continuous futures' returns are reported in the table 2. The mean is annualized based on weekly observation, with most of them having average negative performance in the sample period. Assets' return distribution normality is rejected, suggested by the high moment's column (skewness and kurtosis) as well as Jarque.Bera test (Jarque and Bera, 1987).

[Insert Table 2 around here]

A fully collateralized long-short portfolio approach is used to construct time-series risk factors. We only consider four quantiles (each consuming 25% of total assets) instead of five due to the non-negligible amount of missing values generated during the risk-neutral skewness estimation procedure. Except for those traditional baseline risk factors mentioned above, some other related risk factors proposed in the commodity literature are reported in table 3. We further report the correlation value matrix among risk factors in table 4.

[Insert Table 3 around here]

[Insert Table 4 around here]

From table 3, results for traditional factors like TS, MOM, and HP are consistent with studies and findings in most literature. The long-short portfolio performance suggested from the RNSK factor is superior to all other factor-based portfolios. Regarding the portfolio positive return ratio, risk-neutral skewness measures from either (Bakshi et al., 2003) or (Kozhan et al., 2013) are around 54%, while other risk factors fall into the group with approximately 50% or less. Meanwhile, Sharp ratios of these two risk-neutral skewness measures are outperforming all other portfolios at 0.87 and 1.39, respectively, implying a more robust compensation per unit risk taken. While for the Pearson skewness sorted portfolio performance, the annualized return is only 1.63%, which is far less than 8.01% documented by Fernandez-Perez et al. (2018). The difference might come from data length and assets' category used in portfolio construction. From the risk management point, risk-neutral skewness sorted portfolio is less risky with a lower value on: maximum drawdown (MaxDrawdown) and Value-at-Risk (VaR).

Additionally, from the table 4, the RNSK is less correlated or even negatively correlated with other risk factors, suggesting its benefit on factor investing and portfolio diversification. It is also clear that the RNSK portfolio has the best (increasing and stable) cumulative return over the testing period from the figure 1. Each quantile RNSK performance can be found in figure 2. Overall, RNSK factors show superior performance compared with other commodity risk factors.

[Insert Figure 1 around here]

[Insert Figure 2 around here]

5.2 RNSK Superior Measure Against Pearson Skewness

We first compute the averaged RNSK (SK) across all commodity products and compare them against the S&P GSCI index in figure 3. It is clear to see that the RNSK dynamics generally show a positive trend aligned with the S&P GSCI index, especially around specific major market movements in 2008 (financial crisis), 2012 (global factory sector contracted), and 2015 (global market slowdown with over-supply and less-demand). On the contrary, the SK is not indicating any clear information on market movement. Such difference could be because the RNSK is computed from options' data in a forwarding looking manner, which makes it a natural proxy for viewing the global market dynamics.

[**Insert Figure 3 around here**]

Furthermore, the RNSK is more flexible and has less parametrization concern than the realized skewness (e.g., the Pearson skewness coefficient) in constructing a long-short portfolio. We validate this point via exploring the weakness of the realized skewness measure when the parameter is a choice. Specifically, we consider the realized skewness signal and long-short portfolio performance in the following scenarios: daily and weekly frequency cases, five different window length parameters (from 1 month, 3-month, 6-month, 9-month, to 12-month). Ultimately, we include the RNSK signal and its sorted long-short portfolio correspondingly to compare in figure 4.

[**Insert Figure 4 around here**]

The upper two panels in the figure 4 show that estimation results are not proportional when using the same rolling window with different data frequencies (return is not normally distributed). As the window used in estimation increases, the Pearson skewness value becomes more stable and less sensitive to new data. While looking at the bottom two panels, with daily data (panel 3), the realized skewness sorted long-short portfolio even outperforms the RNSK sorted one at earlier testing period with 252 days set-up, although it underperforms after 2014 thoroughly. In contrast, weekly data in panel 4, the RNSK sorted long-short portfolio completely dominates, and realized skewness with 52 weeks sorted portfolio almost falls into the worst-performing group. Overall, it is clear to see that the RNSK sorted portfolio consistently generates a stable and attractive return.

5.3 Time Series RNSK Portfolio Return

To unveil the potential exposure of RNSK on other commodity risk factors, we regress RNSK sorted portfolio excess return on the excess return of equally weighted portfolio (standing for the overall long-only performance), term structure (market backwardation and contango information), hedging pressure (market expectation from trading participators) and momentum (trend follower in commodity trading) portfolios.

$$PR_{i,t} - rf_t = \alpha_i + \beta_{1,i} * EW_t + \beta_{2,i} * TS_t + \beta_{3,i} * HP_t + \beta_{4,i} * MOM_t + \epsilon_{i,t} \tag{8}$$

Where, $PR_{i,t}$ is the RNSK sorted portfolio return at time t and i is the index referred to quantile portfolio from P1 to P4, for instance $PR_{1,t}$ and $PR_{4,t}$ are matched for P1 (the lowest RNSK quantile) and P4 (the highest RNSK quantile) in this paper at time t respectively, rf_t is the risk-free rate at time t, α_i is the abnormal return in i^{th} portfolio regression analysis, $\epsilon_{i,t}$ is the i^{th} portfolio regressed error term at time t.

[Insert Table 5 around here]

From the table 5, panel A, RNSK sorted HML (long-short) portfolio delivers annualized 13.18% return with Sharp ratio 1.39, which is significantly higher than all other risk factors' based HML portfolios. This Sharp ratio is also better than those mentioned in the literature considering the global futures market so far, e.g., 0.47 term structure strategy in Erb and Harvey (2006), 0.75 hedging pressure strategy in Basu and Miffre (2013), 0.67 carry strategy in Koijen et al. (2018), value and momentum factors less than 1 in a standard case in Asness et al. (2013b), and 1.1 time-series momentum strategy with all available global futures market products in Moskowitz et al. (2012)). However, this might not be a fair comparison given some known different configurations on product selection, data length, frequency usage. Therefore, we use two market indexes as benchmark references and document a strong outperformance of the RNSK sorted portfolio compared with the commodity GSCI index return (-7.4% annual return with -0.29 Sharp ratio) and the equity CRSP index return (4.5% annual return with 0.23 Sharp ratio). This can further motivate comprehensive review in future research once all the different configurations have been reconciled.

From panel B, alpha (abnormal return) is statistically significant for the highest RNSK quantile, offering an extra annualized 18.03% return. On the lowest RNSK quantile, there is still additional statistically significant annualized -7.2% return, implying that commodity assets with a relatively higher RNSK mainly dominate RNSK long-short portfolio return. The alpha from the RNSK long-short portfolio indicates a significant solid result with an annualized return of 12.62%. From the lowest to the highest quantile and HML, RNSK sorted portfolio has little exposure (primarily not significant) to other commodity risk factors-based portfolios but is largely (also significantly) exposed to the excess return of equality weighted portfolio with a ratio around 1. Finally, a small R square value from the HML portfolio regression test suggests that the overall RNSK sorted long-short portfolio return cannot be explained by the existing traditional baseline model.

5.4 Stability of RNSK Signal and Predictability Horizon

The RNSK has been argued to be a short-lived signal that yields abnormal return for the first post-ranking week or even just overnight when using weekly frequency data (Gkionis et al., 2021). Meanwhile, Stilger et al. (2017) show that the RNSK signal is portfolio formation dependent, and its average measure can blur information and lose the predictive ability (abnormal return is no longer statistically significant). They also study that the RNSK can only help predict the first post-ranking month return by using monthly frequency regression with daily observations. Hence, the RNSK signal has been seen as a short-lived mispricing investment opportunity that is quickly corrected in the equity market.

To understand how the RNSK signal adapts to the commodity futures market, we conduct a similar test to validate whether the RNSK signal is concurrent to portfolio formation date and quantify the number of the post-ranking period the RNSK signal can predict. Unlike our benchmark analysis, in which we always use the latest RNSK value to sort assets, we compute the rolling averaged daily RNSK values and use its weekly observation to sort assets to form a portfolio. Moreover, to figure out how long the RNSK signal predicts, we use the latest RNSK signal and its averaging value as time t to form portfolio and compute return at time t+k (k = 1, 2, 3, . . .).

[Insert Table 6 around here]

In general, the table 6 shows that the long-short RNSK sorted portfolio can generate around 10% extra annualized return after controlling the traditional baseline model (equally weighted portfolio, term structure, momentum, and hedging pressure). As the signal averaging window increases, we see a more substantial abnormal return, yielding 14.6% when window length is 30 business days. These results still hold and are even more robust after controlling the realized skewness along with the above baseline factors. Consistent with our findings before, the highest RNSK quantile (P4) consistently provides a significant return, which drives the overall long-short portfolio. In contrast, the lowest RNSK quantile (P1) does lose its predictability when the signal average window is 5 and 10 days.

[**Insert Table 7 around here**]

With the same averaging signal set-up above but different forecasting horizons, the RNSK sorted long-short portfolios generally yield a significant around 6% annual return, up to the 10th post-ranking week across all signal averaging windows from the table 7. There is also a chance that such a signal still price the return after 13 weeks from today, although there is no significance found on the 11th and 12th post-ranking week. Compared with those studies of the RNSK in the equity market, the RNSK signal has a relatively long and persistent predictive ability in the global commodity futures market.

5.5 RNSK Characteristics under Backwardation and Contango

We further investigate the RNSK signal characteristics compared with the backwardation and contango scenario suggested from other traditional commodity risk factors (TS, MoM, and HP) and Skewness (SK). As indicated from the literature[14], a higher (lower) TS, MoM, and HP for speculators are associated with a backwardation (contango) market,

[14]Detailed findings can be referred to Bakshi et al. (2019), Fernandez-Perez et al. (2017), Basu and Miffre (2013), Miffre and Rallis (2007).

which will subsequently predict a rise (fall) price on the futures contract. At the end of each week, we estimate the RNSK, sort all commodity futures assets based on their RNSK values (ranking signal), and group them into four quantiles. Within each quantile, we compute an equally weighted value for all other risk factors (reporting signals) and show them in panel A of table 8. In panel B, we conduct the reverse operation to validate the relationship further. The high-minus-low (HML) value and its t-statistic are reported in both panels to show its quantile difference (P4-P1) significance.

[**Insert Table 8 around here**]

From panel A, all risk factors show a monotonic decreasing (TS, MoM, HP for speculators) pattern, and all their HML values are statistically significant. This sheds some light on the fact that the RNSK signal implies a notable opposite phase in terms of backwardation and contango. When the market is under backwardation suggested by higher TS, MoM and HP for speculators with an associated subsequent positive return, the RNSK has the lowest value and yield a negative return in the subsequent period from the quantile P1. The quantile P4 says that the highest RNSK value is associated with contango (the lowest TS, MoM, and HP for speculators with a subsequent negative return), yielding a positive return. Only the MoM signal shows a significant HML value from panel B, but no consistent monotonic pattern is observed.

