Commodity Futures Momentum: Economic Risks or Behavioural Bias?

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Version: 26th October 2018

Abstract

The sources of return and risk in commodity futures momentum remain elusive due to the dynamic nature of this investment strategy. This study employs both behavioural (market states) and a risk-based (return dispersion) frameworks to extend our understanding of commodity momentum returns. We show that market states capture the profitability of the 52-week high commodity momentum strategy. We also find that return dispersion predicts cross-sectional and time-series momentum in commodity futures. We show that these two momentum strategies exhibit procyclical characteristics with business conditions. Our analysis suggests there are two broad types of commodity momentum strategies. The first type of commodity futures momentum is behavioural in nature (52-week high) while the second group are linked to risk-based explanations (cross-sectional and time series).

JEL Classifications: G13, G14

Keywords: Commodity Futures, Momentum, Return Dispersion, Behavioural bias

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1. Introduction

Commodity markets are an important barometer of the global economy. Previous literature has documented the positive relationship between commodity prices and economic activities. For example, Hong and Yogo (2012) show that higher economic activity leads to greater levels of hedging demand which causes an increase in open interest futures positions across global commodity markets. Studies including Bakshi, Gao and Rossi (2017) and others have proposed commodity-based pricing models to explain the variation of commodity futures returns. These asset pricing models employ average commodity market returns, term structure and momentum as key risk factors to explain the cross-sectional variation in commodity futures returns. The objective of this study is to further the understanding of the sources of risk and return in commodity futures momentum investment strategies.

The literature is beginning to understand the sources of risk and return in momentum, across various asset markets. The origins of momentum from Jegadeesh and Titman (1993) suggests that recent winners persist in their outperformance and recent losers persist in their underperformance, resulting in abnormal returns, which challenges the notion of stock market efficiency. The literature and our understanding of momentum is not limited to equity markets. Empirical studies have also examined momentum in other markets, including commodities. For instance, Miffre and Rallis (2007) and Bianchi, Drew and Fan (2015, 2016) document evidence of momentum in commodity futures markets using various definitions and types of momentum strategies. The literature has attempted to explain commodity momentum however, the sources of risks and return in commodity momentum strategies are mixed and remain inconclusive (Bianchi, Drew and Fan, 2015 & 2016; Fuertes, Miffre and Fernandez-Perez, 2015; Fuertes, Miffre and Rallis, 2010). The purpose of this paper is to extend and make new contributions in the area of commodities momentum. More specifically, this paper examines commodity futures momentum by employing both behavioural and risk-based frameworks within the same study.

Two broad schools of thought have been developed to explain the presence of momentum in returns. The first proposition suggests that momentum is a behavioural phenomenon. The behavioural theories of Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) propose the under- and overreaction hypothesis. This framework suggests that information diffuses slowly which results in short-run and intermediate momentum effects followed by longer term reversals. The empirical work in Cooper, Gutierrez and Hameed (2004) employs a 'market state' framework to capture the returns of momentum profits in equity momentum. In our study, we employ the

Cooper et al (2004) framework in commodity futures and we examine whether market states can explain the behaviour of commodity momentum returns.

The second school of thought suggests that risk-based factors play an important role in explaining momentum profits. A number of studies document the role of commodity markets and their relationship with the macroeconomy and equity risks. Hamilton (1983) and Jones and Kaul (1996) show that oil prices predict the performance of the U.S. economy. Hong and Yogo (2012) reveal that commodity market open interest is related to the macroeconomy, inflation and with other asset classes. More recently, Fernandez-Perez, Fuertes and Miffre (2017) show that backwardation and contango based signals from commodities can predict economic activity. Collectively, these studies support the notion of the empirical relationship between commodities and the macroeconomy. In another strand of literature, research has examined the relationship between commodities and stock prices. Driesprong et al (2008) shows that changes in oil prices predicts global stock returns. The work of Jacobsen et al (2018) demonstrates that changes in industrial metal returns can predict changes in stock prices.

The works of Fernandez-Perez et al (2017) and Stivers and Sun (2010) are especially interesting as they both lie at the intersection of our paper. Fernandez-Perez et al (2017) find that backwardation and contango based portfolios (such as momentum) are leading indicators of economic activity. In an equity setting, Stivers and Sun (2010) find that return dispersion (RD) in monthly equity prices can predict momentum, which in turn predicts economic activity, especially during poor economic conditions. RD is defined as the cross-sectional standard deviation of monthly returns and can be interpreted as a reflection of portfolio reallocations when the expectations of future economic activity change. When there are changes in economic expectations, investors will reallocate capital and their investments, and this portfolio reallocation activity results in RD. For the first time, this study introduces RD in commodity futures markets as a means to examine the intertemporal interaction between RD in commodities momentum and macroeconomic activities in the near future. This research question is important to the literature because RD may exhibit information content beyond traditional risk factors such as commodity beta and carry as suggested in Bakshi et al (2017).

This paper makes four contributions to the literature. The under- and overreaction hypothesis proposed in Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) was developed into an empirical framework in the Cooper et al (2004) market state model. For the first time, we introduce this market state model as a means to empirically test whether this behavioural framework can explain commodity momentum returns. Our findings show that the Cooper et al (2004) market state framework captures the profitability of the 52-

week high momentum strategy. The George and Hwang (2004) 52-week high momentum strategy is associated with anchoring bias behaviour of market participants, which yields intermediate horizon momentum returns in equity markets. Bianchi, Drew and Fan (2016) has previously documented that conventional commodity-based risk factors cannot explain the variation of returns in 52-week high momentum, and therefore, they conjecture the strategy should be considered behavioural in nature. For the first time, we show that the Cooper et al (2004) market state framework captures the profitability of 52-week high momentum strategies in commodity futures markets. This finding suggests that the 52-week high momentum strategy can be explained by the behavioural theory from Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) as expressed in the Cooper et al (2004) framework.

The second contribution of this study is the discovery of RD as an important information variable to describe momentum profits in commodity futures returns (see Stivers and Sun, 2010). We employ RD in commodity futures as a proxy to link momentum with U.S. economic activity. RD is defined by Connolly and Stivers (2003) and Stivers and Sun (2010) as portfolio reallocation activity when investors make changes in their investment opportunities as a result of shifts in economic activity. Our findings reveal that RD is an important information variable that captures the relationship between economic activity and commodity momentum returns. More specifically, RD exhibits a negative relation with subsequent commodity futures momentum returns of cross-sectional and time-series momentum investment strategies. This finding suggests that there may be risk-factor timing implications for investors as suggested in Madhavan, Sobczyk and Ang (2018). The empirical evidence from this study suggests that cross-sectional and time-series momentum are more closely related to risk-based explanations.

The third contribution of this study presents evidence that commodity RD exhibits both contemporaneous and intertemporal relationships with the U.S. economic activity. This finding suggests that investors can employ commodity RD to predict changes in one month ahead U.S. economic activity. Similar to RD calculations in equity markets (see Stivers and Sun, 2010), our findings show that periods of high RD are related to lower levels of subsequent U.S. economic activity. High levels of RD reflects investors reallocating their commodity exposures as well as higher levels of hedging and speculative activity. Together, these market related activities translate into higher levels of RD which reflects market participants reallocating their exposures as there are expectations of lower levels in economic activity. Our work is partially related to Fernandez-Perez et al (2017) which shows that conventional commodity state variables exhibit predictive information over long-horizons of 24 and 60 months. For the first time, we show that commodity RD is an important information variable that provides a new empirical link (beyond traditional factors) between commodity markets and subsequent U.S. economic activity one-month ahead.