In addition, we further explore the quantile signal relation by checking the number of the shared assets selected by both the RNSK and other traditional risk factors in figure 5. For TS, MoM and HP, we count their overlapping assets against the RNSK separately from the same direction quantile (i.e., long assets selected by both the RNSK and TS) and report the output as the top quantile overlapping number of assets. While for the SK, we conduct the opposite approach (long assets selected by the RNSK and short assets chosen by the SK) and report it as the top quantile overlapping number of assets.

[Insert Figure 5 around here]

We group all assets in top and bottom 25% and make sure we have four assets assigned to each quantile at the end of each week in ranking. Theoretically, if two signals select all the same assets in a quantile, the max count of overlapping assets is 4[15]. From the figure 5, all risk factors (TS, MoM, HP, and SK) have generally shared at most 50% overlapping assets against the RNSK from 2008 to 2016. The SK factor shows slightly more overlapping assets at the earlier testing stage, which could be due to the systematic risk impact in 2008, where the same factor drives both futures and options market.

To sum up, the positive return from the highest RNSK quantile is more pronounced under the contango phase, which differs from what traditional commodity risk factors indicate. Lastly, there is no clear evidence that the RNSK shares majority of overlapping pricing information with all other traditional risk factors and the realized skewness.

5.6 Cross-Sectional Analysis

The previous sections have focused on the time-series RNSK pricing ability test and the mechanism behind it. In this part, we leverage one set of Fama and MacBeth (1973) regression to test the RNSK cross-sectional performance further. Following with the same approach used by Stilger et al. (2017), in particular, at the end of each week, we regress all assets' return on lagged RNSK values and also other series of signals (i.e., term structure basis, hedging pressure, 1-year rolling average return, and etc.). At the end of

[15]Although there are 22 commodity assets we included in our analysis, there are the missing values of the RNSK that is non-trivial to ignore during some periods. Therefore, given the data limitation and to keep the number of assets selected in this overlapping analysis fixed, we decided to use four assets on the highest and lowest quantile to the next steps.

last week's regression test, we estimate the averaged coefficient, standard error, and t-test value and report the results in table 9.

[Insert Table 9 around here]

The RNSK shows a solid significant positive pricing ability across nearly all models in table 9. Specifically, models (1) to (13) consider all baseline traditional risk factors (TS, MoM, and HP) and also many other new augmented risk factors as control variables. Among these 13 models, the SK is added in selective models as a different control variable to fully unveil its impact on the RNSK in different combinations. In model tests (14) and (15), we replace the realized Pearson skewness with another two additional skewness measures (idiosyncratic skewness estimated from residuals of regressing assets' return on baseline model and quantile-based skewness). From models (16) to (19), idiosyncratic volatility is tested given its strong predicting ability on idiosyncratic skewness (Boyer et al., 2010). Finally, we consider adding all variables for the complete test and report them in the model (20), which leads to surprisingly insignificant alpha. However, we argue that this is expected as the model (20) includes three different skewness measures, potentially covering most pricing information from the RNSK. It is clear that the RNSK signal also shows a significant correlation with all three realized skewness measures from table 4. The conclusion is clear that the RNSK sorted long-short portfolio presents a significant return that is not challenged by all control variables as long as not all realized skewness measures are considered.

5.7 RNSK Signal Pricing Mechanism

We construct the conditional bivariate sort portfolio to explore further how the RNSK price the futures. Due to the nature of a small number of commodity futures and unavoidable missing values in risk factors, we consider only high and low quantile, with each constituting 50% of total assets[16]. In particular, we first sort all commodity assets based on their RNSK values into two quantiles. We further sort available commodity assets within each quantile based on another proxy factor into the new two quantiles. In the end, we will have four groups, with each taking 25% of the total assets.

To test our conjecture that a high level of arbitrage cost drives the positive relation between the RNSK and return, we use idiosyncratic volatility computed from the rolling second moments of residuals (asset return regressed on traditional baseline risk factors) to proxy the level of arbitrage cost (Chordia et al. (2021), and Cao and Han (2013)). In the equity RNSK research, the negative return from the lowest RNSK group has been attributed to those assets that are more pronounced to be overpriced and illiquid (Stilger et al., 2017). Following two proxies used in their studies, we estimate a 1-month max daily futures return (MaxReturn) of Bali et al. (2011), and the ratio of dollar volume to return (LIQUID) of Amihud et al. (1997) to represent overpricing and liquidity separately. For all conditional sorted portfolios, we further estimate alpha values from time-series regression on existing traditional risk factors (EW, TS, MoM, and HP) and report in table 10.

[**Insert Table 10 around here**]

From panel A of table 10, we can confirm that the significant positive return from the highest RNSK quantile is driven by those assets that are more pronounced to have considerable arbitrage risk (cost). Portfolio with the highest arbitrage risk within the highest RNSK quantile yield a significant 35 bps per week. Finally, within the highest RNSK quantile, the spread return between the portfolio with the most and the portfolio with the least arbitrage risk generates a significant return at 22 bps per week.

[16]This is different from most equity market studies where stocks are generally sorted into tercile.

The panel B results show that the lowest RNSK quantile negative return can be explained by overpricing of underlying assets with the highest maximum past month return, -21.8 bps per week. Within the lowest RNSK quantile, the spread return between the portfolio with the highest and the portfolio with the lowest maximum past month return help generate a significant return at -32.9 bps per week.

Lastly, in panel C, we found that the most positive RNSK portfolio outperformance is led by the commodity assets associated with the lowest liquidity. In particular, the portfolio with the lowest liquidity quantile within the highest RNSK quantile generates 38 bps per week. Moreover, within the highest RNSK quantile, the spread return between a portfolio with the highest liquidity and a portfolio with the lowest liquidity yields a significant return, -22.4 bps per week.

To answer the hypothesis that the information embedded in the realized skewness (SK) can be explained by the risk-neutral skewness (RNSK), we test this via a dependent bivariate sort analysis by Bali et al. (2016) and report the results in table 11.

[**Insert Table 11 around here**]

From panel A of table 11, after controlling the effect of the RNSK, there is no significant relationship between return and the SK in the spread portfolio returns. On the contrary, from panel B, it is clear that the RNSK has presented a significant positive return to all groups. Notably, there is no evidence that this significant positive relation between the RNSK and return is driven by one quantile (highest or lowest SK) group. Instead, we observe consistent significant returns among all scenarios.

With all the above, we confirm that the negative return from the lowest RNSK quantile group in the futures market is driven by overpriced commodities. On the other hand, the positive return's key driver is those assets within the highest RNSK quantile, associated with higher idiosyncratic risk and less liquidity cost. Finally, the RNSK pricing ability on return is significantly positive in all quantile group analyses after controlling the impact of the SK. At the same time, the SK shows no significant connection to return when the RNSK effect is considered.

5.8 Robustness Test

We employ more risk factors discussed in the commodity literature along with the baseline model to clarify whether alpha generated from the RNSK sorted long-short portfolio is still significant. In particular, we consider the following: (1) IDIOSKEW (IDIOVOL), long-short portfolio sorted by skewness (volatility) calculated on the residuals (regression of asset return on traditional commodity baseline model), (2) QuantileSK, long-short portfolio sorted by the difference of return quantiles (3) CV, long-short portfolio sorted by variance-over-mean of daily futures returns over prior 36 months, (4) LIQUID, long-short portfolio sorted by prior 2-month dollar volume over an absolute return, (5) ΔOI, long-short portfolio sorted by the change of entire open interest of commodity futures, (6) Fama_French five factors, motivated by the equity market: Mkt.RF, SMB, HML, RMW and CMA (Fernandez-Perez et al. (2016), Fernandez-Perez et al. (2018), Bowley (1920), Hong and Yogo (2012), Erb and Harvey (2006), Amihud et al. (1997) and Locke and Venkatesh (1997)).

[Insert Table 12 around here]

From the table 12, in general, alpha is still significant through all scenarios regardless of the control factors and realized Pearson skewness (SK) in use, yielding at least 20 bps return per week. It is worth mentioning that the portfolio sorted on the SK shows strong negative relation to the portfolio sorted on the RNSK in all model tests, including the baseline test in table 5. However, no persist robust significance is found on other skewness measures, such as idiosyncratic and quantile-based skewness. One potential reason could be the configuration differences discussed before: window length, regression model choice, and quantile value. Lastly, as expected, there is no significance observed from those equity market factors as commodity futures market shows substantial heterogeneity, consistent with findings of Jagannathan (1985) and Erb and Harvey (2006).

[**Insert Table 13 around here**]

[**Insert Table 14 around here**]

This significance of alpha results is not challenged when switching to another risk-neutral skewness measurement by (Bakshi et al., 2003) and monthly rebalancing frequency in table 13. There is a clear pattern that the alpha has shrunk to some extent via BKM estimator in both weekly and monthly frequency tests. We continue with the above set-up in cross-sectional test to further check the impact of rebalancing frequency and alternative skewness measurement in table 14. The RNSK, with a monthly rebalancing set-up, still positively prices the individual futures return in all model tests. However, the BKM estimator does lose its pricing ability when more control factors are added under the weekly ranking signal and rebalancing case. This becomes even worse when the monthly rebalancing set-up is utilized. One of the possible reasons is mentioned in the methodology section that the RNSK (Kozhan et al., 2013) is argued to be a better choice for commodity market data.

Overall, it is clear that to achieve better pricing results for the futures market, the risk-neutral skewness by Kozhan et al. (2013) is recommended to use, instead of the one by Bakshi et al. (2003).

6 Conclusion

This paper investigates the relation between the risk-neutral skewness (RNSK) and subsequent commodity futures return. A portfolio, buying commodities within the highest RNSK quantile and selling commodities within the lowest RNSK quantile, can generate significant 13.18% returns, which is superior to its counterparty, realized skewness with a long-short portfolio return at only 1.63%. In addition to the remarkable return gained on the RNSK long-short portfolio, it also indicates better measures on risk-adjusted earning (Sharp ratio) and least worst performance (max drawdown).

The above position relation (between the RNSK and individual assets' return) holds in time-series and cross-sectional testing results with different control variables. This implies that the pricing and predictive ability of the RNSK cannot be explained by the traditional commodity baseline factors (market index, term structure, hedging pressure, and momentum) and many other commodity market-specific factors. Moreover, the above findings hold when the realized Pearson skewness is added tests. On the contrary, the relation between the Pearson skewness and return has disappeared when the RNSK is controlled.

As for the RNSK property, we find that the RNSK has opposite characteristics compared against existing traditional commodity baseline factors in the futures market, namely term structure, hedging pressure, and momentum. When those traditional baseline factors suggest a backwardation market with a subsequent positive return, the RNSK instead talks about contango with a negative return and vice versa.

Our empirical results confirm that the RNSK pricing mechanism fits under the directional-learning hypothesis (Easley et al. (1998), and Kang and Park (2008)). In general, investors with positive (negative) information on the future underlying movement will resort to the options market to explore the extra gains by buying more OTM call (put) options, hence leading to a higher (lower) RNSK value. When that information spreads to the underlying market, commodities' prices then increase (decrease) to reflect to correct those beliefs. In fact, we confirm that the large significant positive return generated from the highest RNSK quantile are those commodities associated with higher idiosyncratic volatility and less liquidity. In contrast, the significant negative return from the lowest RNSK quantile is driven by those commodities that have been categorized as overpriced.

Finally, different from the findings in the equity market, we show that the RNSK has a relatively stable and longer pricing predictability in the commodity futures market. The long-short portfolio sorted based on averaging signals of the RNSK over the window (up to 30 days) can yield a significant 14.6% return after correcting traditional commodity baseline factors. Under the same averaging signal set-up but extending the forecasting horizon (weeks), we find that the RNSK sorted portfolio can yield an extra 6% return up to 10 weeks.

Data Availability Statement

Part of the data that support the findings of this study is available from "DataStream". Restrictions apply to the availability of these data, which were used under license for this study.

Part of the data that support the findings of this study is openly available in Kenneth R. French webpage at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`.

Part of the data that support the findings of this study is openly available on the CFTC webpage at `https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm`.

Part of the data that support the findings of this study is openly available on the CRSP webpage at `http://www.crsp.org/products/research-products/crsp-historical-indexes`. Restrictions apply to the availability of these data, which were used under license for this study.

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Table 1: **Risk Factor Description**

Name	Definition	Data Source
Panel A: Baseline four-factor model		
EW	Excess return of equally-weighted long-only portfolio of commodity futures	Datastream
TS	Excess return of long-short portfolio sorted by prior 1 week of term structure basis	Datastream
MoM	Excess return of long-short portfolio sorted by prior 1 year of return	Datastream
HP	Excess return of long-short portfolio sorted by prior 1 week of speculators' hedging pressure	CFTC
Panel B: Skewness measure in literature		
SK	Excess return of long-short portfolio sorted by prior 1 year Pearson skewness of return	Datastream
QuantileSK	Excess return of long-short portfolio sorted by prior 1 year skewness estimated by quantile difference (99%, 1% and 50%)	Datastream
IDIOSKEW	Excess return of long-short portfolio sorted by Pearson skewness of residuals estimated from prior 1 year (commodity return regressed on baseline four-factor model)	Datastream
BKM	Excess return of long-short portfolio sorted by prior 1 week risk-neutral skewness (Bakshi et al., 2003) of options on futures	Datastream
RNSK	Excess return of long-short portfolio sorted by prior 1 week risk-neutral skewness (Kozhan et al., 2013) of options on futures	Datastream
Panel C: Other systematic risk factors		
IDIOVOL	Excess return of long-short portfolio sorted by standard deviation of residuals estimated from prior 1 year (commodity return regressed on baseline four-factor model)	Datastream
LIQUID	Excess return of long-short portfolio sorted by prior 2-month dollar volume over absolute return	Datastream
ΔOI	Excess return of long-short portfolio sorted by changes in current total open interest along entire term structure	Datastream
CV	Excess return of long-short portfolio sorted by variance-over-mean of daily futures returns over prior 3 years	Datastream
Panel D: Risk factors motivated by the equity and commodity literature		
S&P-GSCI	Global commodity futures index published by the S&P	Datastream
CRSP Index	Value-weighted equity market index published by the CRSP	CRSP Research Data Service
Mkt.RF	Excess value-weighted return of all CRSP US firms listed on the NYSE, AMEX, or NASDAQ	K.R. French's website
SMB	Small-minus-large factor (difference in returns between small and large capitalization stocks)	K.R. French's website
HML	High-minus-low factor (difference in returns between high and low book-to-market stocks)	K.R. French's website
RMW	Robust-minus-weak factor (difference between the returns of firms with robust (high) and weak (low) operating profitability)	K.R. French's website
CMA	Conservative-minus-aggressive factor (difference between the returns on diversified portfolios of low and high investment stocks)	K.R. French's website

Table 2: **Summary Statistics for Commodity Futures Return**

The table reports summary statistics of weekly commodity futures returns from 10/10/2007 to 01/03/2016. The first row of this table is for descriptive statistics, and the first column is for specific asset names. Results are organized by sectors based on commodities' attributes: Panel A: Agriculture sector, Panel B: Livestock sector, Panel C: Energy sector, and Panel D: Metal sector. From the second column, we report the following: number of observations; mean, standard deviation, minimum, maximum, skewness, and kurtosis of the return series; Jarque Bera test results for return distribution normality check; autocorrelation with one-week lag coefficient results; and unconditional asset return mean zero T-test statistics.

	N	Mean	SD	Min	Max	Skew	Kurtosis	Jarque.Bera	AR(1)	T test
Panel A: Agriculture Sector										
Cocoa Return	433	0.0573	0.2894	-0.1672	0.1431	0.0514	1.2952	0.0000	0.0143	0.5714
Coffee Return	433	-0.0755	0.3289	-0.1449	0.1766	0.1328	0.8544	0.0006	0.0126	-0.6624
Corn Return	433	-0.0466	0.3192	-0.1649	0.1841	0.0058	1.8113	0.0000	-0.0324	-0.4212
Cotton Return	433	-0.0427	0.3201	-0.1684	0.1615	-0.0283	1.3203	0.0000	0.0250	-0.3845
Oat Return	433	-0.0312	0.3755	-0.2327	0.3337	0.2996	4.9585	0.0000	-0.0625	-0.2396
Orange Return	433	-0.0086	0.3694	-0.2471	0.1837	0.0694	2.2793	0.0000	-0.0246	-0.0674
Rough Rice Return	433	-0.0872	0.2429	-0.1416	0.0989	-0.1952	0.9895	0.0000	0.0700	-1.0355
Soybean Meal Return	433	0.1418	0.3013	-0.1521	0.1321	-0.1026	0.3899	0.1545	-0.0679	1.3583
Soybean Return	433	0.0683	0.2645	-0.1274	0.1134	-0.1831	0.6309	0.0067	-0.0351	0.7455
Soybean Oil Return	433	-0.0814	0.2636	-0.1160	0.1405	0.0505	0.8943	0.0005	0.0023	-0.8910
Sugar Return	433	-0.0460	0.3556	-0.2299	0.1452	-0.2656	1.2478	0.0000	-0.0750	-0.3732
Wheat Return	433	-0.1821	0.3285	-0.1763	0.1465	0.0499	0.9740	0.0001	-0.0217	-1.5995
Panel B: Livestock Sector										
Live Cattle Return	433	-0.0146	0.1510	-0.0887	0.0714	-0.3636	1.1536	0.0000	-0.0182	-0.2784
Lean Hogs Return	433	-0.0575	0.2396	-0.1224	0.1047	-0.3244	0.4643	0.0027	0.0569	-0.6929
Feeder Cattle Return	433	-0.0231	0.1573	-0.1200	0.0798	-0.5773	2.4162	0.0000	0.0132	-0.4234
Panel C: Energy Sector										
RBOB Return	433	-0.0751	0.3565	-0.1826	0.2428	-0.2239	2.3486	0.0000	0.0029	-0.6082
Light Crude Return	433	-0.2335	0.3693	-0.1807	0.2189	-0.1741	1.6303	0.0000	-0.0376	-1.8243
Brent Return	433	-0.1675	0.3483	-0.1756	0.2160	-0.1958	1.8936	0.0000	0.0261	-1.3882
Heating Oil Return	433	-0.1430	0.3194	-0.1443	0.2192	0.1834	1.9918	0.0000	0.0609	-1.2919
Natural Gas Return	433	-0.4498	0.4093	-0.1624	0.2076	0.1174	0.5204	0.0450	-0.0204	-3.1711
Panel D: Metal Sector										
Gold Return	433	0.0555	0.1955	-0.1344	0.1310	-0.0849	3.2349	0.0000	0.0018	0.8189
Silver Return	433	0.0076	0.3487	-0.2414	0.2260	-0.1983	2.5500	0.0000	-0.0047	0.0626

Table 3: **Portfolio Performance Statistics for Commodity Risk Factors**

For all the commodity market-related risk factors in table 1, we report their long-short or long-only portfolios' performance labeled column-wise. The first column summarizes all the statistics used for performance measurement where the mean is annualized with a multiplier of 52 in this table with weekly observations.

	EW	MOM	TS	HP	GSCI Index	CRSP Index	BKM	RNSK	SK	QuantileSK	LIQUID	CV	IDIOVOL	IDIOSKEW	ΔOI
Mean	-0.05566	0.0697	0.07218	0.03305	-0.07438	0.04557	0.08024	0.13187	0.0163	0.0225	0.00537	0.03581	0.06373	0.00888	0.06357
SD	0.15345	0.13133	0.11023	0.08469	0.25037	0.19353	0.09178	0.09479	0.10609	0.09475	0.09375	0.06754	0.11306	0.08264	0.1501
Sharp Ratio	-0.36271	0.53077	0.65481	0.39025	-0.29709	0.23545	0.87428	1.39111	0.15367	0.23751	0.05728	0.53015	0.56372	0.10745	0.42349
Sortino Ratio	-0.06751	0.1054	0.13627	0.07882	-0.05566	0.04283	0.18767	0.33578	0.03155	0.04981	0.01082	0.11246	0.11551	0.0222	0.09154
Omega Sharp Ratio	-0.12821	0.23823	0.30074	0.16356	-0.10558	0.09562	0.37516	0.65537	0.06181	0.09672	0.0223	0.26195	0.24025	0.04191	0.21673
Skewness	-0.17298	-0.465	-0.20588	-0.0959	-0.07171	-1.0972	-0.05355	0.26414	0.33196	0.29784	-0.44113	0.14217	-0.10955	0.40691	0.44715
Kurtosis	4.51714	6.53904	6.50752	5.43871	4.36392	8.24974	4.28012	3.63524	5.89387	5.56578	7.26642	4.85074	4.4197	4.61319	8.81712
99% VAR(Cornish-Fisher)	-0.07654	-0.06077	-0.04872	-0.04211	-0.12388	-0.10387	-0.04287	-0.03184	-0.06594	-0.05601	-0.04632	-0.03504	-0.05428	-0.03582	-0.08185
MaxDrawdown	0.56021	0.17888	0.19026	0.1507	0.74858	0.5649	0.12087	0.08879	0.36786	0.24697	0.25053	0.14136	0.19875	0.25836	0.25865
% of Positive Weeks	0.48268	0.4873	0.46882	0.4642	0.50346	0.59584	0.53811	0.54042	0.45497	0.42263	0.51501	0.34642	0.48268	0.45497	0.38568

Table 4: **Pair-Wise Correlation Matrix of Risk Factors**

This table shows a pair-wise correlation matrix among factors following the sample correlation estimation method from 10/10/2007 to 01/03/2016. In addition to factors specified in table 3, we add five factors in the equity market (Fama_French): Mkt.RF (excess return of long-only market portfolio), SMB (long-short portfolio sorted by company market capitalization), HML (long-short portfolio sorted by book-to-market ratio), RMW (long-short portfolio sorted by firms' operating profitability), CMA (long-short portfolio sorted by investing style).