Finally, we extend our understanding of momentum by demonstrating there are two broad types of commodity futures momentum. The market state framework used to capture the behavioural theory of underreaction and slow information diffusion readily captures and explains the return from the 52-week high momentum strategy, but it cannot explain the variation in returns of the cross-sectional and time-series momentum strategies. Conversely, our risk-based framework which utilises commodity RD predicts cross-sectional momentum and time-series momentum returns but fails at explaining the returns from the 52-week high strategy. For the first time, our analysis differentiates and classifies commodity momentum strategies into two broad categories, that is, those which are driven by risk related factors (ie. cross-sectional and time-series) and those that are truly behavioural in nature (ie. 52-week high strategy).[1]

The remainder of the paper proceeds as follows. Section 2 summarises the methods of analysis employed in the study. Section 3 describes the data and key variables used in our analysis. Section 4 summarises the results and findings. Section 5 provides concluding remarks and discusses the implications of our findings.

2. Data

Our primary futures price dataset is sourced from Commodity Research Bureau (CRB). The dataset includes price data for all available contracts from 26 commodities from July 1959 to December 2017. Consistent with Bianchi, Drew, and Fan (2016) we retain Pork Belly in our dataset to avoid survivorship bias, despite having been delisted in 2012. We do not employ London Metals Exchange (LME) contracts as they are linked to global metal price dynamics rather than the U.S. economy. We do not analyse platinum, palladium and butter as they are realistically non-investable futures contracts due to their inherent illiquid nature. We construct rolling excess returns of front futures contracts using the last price of the last full month, prior to expiry (Gorton, Hayashi, and Rouwenhorst, 2012).

[INSERT TABLE 1 HERE]

Table 1 presents the summary statistics of monthly excess returns for each of the commodity futures in the primary dataset. We note that reported arithmetic mean excess returns are predominantly positive throughout the table, with the exception of Natural Gas; Gold; Pork

[1] We acknowledge there are other definitions and types of commodity futures momentum. Some of these include basis momentum (Boons and Prado, 2018), curve momentum (Paschke, Prokopczuk and Simen, 2017) and microscopic momentum (Bianchi, Drew and Fan, 2017). These various types of momentum are not employed in this study as we are interested in strategies which reflect momentum in commodity futures returns only.

Belly; Lumber; Cocoa; Coffee; Oats; Sugar; Corn; Rough Rice; Wheat; and Kansas Wheat, which all exhibit negative values. Standard deviation values are relatively high for energies (Brent Crude; Gas Oil; Heating Oil; Natural Gas; RBOB Gas; WTI Crude Oil), Pork Belly; Coffee, Orange Juice, and Sugar, with values greater than 0.09.[2] In contrast Gold; Feeder Cattle; Cocoa; and Cotton exhibit the lowest standard deviations, with values less than 0.069. Skewness is predominantly positive across the dataset, with the exception of Brent Crude; Gas Oil; Heating Oil; RBOB Gas; Gold; Pork Belly; and Lumber, which all report negative values. Of the remaining commodities, WTI Crude Oil, Copper, and Rough Rice all report skewness in excess of 1.0. Kurtosis values are varied throughout the dataset. Silver, Oats, and Soybean Meal report the highest, with 16.76, 9.31 and 10.23, respectively. While Heating Oil, Feeder Cattle and Lean Hogs are among the lowest.

Table 2 presents the statistical summary of monthly returns of momentum strategies and six predictive variables featured in this paper. The table reports arithmetic mean, standard deviation, median, *t*-statistics (null equals zero), minimum, maximum, skewness, kurtosis, and 10^{th}, 25^{th}, 75^{th} and 90^{th} percentile from the distribution of returns of each variable from August 1959 to December 2017. From Panel A of the table, we note that each strategy exhibits positive and significant arithmetic returns approximating 1.3% per month for CS and H52, and 1% for TS and L52. Median values are comparable between the strategies, with the exception of H52 which reports a median in excess of its mean at 1.39%. Each strategy denotes positive skewness values for the sample period and kurtosis values ranging from 3.5 in the case of CS and 4.14 the case of the TS strategy. 10^{th} and 20^{th} percentile values remain negative across each strategy, while 75^{th} and 90^{th} percentile values remain positive. We note that CS exhibits the highest return values in the 75^{th} and 90^{th} percentiles and lowest 10^{th} and 25^{th} percentile values over all other strategies.

Panel B of Table 2 reports the summary statistics of the predictive variables employed in this paper. AVG represents the equal-weighted long-only commodity portfolio used in this study. CARRY denotes the carry factor, which is defined as a spread portfolio which holds an equal-weighted long position in five commodity futures markets with the highest levels of backwardation and an equal-weighted short position in five commodity futures markets with the highest levels of contango (see Bakshi et al, 2017). RD represents the monthly level of return dispersion in the full sample of the commodity futures markets employed in this study. RD_{CARRY} is the original RD orthogonal to the CARRY factor and RD_{AVG} is the original RD

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[2] Relatively high standard deviation values about the mean hints to comparatively higher volatility properties in the excess returns of the dataset.

orthogonal to AVG. The variables in this table report a wide range of values across each statistical metric, suggesting that each variable exhibits its respective empirical characteristics throughout the sample period.

[INSERT TABLE 2 HERE]

3. Methodology

3.1 Commodity pricing model

Recently, Bakshi et al. (2017) show that a multi-variate factor model featuring an average market factor, a carry factor (synonymous with term structure) and a momentum factor, is capable of describing the cross-sectional variation of returns in commodity markets. On the foundation of this finding, we employ an average factor (AVG) and a carry factor (CARRY) as control variables when analysing the variation in returns of momentum strategies in a regression framework.

Following Erb and Harvey (2006), Gorton and Rouwenhorst (2006) and Bianchi et al. (2015, 2016), this paper employs a passive long benchmark portfolio, to denote the returns attributed to an equal weighted long portfolio of all commodity futures securities within the dataset. The return series derived from the passive long strategy are incorporated in the factor analysis methods in this paper and are synonymous with the average (AVG) risk-factor (Bakshi et al, 2017). The AVG factor is mathematically expressed as follows:

$$AVG = \frac{1}{N}\sum_{i=1}^{N} RET_{f,it} \qquad (5)$$

where AVG denotes the equal weighted returns of long positions in all markets; and $RET_{f,it}$ denotes the returns of futures contract *i,* over time *t*.

Carry Factor

The carry factor variable identifies the premium obtained from rolling the front futures contracts, to contracts with more distant expiry dates (second nearest futures contracts). This premium is commonly referred to as the 'roll yield'.[3] The carry factor has been employed in the literature as an independent variable to explain the variation in commodity momentum returns (Bakshi et al., 2017). The carry factor identifies the 5 most backwardated contracts ($er_{it} > 0$, synonymous with a positive basis), and 5 most contangoed contracts ($er_{it} < 0$, synonymous with a negative basis), with which to create long and short positions, respectively.[4] The carry signal is mathematically expressed as follows:

[3] See Miffre and Rallis (2007).

[4] Bakshi et al. (2017) defines the carry signal as the slope of the futures curve, where

$$er_{it} = \ln(S_{it}) - \ln(F_{it}) \qquad (6)$$

where er_{it} denotes the roll yield of market *i*, at time *t*; S_{it} denotes the price of the front futures market *i*, at time *t*; and F_{it} denotes the second nearest futures market *i,* at time *t*.

3.2 Momentum Strategy Construction

This paper employs four momentum strategies, each with intrinsically different sorting and signal generation methodologies. This section contains a summary of the portfolio construction methodologies of cross-sectional momentum (CS), time-series momentum (TS), 52-week high momentum (H52) and the 52-week low (L52) momentum strategies.

Cross-sectional Momentum

The cross-sectional momentum strategy of Jegadeesh and Titman (1993) was originally designed as an investment strategy to systematically capture a premium from being long(short) recent high(low) performing stocks.[5] The cross-sectional momentum strategy signal is constructed by generating a twelve-month return of each security. The signal returns are then sorted in descending order (highest-to-lowest) and allocated into three portfolios. The top tercile portfolio is denoted as the winner portfolio, as it contains the securities with the highest twelve-month returns. The bottom tercile portfolio is denoted as the loser portfolio, as it contains the securities with the lowest twelve-month returns. The middle tercile portfolio contains all other securities, which are not allocated to either winner or loser portfolios. The winner portfolio generates returns by holding long positions, whilst the loser portfolio holds short positions. Securities allocated to the middle portfolio do not hold any investment positions in the strategy. The cross-sectional momentum signal is mathematically expressed as follows:

$$CSMOM_{(t)} = \frac{1}{N_{high}}\left(\sum_{i=high} RET_{f,it}\right) - \frac{1}{N_{low}}\left(\sum_{i=low} RET_{f,it}\right) \qquad (1)$$

$Y_t = \frac{F_t^{(1)}}{F_{t/}^{(0)}}$ is the mathematical the expression of the slope. The paper identifies backwardation, where *ln*(Y_t)<0, and contango, where *ln*(Y_t)>0. For the sake of simplicity, Eq. (6) denotes the mathematical equivalent of the Bakshi et al. (2017) carry signal (roll-yield).

[5] Throughout this paper, the cross-sectional momentum strategy is referred to under a number of different names. These include: the *cross-sectional* momentum strategy, the *conventional momentum* strategy, and the *commodity momentum* strategy.

where $CSMOM_{(t)}$ is the cross-sectional momentum returns derived over time *t*; N_{high} is the number of commodities in the highest one-third portfolio of twelve-month return contracts; N_{low} is the number of commodities in the lowest one-third portfolio of twelve-month return contracts and $RET_{f,it}$ is the monthly return of futures contract *i* derived over time *t.*

Time-series Momentum

Despite bearing similarities with the cross-sectional strategy, the comparatively lesser known, 'time-series' (TS) momentum strategy of Moskowitz, Ooi, and Pedersen (2012) measures twelve-month momentum, using a time-varying portfolio sort. The time-varying nature inherent in this strategy provides the critical distinction, separating it from the aforementioned cross-sectional momentum. The TS strategy selectively constructs long and short positions only with contracts which have gained or lost value over the previous twelve-month period. The time-series momentum signal is formed by calculating a twelve-month return for each respective futures contract. The signal is then sorted, allocating all positive twelve-month returns contracts to the winner portfolio, and all negative twelve-month return contracts to the loser portfolio.[6] The time-series momentum signal is mathematically expressed as follows:

$$TSMOM_{(t)} = \frac{1}{N_{pos}}\left(\sum_{i=pos} RET_{f,it}\right) - \frac{1}{N_{neg}}\left(\sum_{i=neg} RET_{f,it}\right) \qquad (2)$$

where $TSMOM_{(t)}$ is the time-series momentum returns derived over time *t*; N_{pos} is the number of positive twelve-month return contracts; N_{neg} is the number of negative twelve-month return contracts; and $RET_{f,it}$ is the monthly return of futures contract *i* derived over time *t.*

52-Week High Momentum

Having first been proposed as an equity investment strategy to capture premiums associated with price anchoring bias through short term underreaction and subsequent long-term overreaction (reversals) to the arrival of new information by George and Hwang (2004), the 52-week high strategy has well established applications upon a variety of other asset classes in the literature (Bianchi, Drew and Fan, 2016). The 52-week high strategy is constructed by employing a price-over-52-week high ratio signal and sorting these ratios in descending order (highest to lowest). Those markets with signals in the top tercile are allocated to the winner portfolio, while the markets with signals in the bottom tercile are allocated to the loser portfolio. The investor creates a long position in the winner portfolio, and a short position in the loser portfolio. There are no investment positions for the remaining markets assigned to the middle

[6] In contrast to Moskowitz, Ooi & Pederson, (2012) We do not employ a volatility scaling approach in the construction of the time-series momentum strategy signal.

tercile portfolio. Consistent with momentum strategies, the 52-week high strategy employs a WML (winner minus loser) approach to calculate momentum returns. The 52-week high momentum signal is mathematically expressed as:

$$52H_{SIGNAL} = \frac{PRICE_{f,it}}{52H_{f,it,t-12}} \tag{3}$$

where $PRICE_{f,t}$ denotes the price of security *f* at time *t,* and $52H_{f,t}$ denotes the highest price of security *f* between time *t* and *t-12.*

52-Week Low Momentum

Similar to the 52-week high momentum strategy, the 52-week low momentum strategy employs a modified signal to capture a security's current price distance from its 52-week low value (George and Hwang, 2004). Signals are ranked in a descending order (highest to lowest), assigning the top tercile of markets to the winner portfolio, and the lowest tercile of markets to the loser portfolio. The strategy constructs long positions in markets which are allocated to the winner portfolio and short positions in markets which are allocated to loser portfolio. There are no investment positions for the remaining markets assigned to the middle tercile portfolio. The 52-week low momentum signal is mathematically expressed as:

$$52L_{SIGNAL} = \frac{PRICE_{f,it}}{52L_{f,it,t-12}} \tag{4}$$

where $PRICE_{f,it}$ denotes the price of security *i* at time *t,* and $52L_{f,it}$ denotes the lowest price of security *f* between time *t* and *t-12* (52-week low).

3.3 Market State Model

To examine information diffusion inherent in the under-and-over reaction hypothesis of Daniel, Hirschleifer and Subramanyam (1998) and Hong and Stein (1999) upon the short-term cross-sectional equity momentum anomaly of Jegadeesh and Titman (1993) and long run reversals of DeBondt and Thaler (1985), the work of Cooper et al. (2004) presents a market state model to identify periods of market prosperity and contraction, based upon a 36-month lagged return of the aggregate market index. From a theoretical perspective, the Cooper et al. (2004) market state model addresses prior assumptions pertaining to investor overconfidence about private information and subsequent overreaction.[7] While the model's theoretical underpinnings are behavioural in nature, the Cooper et al. (2004) market state model has been found to possess explanatory power for conventional momentum returns in equity markets and has been linked to short to intermediate momentum and long run reversals in the cross section of stock returns. The Cooper et al. (2004) market state model defines 'UP' market states as periods with non-

[7] Refer to Daniel, Hirshleifer and Subramanyam (1998).

negative 36-month market returns, while 'DOWN' market states are defined as periods with negative 36-month market returns, between time t and t-36. The market state model is constructed by calculating the 36-month return signal using the long-only aggregate market index. Consistent with the literature, this paper maintains a non-negative 36 month return to denote as an 'UP' state, while a negative 36-month return denotes a 'DOWN' state.