	EW	MOM	TS	HP	Mkt.RF	SMB	HML	RMW	CMA	GSCI Index	CRSP Index	BKM	RNSK	SK	QuantileSK	LIQUID	CV	IDIOVOL	IDIOSKEW	ΔOI
EW																				
MOM	0.0060																			
TS	0.0110	0.6010***																		
HP	0.0887*	0.3450***	0.2733***																	
Mkt.RF	0.0534	0.0145	0.0146	0.0163																
SMB	0.0560	0.0017	-0.01067	0.0150	0.1400***															
HML	-0.01683	0.0050	-0.05320	0.0707	0.5021***	0.0989**														
RMW	-0.02634	0.0652	0.0799*	-0.00213	-0.44586***	-0.30162***	-0.49751***													
CMA	-0.06321	0.0109	-0.01591	-0.00971	-0.15072***	0.0943***	0.1435***	0.0493												
GSCI Index	0.8808***	0.0188	0.0066	0.0444	0.0828**	0.0254	-0.01300	-0.00623	-0.04749											
CRSP Index	0.5548***	0.0174	0.0350	0.0181	0.2986***	0.0710	0.2350***	-0.15971***	-0.05545	0.5805***										
BKM	-0.02676	0.1151**	0.0758	0.0594	0.0177	-0.02845	0.1053***	-0.04758	0.0104	-0.05494	-0.07346									
RNSK	-0.03398	0.0367	0.0205	0.0384	0.0119	0.0068	0.1307***	-0.04285	-0.05660	-0.07405	0.0047	0.7243***								
SK	0.0558	-0.00064	-0.02768	-0.02987	0.0101	-0.00688	-0.06258	0.0008	0.0211	0.0615	-0.02381	-0.18563***	-0.16294***							
QuantileSK	0.0675	-0.04777	-0.06947	-0.03307	0.0455	-0.06498	0.0363	-0.04983	-0.00954	0.0752	0.0077	-0.15285***	-0.10735***	0.6036***						
LIQUID	0.0899*	0.0721	-0.01730	-0.05283	0.0773	0.0019	0.0260	0.0651	-0.01905	0.1036**	0.1080**	-0.19514***	-0.20807***	0.0511	0.0431					
CV	0.0227	-0.00937	0.0502	0.0671	-0.00465	0.0395	0.0066	0.0187	0.0428	-0.01025	0.0196	-0.04305	-0.02064	0.0940*	0.1037**	-0.02249				
IDIOVOL	0.0614	-0.07222	-0.06778	-0.04037	-0.05821	-0.01075	0.0219	-0.00647	-0.01807	0.0515	0.0262	0.0736	-0.02581	0.0654	0.0704	-0.17299***	0.0308			
IDIOSKEW	-0.03244	-0.05756	-0.00829	-0.04049	0.0456	-0.04308	0.0944**	0.0135	-0.01854	-0.04230	-0.00144	0.0287	0.0810*	0.1671***	0.2100***	-0.01209	0.2439***	0.0665		
ΔOI	0.0564	0.0809*	0.0149	0.0183	0.0247	0.1281***	0.0319	-0.09688**	-0.04445	0.0053	0.0166	0.0496	0.0282	-0.00017	0.0052	0.1479***	-0.05971	-0.09538**	-0.02832	

Note: *p<0.1; **p<0.05; ***p<0.01;

Table 5: **Time Series Analysis – Portfolio Property based on RNSK**

The RNSK sorted equally weighted portfolio performance, and regression analysis on baseline models results from 10/10/2007 to 01/03/2016 are reported in this table. In panel A, portfolio performance statistics are reported for long-only portfolios sorted by RNSK from P1 (the lowest RNSK group) to P4 (the highest RNSK group) and HML (P4 minus P1). All mean value is annualized with a multiplier of 52. In panel B, each quantile time-series portfolio is regressed on the baseline model (EW, TS, MOM, and HP) and baseline model plus the SK factor for robustness check. The first row in panel B reports the annualized mean (multiplied by 52). The t-statistic values are reported under the estimated coefficients, with corrected standard error (12 lags) following (Newey and West, 1987).

	P1		**P2**		**P3**		**P4**		**HML**	
Panel A: Quantile Portfolio Performance										
Mean	-0.14356		0.01419		-0.07547		0.12018		0.13187	
SD	0.20881		0.20637		0.24434		0.19089		0.09479	
Sharp Ratio	-0.68753		0.06875		-0.30888		0.62956		1.39111	
Sortino Ratio	-0.12203		0.01341		-0.05823		0.13185		0.33578	
Omega Sharp Ratio	-0.23063		0.02668		-0.10982		0.26509		0.65537	
Skewness	-0.27043		-0.15620		-0.13511		-0.09532		0.26414	
Kurtosis	5.05051		4.70311		4.27249		4.03761		3.63524	
99% VAR(Cornish-Fisher)	-0.10398		-0.10238		-0.11947		-0.08698		-0.03184	
MaxDrawdown	0.77872		0.62986		0.71667		0.42325		0.08879	
% of Positive Week	0.45958		0.47806		0.44573		0.51270		0.54042	
Panel B: Time-Series Regression										
Alpha	-0.07232**	-0.07205**	0.0849	0.0830	-0.02173	-0.02367	0.1790***	0.1803***	0.1256***	0.1262***
	-2.03738	-2.02836	1.51305	1.47807	-0.28983	-0.31811	4.36694	4.38231	4.20880	4.21757
EW	1.1230***	1.1236***	1.0153***	1.0117***	1.0286***	1.0249***	0.9662***	0.9687***	-0.07840*	-0.07740*
	21.19355	21.26112	17.95193	18.12002	13.93646	14.10649	20.11558	20.11505	-1.86729	-1.83895
TS	-0.00071	-0.00118	-0.11457	-0.11132	-0.02921	-0.02584	0.05070	0.04843	0.02570	0.02480
	-0.01153	-0.01926	-1.40082	-1.37929	-0.30062	-0.26527	0.77856	0.72258	0.56949	0.53934
MOM	-0.11386**	-0.11349**	-0.00483	-0.00729	0.08196	0.07941	-0.05702	-0.05531	0.02842	0.02909
	-2.20013	-2.19640	-0.07362	-0.11248	0.99455	0.96587	-0.97296	-0.93872	0.82517	0.83846
HP	0.05488	0.05432	-0.02674	-0.02292	0.11847	0.12243	0.02673	0.02407	-0.01407	-0.01513
	0.75144	0.74590	-0.27692	-0.23720	1.23703	1.25849	0.39486	0.35465	-0.25450	-0.27310
SK		-0.01210		0.08334		0.08641		-0.05814		-0.02302
		-0.21662		1.42178		1.01190		-1.16528		-0.51964
Adj.R.square	0.68240	0.68168	0.56500	0.56581	0.41821	0.41824	0.59972	0.59981	0.01037	0.00869

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: **RNSK Abnormal Return Test with Ranking Signal Treatment**

This table explores the RNSK signal pricing ability impact of different averaging windows configurations from P1 (lowest), P4 (highest), to HML (P4 minus P1) portfolio return. The RNSK grouped portfolio excess return at panel A is regressed on the traditional baseline model (EW, TS, MOM, and HP). In contrast, at panel B, the RNSK grouped portfolio return is regressed on the traditional baseline model (EW, TS, MOM, and HP) and the Pearson skewness. Final regression alpha (annualized) and t-statistic values are reported. All the t-statistic values are adjusted with corrected standard error (12 lags) following (Newey and West, 1987).

Panel A: Time Series Alpha Test With Traditional Model

	P1RNSK Alpha	P1RNSK T-value	P4RNSK Alpha	P4RNSK T-value	HMLRNSK Alpha	HMLRNSK T-value
AveragingDays=1	-0.07232**	-2.03737	0.1790***	4.3669	0.1256***	4.2088
AveragingDays=5	-0.05457	-1.32664	0.1472***	3.8391	0.1009***	3.3703
AveragingDays=10	-0.03695	-0.87791	0.1749***	4.3330	0.1059***	3.3901
AveragingDays=15	-0.09110*	-1.93939	0.1606***	3.8815	0.1258***	3.6547
AveragingDays=20	-0.13600***	-2.96882	0.1556***	3.6625	0.1458***	4.2080
AveragingDays=25	-0.15562***	-3.82613	0.1539***	3.6204	0.1547***	4.7556
AveragingDays=30	-0.12941***	-3.10630	0.1626***	3.6141	0.1460***	4.3398

Panel B: Time Series Alpha Test With Traditional Model and Pearson Skewness

	P1RNSK Alpha	P1RNSK T-value	P4RNSK Alpha	P4RNSK T-value	HMLRNSK Alpha	HMLRNSK T-value
AveragingDays=1	-0.07205**	-2.02836	0.1803***	4.3823	0.1262***	4.2175
AveragingDays=5	-0.05428	-1.30982	0.1465***	3.8400	0.1004***	3.3418
AveragingDays=10	-0.03703	-0.87972	0.1737***	4.3791	0.1053***	3.4130
AveragingDays=15	-0.08989*	-1.94726	0.1611***	3.8612	0.1255***	3.6772
AveragingDays=20	-0.13577***	-2.98667	0.1551***	3.6842	0.1454***	4.2669
AveragingDays=25	-0.15718***	-3.71362	0.1539***	3.6389	0.1555***	4.6707
AveragingDays=30	-0.12942***	-3.10796	0.1626***	3.6219	0.1460***	4.3502

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: **RNSK Abnormal Return Test with Forecasting Horizon Treatment**

This table explores the RNSK signal pricing ability impact with two different configurations: signal averaging window and forecasting horizon. Column headers stand for different window lengths used in averaged RNSK signals calculation (from 1 day to 30 days), and the first column controls different forecasting horizons from 2 weeks to 13 weeks. For each combination set-up, the corresponding RNSK long-short portfolio return is regressed on two sets of model configurations. The RNSK grouped long-short portfolio return at panel A is regressed on the traditional baseline model (EW, TS, MOM, and HP). In contrast, at panel B, the RNSK grouped long-short portfolio return is regressed on the traditional baseline model (EW, TS, MOM, and HP) and the Pearson skewness. Final regression alpha (annualized) and t-statistic values (adjusted with corrected standard error (12 lags) following (Newey and West, 1987)) are reported.