3.4 Return Dispersion

Stivers and Sun (2010) provide compelling evidence to suggest that the cross-sectional dispersion of stock returns (RD) may serve as a leading countercyclical variable state variable in equity markets. In addition, the study finds equity momentum returns are procyclical to economic cycles in U.S. markets. Earlier studies posit that momentum returns are expected to be higher during times of strong macroeconomic performance.[8] This study employs return dispersion as an explanatory variable to condition momentum returns in commodity markets and investigate its propensity to predict subsequent momentum returns. RD is defined as the cross-sectional standard deviation of the monthly disaggregate returns, mathematically expressed as follows:

$$RD_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_{i,t} - R_{\mu,t})^2} \quad (7)$$

where $R_{i,t}$ is the return of market *I* at time *t,* $R_{\mu,t}$ is the mean of the cross-section of returns at time *t*; and n is the number of markets. To control for spurious regressions, we derive orthogonal variables of RD, to control for the effects of carry and the average market factor (AVG). We construct $RD_{CARRY,t}$ and $RD_{AVG,t}$ as the orthogonal to the month CARRY and AVG variables, respectively, at time *t*, and is defined as the estimated residual ε_t and intercept α_1 from the following regressions:

$$RD_t = \alpha_1 + \beta_1 CARRY_t + \varepsilon_t \qquad (8)$$

$$RD_t = \alpha_1 + \beta_1 AVG_t + \varepsilon_t \qquad (9)$$

4. Results

This section contains a review of the results from the empirical investigation of the performance of commodity momentum returns and an examination of two explanatory frameworks (behavioural and risk-based) from the literature. The models are presented as

[8] See Chordia and Shivakumar (2002), Gomes, Kogan and Zhang (2003), Cooper et al. (2004), Zhang (2005), Avramov and Chordia (2006) and Gulen et al. (2008).

proxies of the behavioural (market state) and risk-based (return dispersion) theoretical explanations underpinning momentum returns. We begin with an examination of historical commodity momentum returns.

4.1 Momentum Performance

To gauge a sense of performance through time, Table 3 presents a statistical summary of return performance for the long only benchmark and four momentum strategies over three panels, comprising the winner, loser, and winner minus loser portfolios, from August 1960 to December 2017. Due to the sorting signals inherent in the construction of each strategy, the first 12-month period from July 1959 are attributed to signal generation, and do not contribute strategy returns.

Panel A of Table 3 reports cross-sectional momentum and 52-week high strategy returns exhibit the highest arithmetic mean, t-statistic, and Sharpe ratios of any other strategy. Annualised volatility is markedly high in both CS and L52 strategies, detracting from their risk adjusted return performance for the sample period. With the exception of H52, skewness values for each strategy are markedly negative, with the TS strategy exhibiting the most negative value at -0.64 (approximately double that of the CS strategy). Kurtosis values range as low as 5.01 in the case of L52, and as high 6.93 in the case of the TS strategy. Panel B of Table 2 reports the loser return portfolio of each strategy over the full sample period August 1960 to December 2017. With the exception of the long-only benchmark, all strategies report negative annualised arithmetic mean returns, and t-statistic values approximating -3.0. Sharpe ratios show that the CS strategy report the lowest risk adjusted return of any other strategy. Panel C reports the returns attributed to the winner minus loser portfolio. From the table we note statistical significance in the mean return across each strategy. From a risk adjusted perspective, H52 reports the highest return, reporting a Sharpe ratio of 0.83 over the full sample. CS reports the largest drawdown return at -0.59. We note that the length of consecutive drawdowns vary across each strategy, ranging from 18 in the case of H52, through to 32 in the case of TS. Interestingly, the H52 strategy reports the highest number of consecutive runup months with a value of 10 and the highest percentage of positive returns at 0.63.

[INSERT TABLE 3 HERE]

Reported performance of momentum strategies from Panel C are relatively high yielding, highly statistically significant, and exhibit skewness and kurtosis values which approximate normality in the distribution of returns.[9] Through the incorporation of an extensive dataset

[9] We denote skewness of 0.0 and kurtosis of 3.0 as approximate values to proxy for the test of normality.

stretching back to July 1959, we are interested to examine how the performance of commodity momentum strategies have varied through time. With this question in mind, we now proceed to examine cumulative returns performance.

Figure 1 presents the log scaled cumulative returns of $1 dollar invested through time. The figure illustrates returns of each of the five strategies across four time-horizons, approximating 20 years in duration. From the full sample figure, we observe the highest performance from the 52-week high strategy, which can be seen to out-perform all other strategies from approximately 1975 onward. Interestingly, the 52-week high strategy is depicted to underperform the conventional momentum strategy, tracking closely with the cumulative return of both time series momentum and the 52-week low throughout the first sub-sample period August 1960 to December 1979. The sub-sample period January 1980 to December 1999 depicts a different trend, with the passive benchmark strategy retaining a negative cumulative return throughout the entire sub-period. While we observe relatively flat returns performance across all strategies in the most recent January 2000 to December 2017. We note a consistent outperformance from the cross-sectional momentum strategy over all others, while the 52-week high strategy approximately tracks both time-series momentum and 52-week low strategies.

[INSERT FIGURE 1 HERE]

From the plots, we note variation in the returns of commodity momentum strategies through time. While the returns of the first and second sub-periods remain relatively strong, the returns of the most recent sub-period yield comparatively flatter cumulative returns. To test for the presence of a time-varying trend in the returns of commodity momentum strategies, we proceed to examine rolled return plots.

Figure 2 presents the five-year rolling returns of each strategy from August 1965 to December 2017. The dotted line denotes the point of zero return, the straight thin line denotes the trend of the rolled return over the sample period (constructed using an OLS regression with a constant and a time trend), and the thick line denotes the five-year rolled return of each strategy. For consistency throughout the figures, the vertical axis maintains fixed upper and lower bounds (0.05 and -0.01) and incremental values (0.01). The horizontal axis plots time in 5-year increments. The benchmark strategy plot provides an exception, with rolled returns beginning in August 1964 because of the lack of 12-month signal in the strategy's construction.

[INSERT FIGURE 2 HERE]

From the figure, we observe a clear downward trend in 5-year rolling returns over time. Plots from all strategies depict negative and close to zero rolled return values by 2017. The H52 strategy shows a clear upward trend from 1970 to 1980, which has since receded over time. Returns of the CS strategy appear the most volatile between the four momentum strategies.

From the plot, CS reached its lowest point around 2000, somewhat recovering thereafter, before dropping to its most recent negative rolled return value after 2012. The benchmark strategy depicts extremely undulated and volatile performance over time. Despite a downward trend, the figure shows several peak return periods across the sample period, the highest of which being in the period around 1975, with a return approximating 0.02. Interestingly, the lowest peak value approximates 1985 with a return approximating -0.015. Despite observing peak and trough values in figure, there is a clear declining trend in the returns performance in each strategy. With the observation of a downward trend in momentum premiums, the question of what may be driving it remains unresolved.