Panel A: Time Series Alpha Test with Traditional Model

	AvgDays=1		AvgDays=5		AvgDays=10		AvgDays=15		AvgDays=20		AvgDays=25		AvgDays=30	
Forecasting Horizon (Weeks)	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value
T=2	0.1187***	4.3097	0.0926***	3.2116	0.0989***	3.1963	0.1216***	4.1459	0.1177***	3.6995	0.1248***	3.9681	0.1251***	3.9974
T=3	0.1032***	3.3251	0.1195***	3.8488	0.1178***	3.6783	0.1164***	3.4865	0.1075***	4.3671	0.1141***	3.9617	0.0894***	3.2217
T=4	0.0969***	3.4821	0.0867***	3.5716	0.1087***	3.7195	0.0984***	2.6761	0.0946***	2.6791	0.1070***	2.9597	0.0876***	2.7304
T=5	0.1108***	3.0760	0.0934***	2.9576	0.1382***	4.3933	0.1023***	2.8668	0.1120***	3.4575	0.0963***	3.3962	0.0870***	3.2000
T=6	0.0819***	2.7288	0.0913**	2.4841	0.0686**	2.2321	0.0554*	1.7088	0.0644**	2.0968	0.0812***	3.0385	0.0624***	2.7977
T=7	0.0503***	3.0859	0.0437*	1.8792	0.0647***	3.5535	0.0589***	2.9211	0.0663***	3.6418	0.0609***	3.8026	0.0610***	3.3550
T=8	0.0902***	4.4068	0.0726***	3.4489	0.0848***	3.1758	0.0734***	3.4839	0.0701***	3.4567	0.0840***	4.0586	0.0615***	4.0051
T=9	0.0677**	2.3247	0.0914***	3.8039	0.0782***	3.1165	0.0582**	2.4762	0.0597**	2.2579	0.0659**	2.5142	0.0445**	2.0815
T=10	0.0670***	5.8913	0.0673***	5.0285	0.0821***	5.1001	0.0637***	3.0239	0.0754***	3.4590	0.0696***	3.8640	0.0547**	2.4678
T=11	0.0204	0.7088	0.0597	1.5805	0.0401	1.2424	0.0234	0.7782	0.0246	0.9809	0.0177	0.7219	0.0276	0.7545
T=12	0.0149	0.7355	0.0432***	2.7283	0.0083	0.5618	-0.012	-0.948	0.0043	0.3722	0.0111	0.7367	0.0202	1.2554
T=13	0.0729**	2.3687	0.0540**	1.9922	0.0551***	3.4520	0.0378***	2.6758	0.0409***	2.8946	0.0601***	4.9655	0.0485***	3.3081

Panel B: Time Series Alpha Test with Traditional Model and Skewness

	AvgDays=1		AvgDays=5		AvgDays=10		AvgDays=15		AvgDays=20		AvgDays=25		AvgDays=30	
Forecasting Horizon (Weeks)	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value	Alpha	T-Value
T=2	0.1189***	4.3008	0.0926***	3.2291	0.0986***	3.2161	0.1215***	3.9628	0.1175***	3.7832	0.1247***	4.1335	0.1258***	3.9911
T=3	0.1020***	3.1494	0.1195***	3.8305	0.1147***	3.7555	0.1161***	3.3857	0.1079***	4.6321	0.1163***	3.9194	0.0886***	3.1447
T=4	0.0969***	3.6313	0.0849***	3.3131	0.1090***	3.7430	0.0953***	2.8704	0.0945***	2.6642	0.1079***	3.0762	0.0898***	2.6558
T=5	0.1134***	3.1365	0.0867***	2.6218	0.1374***	4.0432	0.0968***	2.7954	0.1139***	3.4792	0.0948***	3.2997	0.0882***	3.4450
T=6	0.0851***	2.8439	0.0932***	2.6145	0.0698**	2.3097	0.0576**	2.3262	0.0639**	2.1035	0.0803***	3.2724	0.0611***	2.7636
T=7	0.0650***	3.9851	0.0382*	1.6945	0.0638***	3.2738	0.0714***	3.3308	0.0663***	3.5899	0.0594***	3.8839	0.0604***	3.1774
T=8	0.0901***	4.3332	0.0719***	3.0746	0.0847***	3.2200	0.0703***	4.4935	0.0711***	3.5383	0.0775***	2.8187	0.0618***	3.9968
T=9	0.0766***	2.6273	0.0920***	3.5290	0.1116***	5.0994	0.0605**	2.3569	0.0613*	1.9068	0.0665**	2.3940	0.0448**	2.0582
T=10	0.0627***	4.6798	0.0704***	5.7764	0.0827***	4.9311	0.0629***	3.5775	0.0760***	3.3503	0.0610***	5.1303	0.0549**	2.4389
T=11	0.0228	0.7582	0.0585	1.4588	0.0385	1.1480	0.0221	0.7966	0.0241	0.8747	0.0177	0.7324	0.0250	0.7293
T=12	0.0129	0.6427	0.0421**	2.4659	0.0084	0.5579	-0.012	-1.019	0.0001	0.0103	0.0069	0.4159	0.0206	1.1616
T=13	0.0764**	2.4311	0.0565**	2.1260	0.0552***	3.6582	0.0327**	2.0200	0.0344**	2.2593	0.0594***	4.7295	0.0480***	3.2437

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: **RNSK Quantile Characteristics on Backwardation**

In panel A, all commodity assets are first grouped by the ranking signal (the RNSK value) in ascending order from lowest (P1) to the highest (P4) quantile. Within each quantile, the averaged signal (reporting signals) is computed. In panel B, futures products are first sorted based on each ranking signal, respectively, and then the averaged RNSK signal from each quantile group is computed. We also report high-minus-low (HML) and its correspondingly t-statistics value in the last two columns.

Ranking Signal	Reporting Signal	P1	P2	P3	P4	HML	T-Value (HML)
Panel A: Pre-Ranking Via RNSK Signals							
RNSK	RNSK	-2.45740	-0.20904	0.63971	2.40979	2.43359***	47.28818
RNSK	SK	-0.13622	-0.08112	-0.07788	-0.08179	0.02721***	4.78439
RNSK	TS	-0.00014	-0.00025	-0.00085	-0.00129	-0.00057***	-7.22483
RNSK	MoM	0.00057	-0.00015	-0.00096	-0.00128	-0.00092***	-11.58445
RNSK	HP (hedgers long only)	0.41118	0.43176	0.44921	0.45452	0.02166***	13.49335
RNSK	HP (speculators long only)	0.63848	0.62124	0.60457	0.59840	-0.02004***	-7.39164
Panel B: Pre-Ranking Via Other Commodity Risk Factor Signals							
SK	RNSK	-0.13886	-0.18937	-0.42884	0.09168	0.15538	1.60650
TS	RNSK	-0.17110	0.09061	0.17636	-0.24557	-0.07258	-1.16890
MoM	RNSK	0.26228	0.00706	0.79760	-0.25644	-0.18716**	-2.06686
HP (hedgers long only)	RNSK	-0.02432	-0.09052	0.57051	0.08617	0.03500	0.70445
HP (speculators long only)	RNSK	0.07815	0.09180	-1.31232	-0.10435	0.01826	0.52418

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: **RNSK Cross-Sectional Fama_Macbeth Regression**

At the end of each week, we run all assets' returns on lagged signals and report the averaged coefficients in the spirit of Fama and MacBeth (1973). The t-statistic value is listed underneath the estimated coefficient with adjustment by autocorrelation and heterogeneity with lag 12 based on (Newey and West, 1987). Models (1) to (13) compare the regression results on the RNSK (Kozhan et al., 2013) with and without adding SK as a control variable. We also test another two skewness measures in the model (14) and (15), named IDIOSKEW (skewness measured on residuals from regressions of assets' return on traditional baseline model (EW, TS, MoM, and HP)) and QuantileSK (quantile-based skewness using quantile value 99%, 50%, and 1%). Models (16) to (19) validate the impact of idiosyncratic volatility on the RNSK, and the last model (20) validates the full model performance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α	-0.00021	-0.00010	0.0010	0.0023	-0.00016	0.0011	0.0024	0.0003	0.0010	0.0014
	-0.18765	-0.09032	0.4823	0.8978	-0.06021	0.5525	0.8824	0.1126	0.4978	0.5365
RNSK	0.0006***	0.0007***		0.0005**	0.0006**		0.0005**	0.0007**		0.0005**
	2.6807	2.7330		2.1309	2.3843		2.0133	2.4143		2.0298
SK		-0.00120			0.3927			0.4862		
		-0.67068			1.4724			1.5692		
TS			0.1108	0.3243	0.1395	0.1085	0.4218	0.1168	0.1118	0.4078
			0.8313	1.2729	0.8058	0.8052	1.5658	0.6474	0.8262	1.5692
MOM			0.3486**	0.1972	-0.00059	0.3580**	0.1839	-0.00159	0.3524**	0.1438
			2.3145	1.1689	-0.15870	2.3582	1.0684	-0.38342	2.2953	0.8235
HP			-0.00228	-0.00407	-0.00235	-0.00331	-0.00405	-0.00000	-0.00257	-0.00277
			-0.77060	-1.16592	-1.15760	-1.05220	-1.05492	-0.04314	-0.84102	-0.77786
LIQUID						0.0000	-0.00000	-0.00144		
						1.4507	-0.20918	-0.60348		
ΔOI									-0.00000***	-0.00000*
									-2.43627	-1.86681
IDIOSKEW										
QuantileSK										
IDIOVOL										
adj.RSquare	0.0057	0.0207	0.0772	0.0715	0.0776	0.0704	0.0580	0.0678	0.0772	0.0703

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
α	-0.00145	0.0016	-0.00065	0.0031	0.0003	0.0017	-0.00031	-0.00154	0.0019	-0.00296
	-0.49276	0.5904	-0.20247	1.1444	0.1327	0.6718	-0.09309	-0.43811	0.6116	-0.35937
RNSK	0.0007**	0.0006**	0.0008**	0.0006**	0.0006**	0.0005**	0.0011***	0.0009***	0.0008***	-0.00018
	2.5484	2.0231	2.4721	2.0980	2.2972	2.2027	3.2771	2.7856	2.7548	-0.10238
SK	0.4978*		0.6076*				0.4781			-0.44957
	1.8159		1.8540				1.2820			-0.46659
TS	0.0914	0.5456*	0.0826	0.2496	0.3755	0.1852	0.2720	0.2845	0.0751	0.7455
	0.5167	1.9198	0.4421	0.9033	1.3461	0.6693	1.3320	0.7529	0.2078	1.4152
MOM	0.0010	0.1300	-0.00040	0.1886	0.1457	0.3488*	-0.00101	0.2986	0.4719**	-0.00488
	0.2565	0.7195	-0.09321	1.0689	0.8410	1.9040	-0.22118	1.3857	2.2483	-0.55561
HP	-0.00000	-0.00294	0.00000	-0.00506	-0.00157	-0.00409	-0.00000	-0.00008	-0.00473	0.0000
	-1.54610	-0.74159	0.0576	-1.40457	-0.42531	-1.19754	-1.07309	-0.01974	-1.05428	0.5062
LIQUID		-0.00000	-0.00000				-0.00000	-0.00000	-0.00000	-0.00000
		-0.23185	-1.36453				-0.86263	-0.82661	-0.91988	-1.14452
ΔOI	-0.00174	-0.00000	0.0004				0.1352	-0.00000	-0.00000	2.5869
	-0.74871	-1.42452	0.1492				0.1214	-1.30209	-1.02038	1.2144
IDIOSKEW				0.0001					0.0712	0.0106
				0.1653					0.0624	1.0947
QuantileSK					-0.00556			0.2501		0.0003
					-0.78779			0.2186		0.1463
IDIOVOL						0.3147	-0.00066	0.0088	-0.00017	-0.00628
						0.3184	-0.22106	0.8552	-0.11632	-0.27335
adj.RSquare	0.0812	0.0516	0.0637	0.0500	0.0689	0.1243	0.1229	0.1181	0.0852	0.1107

Note: *p <0.1; **p<0.05; ***p<0.01

Table 10: **Bivariate Conditional Portfolio Sorts: RNSK and Arbitrage Risk, Overpricing and Illiquidity**

This table shows the performance of bivariate commodity futures portfolios constructed based on the RNSK and three proxy variables: arbitrage risk, overpricing valuation, and liquidity risk from 10/10/2007 to 01/03/2016. Arbitrage risk is approximated by idiosyncratic volatility (IDIOVOL) computed from residuals of regressing individual futures return on traditional risk factors (EW, TS, MoM, and HP) in the spirit of (Chordia et al., 2021). Overpricing (MaxReturn) proxy is estimated using the rolling 1-month max return (Bali et al., 2011). Liquidity (LIQUID) is proxied by the ratio of dollar volume to absolute return (Amihud et al., 1997). Commodity assets are sorted in ascending order at the end of each week according to their RNSK values and assigned to the highest and lowest quantile groups. Within each RNSK group, we further sort commodity assets according to each proxy value and create two new highest and lowest quantile groups. The equally weighted return of each quarter group is computed at the end of week+1 (post-ranking week return). We report this averaged alpha value by regressing each quantile portfolio excess return on traditional risk factors (EW, TS, MoM, and HP) in this table with its corresponding t-statistic value underneath adjusted by autocorrelation and heterogeneity with lag 12 based on (Newey and West, 1987). The column (row) labeled 'Difference' reports the alpha of the spread return between the highest quantile portfolio and the lowest quantile portfolio.

Panel A: Idiosyncratic Volatility (IDIOVOL)			
	IDIOVOL (Lowest)	IDIOVOL (Highest)	Difference
RNSK (Lowest)	0.0004	-0.00042	-0.00092
	0.8986	-0.33888	-0.67370
RNSK (Highest)	0.0013*	0.0035***	0.0022*
	1.7753	3.2543	1.7268
Difference	0.0008	0.0040**	
	0.8112	2.4227	
Panel B: 1 Month Max Daily Return (MaxReturn)			
	MaxReturn (Lowest)	MaxReturn (Highest)	Difference
RNSK (Lowest)	0.0011	-0.00218**	-0.00329**
	1.2734	-2.34043	-2.27766
RNSK (Highest)	0.0029***	0.0024**	-0.00056
	3.3888	2.5157	-0.43735
Difference	0.0018	0.0046***	
	1.5729	3.0732	
Panel C: Liquid Proxy (LIQUID)			
	LIQUID (Lowest)	LIQUID (Highest)	Difference
RNSK (Lowest)	-0.00191**	-0.00025	0.0016
	-2.00747	-0.31894	1.2804
RNSK (Highest)	0.0038***	0.0015*	-0.00224*
	4.3843	1.6774	-1.85170
Difference	0.0057***	0.0018	
	4.0901	1.3921	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: **Bivariate Conditional Portfolio Sorts: RNSK and SK**

This table shows the performance of bivariate commodity futures portfolios constructed based on the RNSK and Pearson skewness coefficient. Commodity assets are first sorted in ascending order at the end of each week according to their RNSK values and assigned to the highest and lowest quantile groups. Within each RNSK group, we further sort commodity assets based on the Pearson skewness value and create new highest and lowest quantile groups. The equally weighted return of each quarter group is computed at the end of week+1 (post-ranking week return). The results are reported in panel A. We proceed with the opposite bivariate sorting process and report results in panel B. We estimate the averaged alpha value for both panels by regressing each quantile portfolio excess return on traditional risk factors (EW, TS, MoM, and HP) in this table with its corresponding t-statistic value underneath adjusted by autocorrelation and heterogeneity with lag 12 based on (Newey and West, 1987). The column labeled 'Difference' reports the alpha of the spread return between the highest and lowest portfolios. The row labeled 'Average' reports the alpha of average return between the portfolio's highest and lowest quantile from each column.

Panel A: Pearson Skewness (SK)			
	SK (Lowest)	SK (Highest)	Difference
RNSK (Lowest)	-0.00014	-0.00101	-0.00087
	-0.16528	-1.11686	-0.62695
RNSK (Highest)	0.0024***	0.0017**	-0.00073
	3.0141	2.1047	-0.65463
Average	0.0023**	0.0007	-0.00160
	2.1638	0.6689	-0.86429
Panel B: Risk-Neutral Skewness (RNSK)			
	RNSK (Lowest)	RNSK (Highest)	Difference
SK (Lowest)	-0.00155*	0.0024***	0.0039***
	-1.94410	3.2654	3.4246
SK (Highest)	-0.00181**	0.0016***	0.0035***
	-2.15108	2.8369	3.1681
Average	-0.00335***	0.0041***	0.0074***
	-3.33874	4.8149	4.1768

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: **Time Series Augmented Risk Factor Test – RNSK Portfolio Performance**

At the end of each week, the long-short portfolio is sorted on the following signals: RNSK, all other commodity risk factors (CV, IDIOSKEW, LIQUID, and ΔOI), traditional baseline model (EW, TS, MoM, and HP), and SK with weekly observation. Then we regress the long-short portfolio return based on the RNSK (Kozhan et al., 2013) on all other factor-based portfolios in a time-series manner and estimate the coefficient and alpha values for each model test. Standard equity factors (Mkt.RF, SMB, HML, RMW, and CMA) are included to control the equity market impact on commodity futures. We report Newey-West corrected standard error in the bracket with 12 weeks lags setting.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
CV	−0.029	−0.008															−0.040
	(0.062)	(0.061)															(0.069)
SK		−0.145***		−0.162***		−0.138**		−0.145***		−0.136***		−0.146***		−0.132***		−0.131***	−0.113*
		(0.045)		(0.047)		(0.058)		(0.044)		(0.045)		(0.045)		(0.049)		(0.049)	(0.058)
IDIOSKEW			0.093	0.128**													0.122*
			(0.062)	(0.063)													(0.071)
QuantileSK					−0.107*	−0.014											−0.037
					(0.060)	(0.072)											(0.071)
IDIOVOL							−0.022	−0.013									−0.053
							(0.058)	(0.054)									(0.046)
LIQUID									−0.210***	−0.202***							−0.229***
									(0.066)	(0.070)							(0.070)
ΔOI											0.018	0.018					0.029
											(0.055)	(0.054)					(0.046)
EW															−0.021	−0.016	0.002
															(0.024)	(0.025)	(0.023)
TS															0.009	0.003	−0.019
															(0.044)	(0.045)	(0.041)
MOM															0.018	0.022	0.045
															(0.039)	(0.039)	(0.038)
HP															0.018	0.013	−0.005
															(0.059)	(0.059)	(0.054)
Mkt.RF													−0.091	−0.082	−0.090*	−0.082	−0.065
													(0.055)	(0.055)	(0.054)	(0.054)	(0.048)
SMB													0.037	0.031	0.039	0.032	0.033
													(0.087)	(0.084)	(0.087)	(0.084)	(0.090)
HML													0.333***	0.305***	0.327***	0.300***	0.303***
													(0.091)	(0.094)	(0.090)	(0.094)	(0.095)
RMW													0.092	0.072	0.076	0.057	0.148
													(0.176)	(0.176)	(0.180)	(0.181)	(0.174)
CMA													−0.456**	−0.423*	−0.462**	−0.428**	−0.423**
													(0.220)	(0.218)	(0.215)	(0.214)	(0.203)
α	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.002***	0.003***	0.002***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: **Time Series Robustness Test – Monthly Rebalanced and Alternative Risk-Neutral Skewness Measure**

Following table 12, we report the time-series regression results for the RNSK (Kozhan et al., 2013) with monthly rebalancing portfolio in panel A. Similarly, we report the results via an alternative risk-neutral skewness measurement (BKM) by (Bakshi et al., 2003) with weekly and monthly rebalancing in panels B and C, respectively. All standard errors in bracket are adjusted by autocorrelation and heterogeneity with lag 12 based on (Newey and West, 1987).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Weekly Signal and Monthly Rebalanced Portfolio on RNSK									
CV	0.145									0.111
	(0.108)									(0.133)
IDIOSKEW		0.052								0.197
		(0.134)								(0.123)
QuantileSK			-0.352^{***}							-0.315^{***}
			(0.082)							(0.100)
IDIOVOL				−0.084						-0.185^{*}
				(0.060)						(0.101)
LIQUID					−0.102					−0.016
					(0.062)					(0.105)
ΔOI						−0.075				−0.077
						(0.060)				(0.063)
EW							−0.047		−0.059	-0.193^{**}
							(0.043)		(0.069)	(0.095)
TS							−0.060		−0.070	−0.086
							(0.111)		(0.103)	(0.103)
MOM							−0.079		−0.088	−0.094
							(0.071)		(0.085)	(0.092)
HP							0.013		0.067	0.120
							(0.106)		(0.093)	(0.086)
Mkt.RF								−0.022	−0.169	-0.292^{*}
								(0.152)	(0.195)	(0.168)
SMB								−0.137	−0.086	−0.015
								(0.322)	(0.337)	(0.349)
HML								0.459	0.521	0.525
								(0.417)	(0.400)	(0.373)
RMW								−0.407	−0.518	−0.525
								(0.675)	(0.708)	(0.647)
CMA								0.119	−0.454	−0.681
								(0.882)	(1.009)	(0.888)
SK	-0.219^{***}	-0.208^{***}	0.010	-0.203^{***}	-0.215^{***}	-0.215^{***}	-0.204^{***}	-0.197^{***}	-0.210^{***}	−0.035
	(0.052)	(0.056)	(0.081)	(0.061)	(0.054)	(0.055)	(0.071)	(0.059)	(0.080)	(0.127)
α	0.007^{***}	0.007^{***}	0.008^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.008^{***}	0.007^{***}	0.008^{***}	0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
	Panel B: Weekly Signal and Weekly Rebalanced Portfolio on BKM									
α	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)
	Panel C: Weekly Signal and Monthly Rebalanced Portfolio on BKM									
α	0.004^{*}	0.004^{*}	0.005^{**}	0.004^{*}	0.004^{*}	0.004^{*}	0.004^{*}	0.005^{**}	0.005^{**}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: **Cross Sectional Robustness Check - Monthly Rebalanced and Alternative Risk-Neutral Skewness Measure**