In a seminal study, Bakshi, et al. (2017) present evidence to link the volatility of commodity market returns with a multi-factor regression model featuring a carry, market average, and a momentum risk-factor. On the basis of empirics from this research, we are interested to examine the link between commodity momentum premiums and carry and market average risk factors. To begin this investigation, we proceed to examine correlation matrix performance between momentum strategy returns and the predictive variables employed in this study.

Table 4 presents the results of paired correlations of monthly returns from each strategy, carry factor, average (AVG) factor, the various forms of RD and the Chicago Federal National Aggregate Index (CFNAI). Correlation results have been constructed using the maximum available history of returns, August 1960 to December 2017 and March 1967 to December 2017 for correlations employing the CFNAI.

Panel A of the table reports statistically significant, high and positive correlation values for the cross-sectional and time-series momentum with 52-week high and low strategies. We note the benchmark strategy correlates with the other strategies to a lesser degree and varies in statistical significance. The 52-week high strategy is shown to load negatively, and is insignificant, while the 52-week low loads positive and is significant at the 1% level. Panel B denotes factor correlation values upon each strategy. Results from the panel show strong positive and significant correlation for the carry factor with reported values approximating 0.3, while AVG reports mixed results. AVG is positively correlated to CS (9.55%, 5% significance), TS (11.98%, 1% significance) and L52 (18.78%, 1% significance), while H52 reports a negative and insignificant value. RD and the two orthogonal variables retain comparatively similar correlation values throughout each strategy, and the CFNAI reports mixed results.[10]

[10] We declare the CFNAI as the monthly Chicago Federal National Aggregate Index. The CFNAI comprises monthly data from March 1967 to December 2017 and is available from the FRED website.

Unsurprisingly, the table reports positive and significant correlations between each strategy pair, with the exception of the 52-week high and the long-only benchmark.[11] The intuition from such an observation would expect to see high(low) momentum returns performance during periods of high(low) market performance for each strategy. Statistically significant correlations within Panel B suggest that CARRY, AVG and RD are useful when attempting to rationalise historical returns of commodity momentum strategies. We note that CARRY reports the highest significant paired correlations of any other factor, with reported values approximating 0.3 across each strategy.

[INSERT TABLE 4 HERE]

On the foundation of empirics from an established literature and the statistically significant correlation paired results reported in Table 4, we are interested to further examine the usefulness of CARRY and AVG risk-factors against commodity momentum strategy premiums achieved throughout our sample period. While we recognise that the usefulness of risk-factors through the lens of static regressions, we propose to examine the dynamic nature of factor loadings through employing a five-year rolling regression approach.[12]

Inspired by Ang, Madhavan, and Sobczyk (2017), this paper employs a rolling regression methodology approach to measure the dynamic variation in risk factor loadings from a series of risk-factor mimicking portfolios from the commodities literature upon momentum strategy returns. The 5-year rolling regressions are mathematically expressed as:

$$DV = \alpha + \beta_t \gamma + \varepsilon \qquad (8)$$

where DV denotes the dependant variable, in this case, momentum strategy returns; α denotes the intercept term; and γ is a vector of AVG or CARRY risk-factor variables.

Figure 3 presents the five-year rolling factor loadings of the CARRY, and passive long (AVG) risk factors upon each momentum strategy from August 1964 to December 2017. Plot 1 of Figure 3 presents the five-year rolling factor loading of the AVG risk factor upon CS, TS, H52 and L52 from August 1964 to December 2017. Of the notable observations from the plot, L52

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[11] Referring to the reported results of prior literature which have proven each factor statistically useful to the end of rationalising historical returns of momentum strategies in the commodity momentum literature.

[12] We note the intuition motivating a five-year roll period is to reduce the influence of short term volatility to observe factors loadings upon long-term time varying trends in the returns of commodity momentum strategies.

retains the highest AVG loading throughout the sample period. Loadings from the AVG factor tracks relatively closely upon each strategy through time, with a few notable periods of deviation. Plot 2 of Figure 3 presents the five-year rolling factor loading of the CARRY risk factor upon CS, TS, H52 and L52 strategies from July 1964 to December 2017. From the plot, we note the early period from 1964 to approximately 1973 depicts a deviated loading from CARRY upon CS, when compared to TS, H52 and L52 which are shown to track relatively closely together. The remainder of the plot shows the CARRY factor retaining relatively close loadings upon each strategy. The plot depicts two periods of negative loadings through time, with the remainder of the sample period retaining a positive loading.

[INSERT FIGURE 3 HERE]

The rolling regression risk-factor loadings in Figure 3 show the observation of dynamic time-varying risk-factor loadings. Further, the illustration highlights episodic periods where these risk factors exhibit negative loadings on a few occasions throughout the sample period. Figure 3 illustrates the time-varying relationship between these factors over long periods of time and how these relationships change throughout the sample period.

4.2 Behavioural Proxy (Market States)

The results from the evaluation of commodity momentum strategy performance depict a long-term declining trend in returns over time. While we acknowledge the wide array of conjectured explanations from prior studies to account for the recent poor returns, the literature fails to definitive identify the driver of the observable structural decline in the premiums of commodity momentum strategies.[13] In an empirical attempt to address this issue, we propose to examine the behavioural nature of commodity momentum strategies through the lens of Market States.

Cooper et al. (2004) presents a market state model designed to systematically capture equity momentum returns associated with investor tendencies to underweight news and information in the short term and subsequently overreact in the medium term, when new information confirms prior assumptions, and denote this behaviour to self-attribution bias in individual investors. Cooper et al. (2004) reports strong equity momentum returns following 'DOWN' states and poor or negative returns following 'UP' state periods in equity markets. Where 'UP' ('DOWN') state periods are defined by non-negative (negative) lagged 36-month return of the market (equal weighted long-only portfolio). Moreover, Cooper et al. (2004) shows that momentum profitability critically depends upon the state of the market. With the presence of a strong rationale to explain the dynamic returns of momentum strategies in equity markets, we

[13] We refer to the role of financialization of commodities and the limits to arbitrage through the adaptive market hypothesis (see Bianchi, Drew and Fan, 2016).

question whether market state conditioning may also provide rationalization for dynamic returns of momentum strategies in commodity markets as well.

Figure 4 depicts the 36-month lagged return of the market over the full sample period, July 1962 to December 2017. The figure plots two y-axis. The left vertical axis denotes the 36-month lagged return of the market, and is denoted by the thick solid line, over time. The right y-axis denotes the state of the market, over time. The thin solid line denotes the market state and denotes a value of 1 when the market is in an 'UP' state, or a 0 if the market is in a 'DOWN' state. The horizontal dotted line denotes the point of zero market return.

[INSERT FIGURE 4 HERE]

From the plot we can see clear periods of variation in lagged market return and market state. The most recent five-year period is shown to be in a predominantly 'DOWN' state. The longest period of 'UP' state is depicted in the period of approximately 1970 to 1975. While we observe periods of volatility in the state of the market, much of the plot shows market states persist for three to five years before shifting.