Following table 9, we report the cross-sectional regression results for the RNSK (Kozhan et al., 2013) with monthly rebalancing portfolio in panel A. Similarly, we report the results via an alternative risk-neutral skewness measurement (BKM) by (Bakshi et al., 2003) with weekly and monthly rebalancing in panels B and C, respectively. All t-statistic values underneath the estimated coefficients are adjusted by autocorrelation and heterogeneity with lag 12 based on (Newey and West, 1987).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A: Weekly Signal and Monthly Rebalanced Portfolio on RNSK													
α	-0.00235	-0.00338	-0.00756	-0.00588	-0.00646	-0.00250	0.0008	-0.00523	0.0024	0.0004	0.0049	0.0043	-0.01107
	-0.52037	-0.72831	-0.66448	-0.50556	-0.53788	-0.19926	0.0883	-0.45934	0.2359	0.0342	0.3766	0.3752	-0.64791
RNSK	0.0023**	0.0026**	0.0029***	0.0033***	0.0032***	0.0036***	0.0029***	0.0030***	0.0025***	0.0034***	0.0036***	0.0031***	0.0039***
	2.1702	2.4287	3.1204	3.2721	3.0594	3.2995	3.1053	3.2970	2.7575	3.1171	3.3522	3.0472	2.9784
SK		-0.00000	0.8776	1.4120	1.2023	1.5259				1.5460			-3.05845
		-0.00127	0.7819	1.2372	0.9836	1.2033				1.2093			-0.78212
TS			0.9556	0.9336	0.9323	1.0379*	0.8057	0.7349	1.0127	1.2009*	1.3197	1.1454	4.1531
			1.6201	1.5313	1.4988	1.6773	0.7553	0.6438	0.9474	1.9353	1.0068	0.9701	1.3749
MOM			0.0050	0.0033	0.0030	-0.00357	0.9417	1.0666*	1.1601**	-0.00872	1.3777**	1.5037**	-0.00961
			0.3658	0.2406	0.2386	-0.25138	1.5756	1.7038	2.1266	-0.58359	2.2284	2.3733	-0.39575
HP			-0.00448	-0.00000	-0.00000	-0.00000	-0.00784	0.0020	-0.00821	-0.00000	-0.01125	-0.01898	0.0000
			-0.60006	-0.00000	-0.00048	-0.00000	-0.68015	0.1512	-0.02949	-0.00000	-0.80409	-1.63046	0.0000
LIQUID				-0.00360		-0.00000				-0.00000	-0.00000	-0.00000	-0.00000
				-0.05628		-0.00000				-0.00002	-0.00000	-0.00000	-0.00002
ΔOI					-0.00070	0.0012				0.0518	-0.00000	-0.00000	3.0785
					-0.01118	0.0153				0.0175	-0.00002	-0.00001	0.3935
IDIOSKEW							0.0023					0.8925	0.0314
							0.4619					0.2920	0.0490
QuantileSK								-0.02085			-1.69795		0.0097
								-0.84337			-0.57580		0.5113
IDIOVOL									-1.01740	0.0051	0.0440	0.0013	0.0216
									-0.38613	0.0080	0.0688	0.0021	0.0455
Panel B: Weekly Signal and Weekly Rebalanced Portfolio on BKM													
BKM	0.0004**	0.0004**	0.0004*	0.0005**	0.0005**	0.0006**	0.0004	0.0003	0.0001	0.0003	0.0000	0.0001	0.0010
	1.9844	2.0470	1.8653	2.0034	2.0087	2.1724	1.5946	1.4080	0.7238	1.1146	0.0500	0.5110	1.4997
Panel C: Weekly Signal and Monthly Rebalanced Portfolio on BKM													
BKM	0.0001	0.0003	0.0006	0.0009	0.0012	0.0018*	0.0003	0.0003	-0.00032	0.0009	0.0007	0.0001	0.0012
	0.1380	0.3339	0.7843	1.0371	1.4718	1.8796	0.3538	0.4030	-0.34286	1.0038	0.7143	0.1015	1.0612

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 1: **Cumulative Log Return of Risk Factors Sorted Portfolios**

At the end of each week, we rank the commodity assets according to their signal values and assign them to four quantiles in ascending order, from the lowest quantile (P1) to the highest quantile (P4). We then compute the spread return with buying (selling) the highest quantile assets and selling (buying) the lowest quantile assets in an equally weighted portfolio manner, denoted as L-S (S-L) spread return. We process this spread portfolio return calculation from 10/10/2007 to 01/03/2016 for the following signals: TS (term structure sorted L-S portfolio), MOM (momentum sorted L-S portfolio), HP (large non-commercial traders percentage long position sorted L-S portfolio), RNSK (risk-neutral skewness sorted L-S portfolio from (Kozhan et al., 2013)) and SK (Pearson skewness coefficient sorted S-L portfolio). The only exception is EW that is computed using all assets with equal weight and long-only.

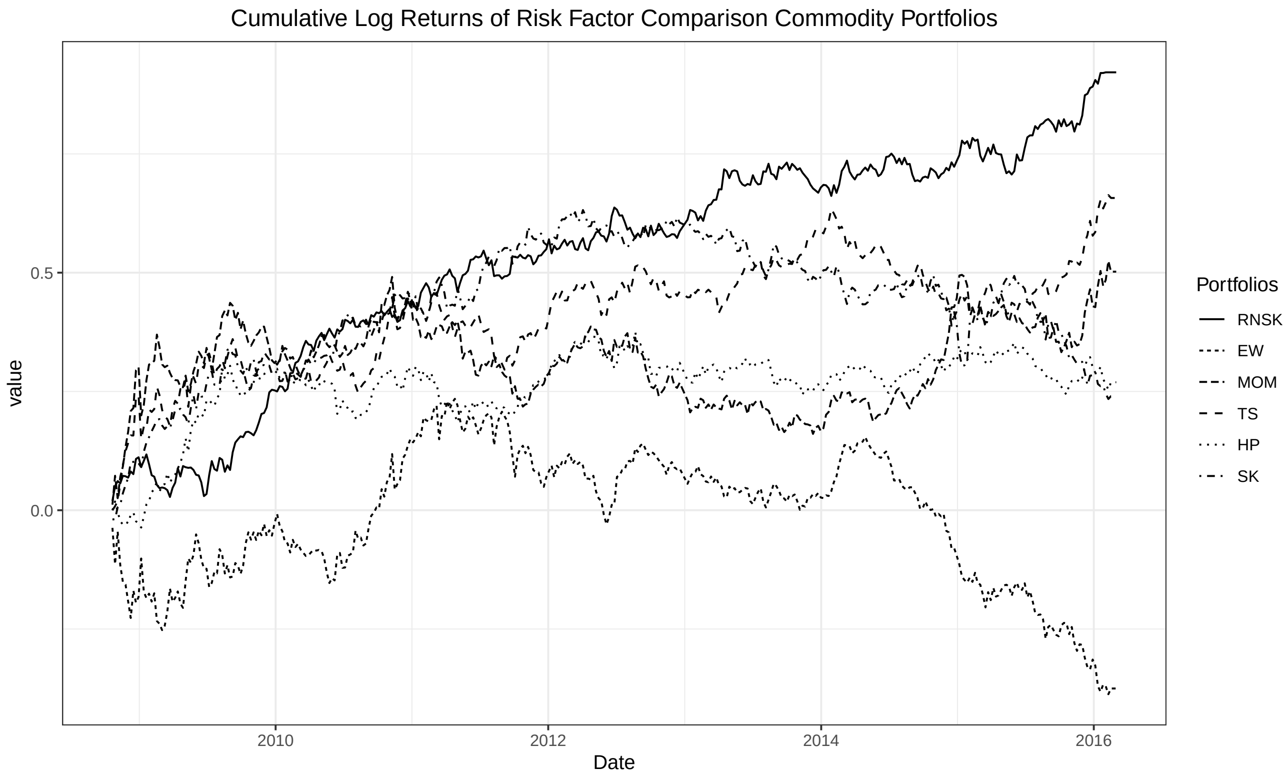


Figure 2: **Risk-Netural Skewness based Quantile Portfolio Cumulative Log Return**

At the end of each week, we rank the commodity assets according to their RNSK values and assign them to four quantiles in ascending order, from the lowest quantile (P1) to the highest quantile (P4). For each quantile, all assets are assigned equal weight to compute the portfolio return. We also compute the portfolio return by longing all assets in the highest quantile and shorting all assets in the lowest quantile, denoted as HML. All returns are realized at post-ranking week. We repeat this process from 10/10/2007 to 01/03/2016 and plot their corresponding cumulative return in this figure.

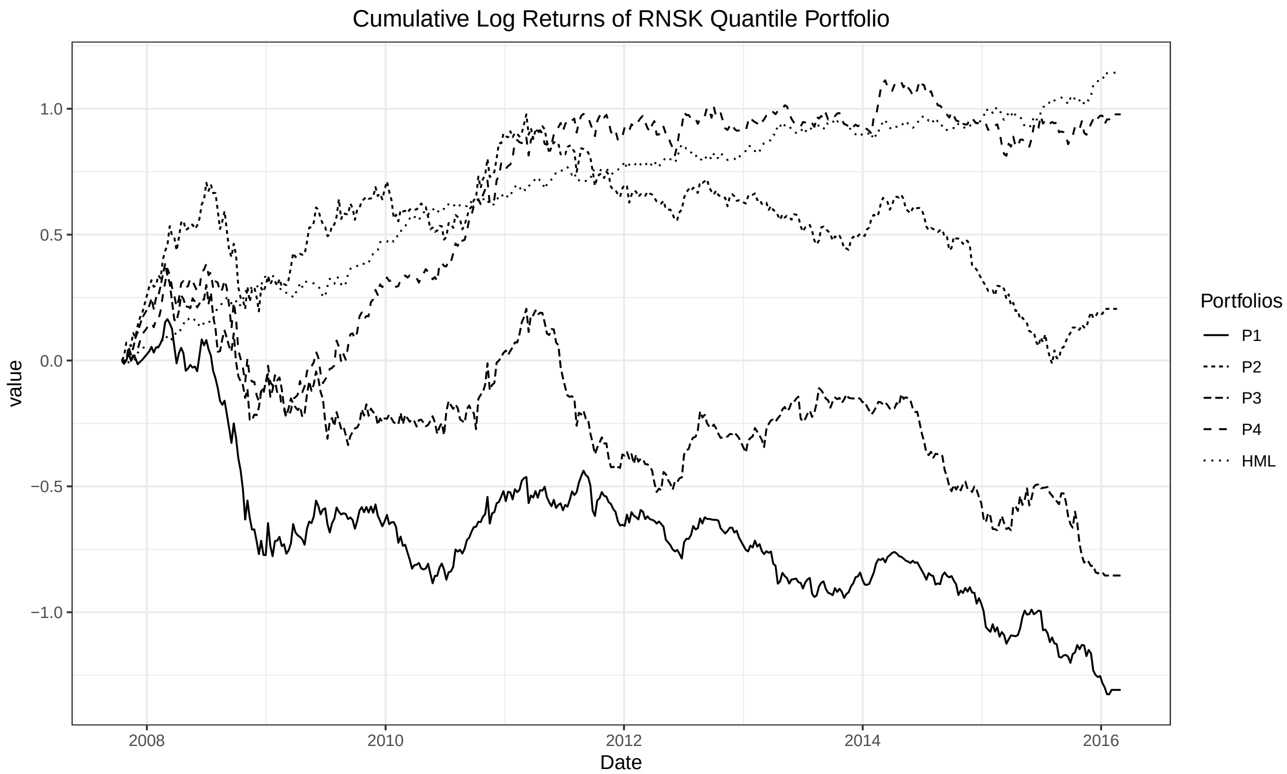
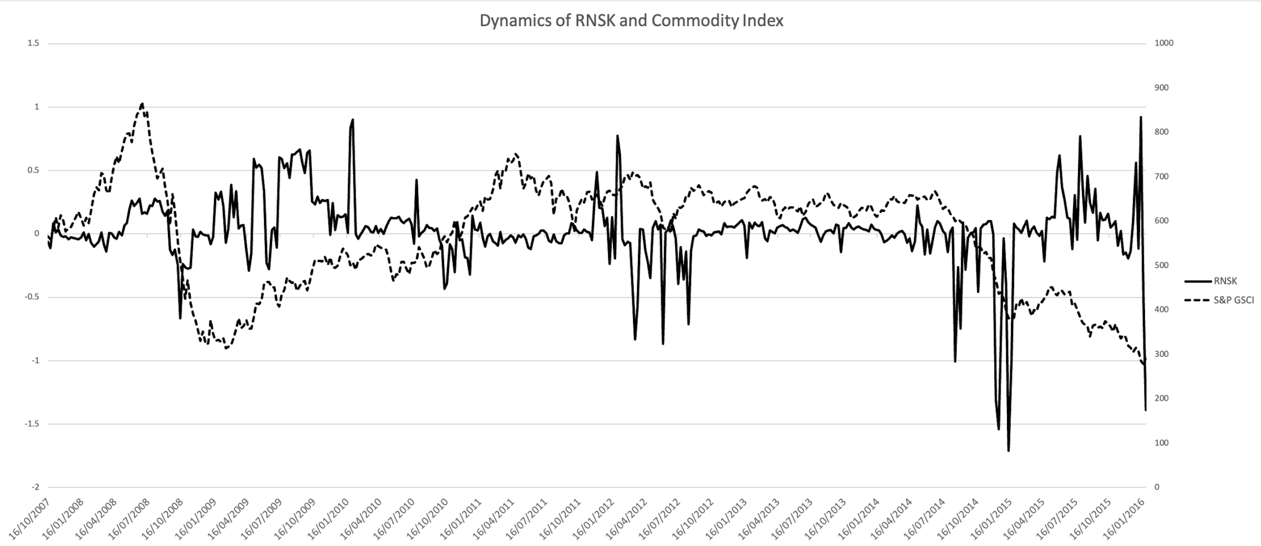


Figure 3: **Skewness Dynamics on Global Commodity Market**

At the end of each week, we compute the averaged RNSK and SK value across all available commodity products, repeat this process from 10/10/2007 to 01/03/2016, and finally plot their time-series values (left y-axis) against S&P GSCI (right y-axis) in the below two figures.



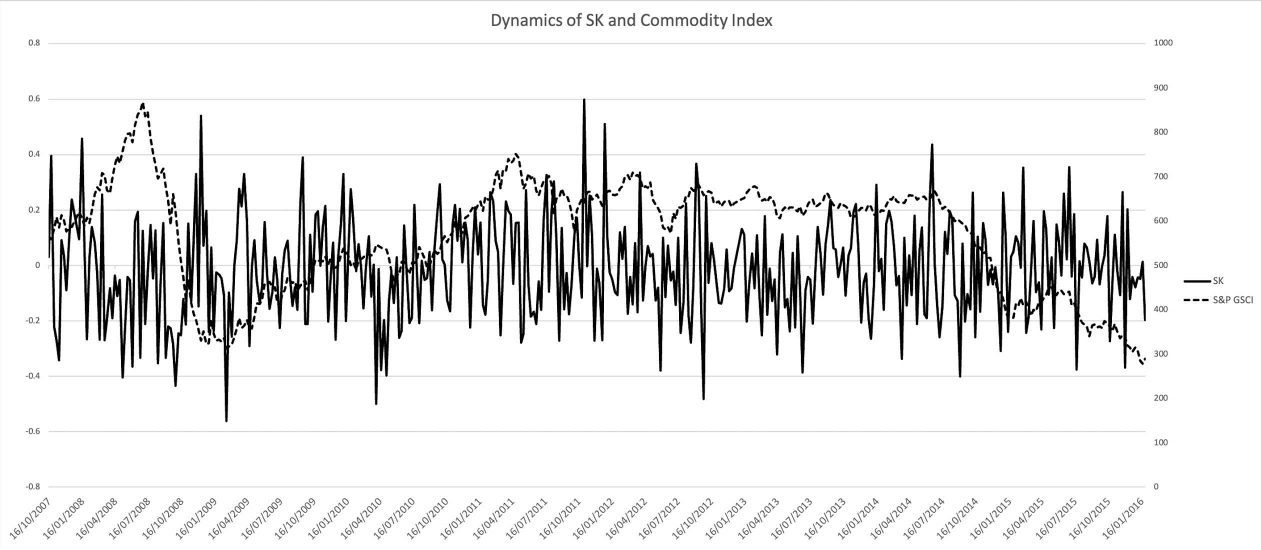


Figure 4: **Skewness Comparison Analysis - Parametrization Problem**

These four charts explore the impact of estimation window and data frequency usage on constructing the realized skewness signal (Pearson skewness coefficient used here, the same method used in (Fernandez-Perez et al., 2018)). From the top to the bottom chart, the data frequency in use is following: daily, weekly, daily, and weekly. Therefore, for the first and the third charts, daily observation starts from 10/10/2007 to 01/03/2016, with T = 1, . . . , 2119; for the second and the fourth charts, data is on the same period but T = 1, . . . , 433. The rolling window is scheduled as (30, 90, 125, 252, and 504) days and (5, 15, 26, 52, and 104) weeks for signal and portfolio generation separately. Regarding the value of charts, the upper two charts display the dynamics of averaged cross-sectional Pearson skewness coefficient estimators based on different rolling windows and data frequencies. The individual signal in a rolling manner is first obtained, and then cross-sectional commodities' values mean are calculated and reported in these two charts. The bottom two charts are the cumulative return of a long-short portfolio based on the top two corresponding rolling window signals. Finally, the RNSK signal (latest with no rolling window) and its sorted long-short portfolio are reported for comparison.

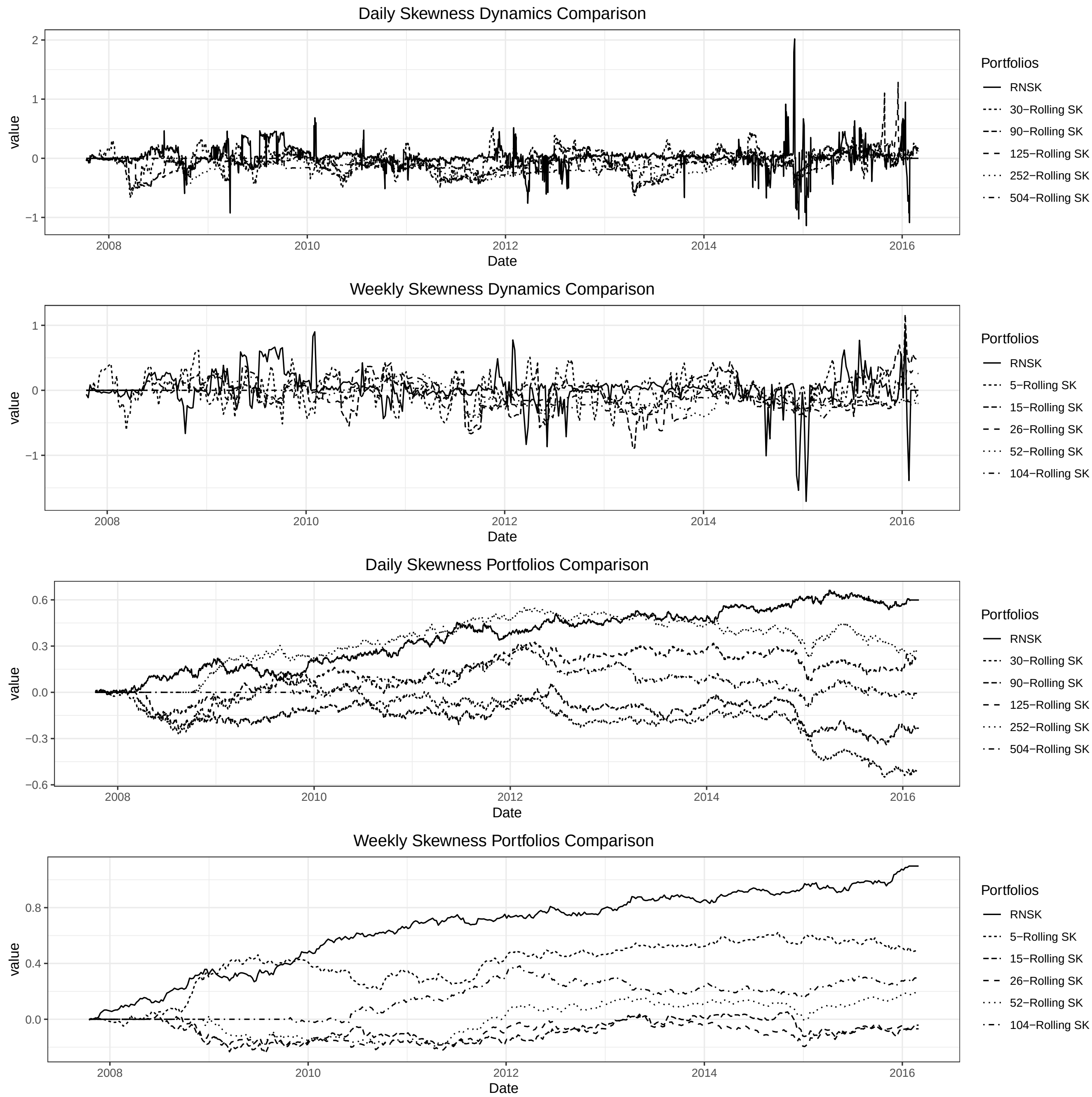


Figure 5: **Signal Quantile Overlapping Analysis**

At the end of each week, commodity futures are grouped based on corresponding signal values, ascending order for (RNSK, TS, HP, and MoM), and descending order for SK. We then count the number of assets jointly selected by the RNSK signal from the top quantile and those chosen by the SK from the bottom quantile and report this number in "Top". For other traditional factors (TS, HP, and MoM), we count their corresponding overlapping number of assets concerning the RNSK from the same quantile group (i.e., top to top) and report this number in "Top". Repeating this entire process from 10/10/2007 to 01/03/2016 to plot the number of overlapping assets in a time-series manner.