Table 5 presents the results of returns derived by momentum strategies when conditioned following 'UP' and 'DOWN' market states. Consistent with the reported performance in Cooper et al. (2004), momentum performance is examined on a one-month, a six-month, and twelve-month holding period basis.[14] While we do note a slight variation in performance of the arithmetic mean return when conditioning returns following 'UP' and 'DOWN' market states, the vast majority of market state conditioned returns are found to be not statistically different following 'UP' and 'DOWN' states. Of the few exceptions, the benchmark strategy (AVG) reports statistical difference at the 1% and 5% levels, with a diminishing effect as the holding period in increased to twelve months. The benchmark strategy reports negative returns performance when conditioned to follow 'DOWN' states, and positive returns performance when conditioned to follow 'UP' states. Despite market state conditioned returns remaining positive and significant across all holding periods, the H52 strategy reports statistical difference in mean returns in H52 (1-6), which increases as the holding period is extended out to twelve months (H52 (1-12)) with a *t*-statistic of 2.69 and -4.05, respectively. In contrast with the findings from Cooper et al. (2004) we note the count of market states periods remain approximately even throughout the sample period.[15]

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[14] Long term reversals are a well-established phenomenon in the commodity momentum literature (Bianchi, Drew and Fan, 2016). We do not report 13-60 month holding period returns.

[15] For robustness, we have applied a secondary market state framework according to Grundy and Martin (2001). Results from this approach remain consistent with our presented findings and are available upon request.

[INSERT TABLE 5 HERE]

The results in Table 5 reveal variation in the returns of commodity momentum strategies, throughout multiple strategies and holding periods. While we do observe some returns variation across states, we conjecture that both conventional momentum strategies (CS and TS) exhibit insignificant differences in the returns following both ‘UP’ and ‘DOWN’ market states. However, we note strong significant performance variation between ‘UP’ and ‘DOWN’ states in the H52 strategy over the short (1-6 month) and medium term (1-12) holding periods and can draw some intuition based upon the foundational underpinnings of the market state model. Cooper et al. (2004) present the market state model as an empirical model to test for the presence of short term underreaction and subsequent overreaction in equity momentum, following periods of positive market gains. They attribute this tendency to self-attribution and confirmation biases of individual investors. George and Hwang (2004) attribute momentum premiums from the H52 strategy to reflect price anchoring behaviour from individual investors. It is intuitive that a market state model designed to capture behavioural premiums from momentum in equity markets should capture statically significant variation from price anchoring behaviour in H52 momentum within commodity markets.

4.3 Risk Based Proxy (Return Dispersion)

To better understand the dynamic performance of momentum strategies through the lens of risk, we now proceed to examine the statistical summary of RD. Panel A of Table 6 presents a statistical summary of performance of the RD and the two orthogonal RD variables (controlling for CARRY and AVG risk factor returns). The panel comprises of the arithmetic mean, median, standard deviation and intertemporal correlations for each variable over the full sample period August 1959 to December 2017. With the exception of mean and median values, we note near identical performance between RD_{CARRY} and RD_{AVG} throughout each metric, with the exception of intertemporal correlations, which vary to a minor degree between each variable. We note negative median values in RD_{CARRY} and RD_{AVG} while RD reports positive values. Panel B of the table denotes summary statistics for 3-month and 6-month moving average variables of RD, RD_{CARRY} and $RD_{AVG.}$ We are interested in the moving average of the RD variables as we intend to employ them as a predictor variable. From the table, AC denotes the autocorrelation between the 3 and 6 month moving average variables. We note statistically significant AC values approximating 0.77 (significant at the 1% level) for each variable. In an attempt to better understanding the performance variation of RD, RD_{CARRY} and $RD_{AVG,}$ we now proceed to examine the time variation of the performance of RD.

[INSERT TABLE 6 HERE]

Figure 5 presents the time series plot of RD, RD_{CARRY} and RD_{AVG}. For the sake of comparison between each figure, x-axis values are spaced at approximate three-year intervals. Between the plots, we note that RD (as a measure of standard deviation) retains a positive value for the entirety of the sample period, while RD_{CARRY} and RD_{AVG} fluctuate about zero. Of the noteworthy observations from the plot, there are seven months in the top 1 percentile of the distribution of values. Including August 1973; March 1974; July 1974; December 1979; August 1986; June 1988 and August 1990. Of these months, we note three months which coincide with economic recession in the U.S., namely March 1974, July 1974 and August 1990.[16] We proceed to test whether RD exhibits explanatory power in predicting commodity momentum returns.

[INSERT FIGURE 5 HERE]

4.4 Predictive Regressions

Table 7 reports the predictive regressions with momentum as the dependent variable, the moving average of RD as the independent variable and market states as an additional control variable. To ensure we control for all major risk factors, we follow the Bakshi et al (2017) three-factor commodity pricing model. We employ three types of RD, namely, the calculation in its raw form, RD orthogonal to commodity market returns (AVG) and RD orthogonal to the carry risk factor (Carry). We employ the 6-month average of RD at time *t*-1 and the 3-month average of RD at time *t*-5 which is more dynamic and exhibits quantitatively similar parameters.

Panels A to C of Table 7 show that the 6-month average of RD reports a significant and negative β_1 with cross-sectional momentum and time-series momentum. The coefficient is insignificant with 52-week high momentum and 52-week low momentum. The RD estimates orthogonal to AVG and Carry also report consistently similar results. The regression results using the 3-month average of RD as the independent variable reports the same findings.

There are two key findings and implications from the results in Table 7. First, the results reveal an intertemporal negative relation between cross-sectional momentum and time-series momentum and RD. Essentially, RD predicts subsequent momentum returns. This finding is consistent with the equity literature which also finds a negative relation between equity RD and subsequent equity momentum returns (Connolly and Stivers, 2003; Stivers and Sun, 2010). This finding suggests that a commonality may potentially exist between RD and momentum, in general. Second, the significant negative relation with RD is found with cross-sectional and time-series momentum; however, this relation cannot be identified with the 52-week high

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[16] We gathered monthly recessionary data from the St Louis Federal Reserve Economic Database website.

momentum strategy. This finding suggests there are two types of commodity momentum. That is, cross-sectional and time-series momentum tend to be negatively related with U.S. economic conditions while the 52-week high momentum strategy appears to be unrelated to economic risks and is deemed to be driven by behavioural factors. These results provide us with evidence of a risk-based explanation for cross-sectional and time-series commodity futures momentum profits.

[INSERT TABLE 7 HERE]

Return Dispersion and U.S. Economic Activity

To test the presence of a relationship between U.S. economic activity and commodity RD, we estimate a number of regressions. Table 8 reports a variety of regressions with the Chicago Federal National Aggregate Index (CFNAI) as the dependent variable and the demeaned RD, the 3-month average of the demeaned RD and the 6-month average of the demeaned RD as the independent variables.[17] Panel A reports a significant negative coefficient with RD at time *t*, while predictive regressions at *t*-1 and *t*-2 are significant at the 10% level only. These results suggest the presence of a significant contemporaneous relation between RD and U.S economic activity with marginal significance with predictive variables at *t*-1 and *t*-2. Panel B employs the 3-month average of RD as the independent variable and reports a significant coefficient at time *t* and *t*-1 with 10% significance at *t*-2 and *t*-3. These results suggest that the 3-month average of commodity RD is a useful predictor of U.S. economic activity. Panel C employs the 6-month average of RD and reveals significance at time *t* and marginal significance at lags from *t*-1 to *t*-3.

[INSERT TABLE 8 HERE]

In summary, the regression results in Table 8 suggest that commodity RD is a significant information variable that provides useful current and predictive information in relation to the CFNAI. The significant negative coefficients in Table 8 suggest that higher levels of RD are related to negative observations in the CFNAI. Put simply, higher observations in commodity RD are related to poor or worsening U.S economic activity. The significant negative loadings at time *t* suggest there is a contemporaneous negative relation between RD and U.S economic activity. Furthermore, the significant negative loadings at t- 1 to t-3 also suggest the presence of an intertemporal relation between RD and U.S. economic activity. Taken together, the

[17] We employ the Chicago Federal National Aggregate Index (CFNAI) as the proxy for U.S. economic activity.

results in Tables 7 and 8 demonstrate the significance of RD as an important information variable in predicting commodity momentum returns and U.S. economic activity.

Return Dispersion and Low U.S. Economic Activity

As a form of robustness test, we implement a parametric test via a logit model to examine the presence of clustering between U.S. economic conditions and commodity RD. The information from commodity RD is valuable when it is related to economic conditions. The logit regression allows us to examine specific components of the economic cycle and RD. In this case, we test for the presence of clustering between the worst observations in U.S. economic activity and the highest observations in RD.

Table 9 reports the logit regression results between the CFNAI and commodity RD. Panel A of Table 9 employs the CFNAI as the dependent variable with the indicator variable set to one if the time series observations are in the bottom quartile (i.e. worst 25% of observations of U.S. economic activity) across the entire time series. The independent variable in the regression is the commodity futures RD with the indicator variable set to one if the observation is in the top quartile (i.e. highest levels of dispersion) of the entire time series. The logit results exhibit a significant positive relation between the lowest quartile of observations in the CFNAI and the highest quartile of monthly commodity RD observations. The findings also show that RD exhibits significant predictive explanatory power at times *t*-1 and *t*-2. To examine the extreme values, Panel A also reports logit regressions based on quintile and decile-based observations and we report consistently similar results. At the extreme decile sorts, we can observe a contemporaneous relation between the CFNAI and RD only.

It is unclear whether commodity RD explains or predicts U.S. economic activity, or the opposite effect, therefore for completeness, Panel B of Table 9 reports the same logit regressions but with the two variables in reverse. Again, we report similar significant contemporaneous and predictive explanatory power for both quartile and quintile sorts. An interesting finding are the decile-based results showing that the CFNAI is a significant predictor of commodity RD up to time *t*-6 months.

Overall, the findings in Table 9 suggest there is an inherent significant positive relation between poor U.S. economic activity and high levels of commodity RD. The relationship works in both directions. Most importantly in this study, commodity RD is an important information variable that can predict U.S. economic activity as far back as time *t*-2 months. With these results, we can conclude that commodity RD is an important information variable that can predict both U.S. economic activity and commodity momentum returns.

[INSERT TABLE 9 HERE]

5. Conclusion

The current state of the literature in understanding the sources of risk and return in commodity momentum remains unresolved. Furthermore, less research attention has been dedicated to commodity momentum than in the equity literature. Current researchers tend to classify commodity momentum strategies into one large homogeneous group which delivers the same returns, risks and are predominantly behavioural in nature. In contrast, recent empirical studies by Asness, Moskowitz and Pedersen (2013) and Stivers and Sun (2010) and show that equity momentum strategies tend to be inversely related with value strategies and momentum tends to be a procyclical risk premium. Our study extends the current understanding of commodity market dynamics by examining whether the behaviour of the commodity momentum premium is procyclical in nature or whether it is simply driven by behavioural factors.

For the first time in the commodity literature, this paper introduces the market state framework to test the behavioural theory of the under- and overreaction hypothesis on commodity momentum returns. The findings reveal that the market state framework captures the behavioural dynamics of the 52-week high momentum strategy and it cannot explain the returns from the cross-sectional and time-series momentum strategies. This finding suggests that the behavioural theory of under-reaction explains the 52-week high momentum strategy but does not explain the dynamics of the cross-sectional and time-series momentum strategies. This finding implies that behavioural factors may not be the source of risk and returns in cross-sectional and time-series commodity futures momentum.

For the first time, we introduce the return dispersion calculation as a predictive information variable to capture the risk-based relation between commodity futures momentum and U.S. economic activity. Our analysis reveals two broad types of commodity momentum which can be differentiated by their sources of risk and return with U.S. economic activity. Commodity return dispersion can be used as a predictive variable to understand the commonalities and differences between specific types of commodity momentum investment strategies. Our results show that the first type of commodity momentum (cross-sectional and time-series) exhibit a procyclical relation with economic conditions. The second type of momentum strategies (52-week high) are unrelated to economic risks and are genuinely behavioural in nature.

We also find that commodity return dispersion not only acts as an information variable for commodity momentum, but, it is also related to U.S. economic activity. OLS and logit regressions show that high levels of commodity return dispersion can predict poor U.S. economic activity. For the first time, we can document a direct relation between commodity futures and U.S. economic activity by using commodity return dispersion as an information transmission variable.

Our finding suggest that commodity futures return dispersion is an important information variable which is of interest to investors. In terms of practical implementation, the calculation of monthly return dispersion from 26 commodity futures markets is significantly easier to operationalise in comparison to the multitudes of calculations required when constructing equity momentum portfolios from hundreds and/or even thousands of equity securities. Essentially, investors can extract important information on commodity momentum and the U.S. economy by calculating monthly return dispersion from a small number of commodity futures markets.

These two broad types of commodity momentum strategies (i.e. behavioural versus risk-based) suggest that portfolio construction can be tilted towards strategies exposed to economic risks and those that are not. For industry professionals, our new finding raises the interesting question of whether they desire to earn commodity momentum returns which are exposed to economic risks or to returns which are exposed to behavioural factors and are unrelated to the economic conditions. The differentiation of two broad types of commodity momentum strategies means that investment portfolios can be constructed to embed economic risks or mitigate economic risks depending on the selection of the commodity momentum strategy. We leave this interesting question as an avenue for future research.

6. References

Ang, A., Madhavan, A., & Sobczyk, A. (2017). Estimating Time-Varying Factor Exposures. *Financial Analysts Journal*, 73(4), 41-54.

Asness, C., Moskowitz, T. and Pedersen, L., 2013, Value and momentum everywhere. *Journal of Finance*, 68(3), 929-985.

Avramov, D., & Chordia, T. (2006). Asset Pricing Models and Financial Market Anomalies. *Review of Financial Studies*, 19(3), 1001-1040.

Bakshi, G., Gao, X., & Rossi, A. G. (2017). Understanding the Sources of Risk Underlying the Cross Section of Commodity Returns. *Management Science*, Forthcoming.

Barberis, N., Shleifer, A. and Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics,* 49, 307-343.

Bianchi, R., Drew, M. and Fan, J. (2015). Combining momentum with reversal in commodity futures. *Journal of Banking & Fin*ance, 59, 423-444.

Bianchi, R. J., Drew, M. E., & Fan, J. H. (2016). Commodities momentum: A behavioral perspective. *Journal of Banking and Finance*, 72, 133-150.

Bianchi, R. J., Drew, M. E., & Fan, J. H. (2017). Microscopic momentum. *Working Paper*, Griffith Business School, Department of Accounting, Finance and Economics, Griffith University.

Boons, M. & Prado, M. (2018). Basis momentum. *Journal of Finance*, forthcoming.

Chordia, T., & Shivakumar, L. (2002). Momentum, Business Cycle, and Time-Varying Expected Returns. *Journal of Finance*, 57(2), 985-1019.

Connolly, R. and Stivers, C., 2003, Momentum and reversals in equity-index returns during periods of abnormal turnover and return dispersion. *Journal of Finance,* 58(4), 1521-1555.

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market States and Momentum. *Journal of Finance*, 59(3), 1345-1365.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market under- and Overreactions. *Journal of Finance*, 53(6), 1839-1885.

De Bondt, F. M. W., & Thaler, R. (1985). Does the Stock Market Overreact? *Journal of Finance*, 40(3), 793-805.

Driesprong, G., Jacobsen, B. & Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics*, 89(2), 307-327.

Erb, C. B., & Harvey, C. R. (2006). The Strategic and Tactical Value of Commodity Futures. *Financial Analysts Journal*, 62(2), 69-97.

Fernandez-Perez, A., Fuertes, A., Miffre, J. (2017). Commodity markets, long-run predictability, and intertemporal pricing. *Review of Finance,* 21(3), 1159-1188.

Fuertes, A., Miffre, J. and Fernandez-Perez, A., 2015, Commodity strategies based on momentum, term structure and idiosyncratic volatility. *Journal of Futures Markets,* 35(3), 274-297.

Fuertes, A., Miffre, J. and Rallis, G., 2010, Tactical allocation in commodity futures markets: Combining momentum and term structure signals. *Journal of Banking & Finance,* 34, 2530-2548.

George, T. J., & Hwang, C.-Y. (2004). The 52-Week High and Momentum Investing. *Journal of Finance*, 59(5), 2145-2176.

Gomes, J., Kogan, L., & Zhang, L. (2003). Equilibrium Cross Section of Returns. *Journal of Political Economy*, 111(4), 693-732.

Gorton, G. B., Hayashi, F., & Rouwenhorst, K. G. (2012). The fundamentals of commodity futures returns. *Review of Finance*, 17(1), 35-105.

Grundy, B. D., & Martin, J. S. (2001). Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. *Review of Financial Studies*, 14(1), 29-78.

Gulen, H., Xing, Y., & Zhang, L. (2011). Value versus Growth: Time-Varying Expected Stock Returns. *Financial Management*, 40(2), 381-407.

Hamilton, J. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy* 91(2), 228-248.

Hong, H. and Stein, J. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54(6), 2143-2184.

Hong, H. and Yogo, M. (2012). What does futures market interest tell us about the macroeconomy and asset prices?. *Journal of Financial Economics* 105, 473-490.

Jacobsen, B., Marshall, B. & Visaltanachoti, N. (2018). Stock market predictability and industrial metal returns. *Management Science*, in press.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1), 65-91.

Johnson, T. (2002). Rational momentum effects. *Journal of Finance* 57(2), 585-608.

Jones, C. & Kaul, G. (1996). Oil and the stock markets. *Journal of Finance*, 51(2), 463-491.

Liu, L. and Zhang, L. (2008). Macroeconomic profits, factor pricing, and macroeconomic risk, *Review of Financial Studies,* 21(6), 2417-2448.

Madhavan, A., Sobczyk, A. & Ang, A. (2018). What's in your benchmark? A factor analysis of major market indexes. *Journal of Portfolio Management*, 44(4), 46-59.

Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. *Journal of Banking and Finance*, 31(6), 1863-1886.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2), 228-250.

Paschke, R., Prokopczuk, M. & Simen, C.W., (2017). Curve momentum. *Working Paper*, Leibniz University Hannover, Germany.

Stivers, C., & Sun, L. (2010). Cross-Sectional Return Dispersion and Time Variation in Value and Momentum Premiums. *Journal of Financial and Quantitative Analysis*, 45(4), 987-1014.

7. Appendix

Appendix 1 presents a statistical summary of strategy returns conditioned upon high and low macroeconomic sorting variables, including TED spread, OVX index, VIX index, US recession probability, and the term premium derived through the spread between short and long-term US treasury bills. The table is presented over three panels: Panel A reports momentum strategy returns performance of strategies comprised of returns derived during periods of low values (Q1 – low tercile) of each macroeconomic sort variable. Panel B reports strategy returns performance derived during periods of high macroeconomic sort variable (Q2 – upper tercile).[18] Panel C presents the results for welch test of equal means between each strategy return dataset from panel A and panel B.

Between the performance tables of panels, A and B, mean returns and test-statistics relatively high and significant for CS, TS, H52, L52, when conditioned upon high and low values of US recession probability, US industrial production and term premium variables. TED spread conditioned CS and TS momentum returns remain statistically significant and report marginally higher return during periods with low TED spread values (Q1). OVX conditioned strategy returns remain statistically insignificant at both high and low quantiles for all strategies with the exception of the long-only benchmark (AVG). Of the strategies examined strategies, only the passive long benchmark reports sufficient conditioned returns variation. Reporting positive (negative) and significant mean returns when conditioned on low (high) tercile breakpoint values of OVX, VIX, and US recession probability. US industrial production and term premium conditioned returns also exhibit strong influence upon the returns of the benchmark strategy, which exhibits negative and insignificant returns during periods of low quantile values, and positive and insignificant returns during periods of high quantile conditioning values.

[INSERT APPENDIX 1 HERE]

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[18] For robustness purposes, we augmented indicator breakpoints to examine quantiles, quintiles, and deciles in an investigative attempt to measure performance variation in the returns of momentum strategies. While we observe minor variation through augmenting the breakpoints of each conditioning variable, results are indistinguishable from the median breakpoint and have been excluded from this study as a result.

While we note some performance variation across the two panels of the table, there is little distinction between upper and lower tercile conditioned momentum strategy return performance using both financial and macroeconomic sort variables. Panel C reveals no statistical difference in the mean values of the return strategy using any conditioning variables in this study, suggesting that the conditioning variables examined are insufficient timing measures to capture variation in the returns performance of commodity momentum strategies. The key exception is found in the long-only benchmark, which reflects the sensitivity of the pricing of commodity futures contracts to fluctuations in the level of OVX, VIX, US recession probability, and US Industrial production.

Table 1 - Dataset Summary

This table reports summary statistics of futures contracts provided from the Commodities Research Bureau (CRB) database from July 1959 to December 2017. The table reports arithmetic mean return, standard deviation of returns, skewness and kurtosis, for each of the 26 commodity futures markets. Markets have been divided by sector, and denote CRB ticker codes, start dates, first contract, and the respective exchange where each market is traded.

Sector	**Commodity**	**CRB Code**	**First Contract**	**Exchange**	**Start Date**	**Mean**	**Std. Dev**	**Skew.**	**Kurt.**
Energy	Brent Crude	CB	CB1989U	ICE(US)	Jul-89	0.0049	0.0924	-0.1939	5.5291
	Gas Oil	LF	LF1986M	ICE(US)	Jun-86	0.0058	0.0930	-0.0544	4.2521
	Heating Oil	HO	HO1979G	NYMEX	Nov-79	0.0066	0.0971	-0.3666	0.4996
	Natural Gas	NG	NG1990M	NYMEX	Apr-90	-0.0166	0.1372	0.0175	3.6812
	RBOB Gas	RB	RB1985G	NYMEX	Dec-84	0.0111	0.1075	-0.0218	5.9122
	WTI Crude	CL	CL1983M	NYMEX	Mar-83	0.0019	0.0939	1.7571	5.9516
Precious Metals	Gold	GC	GC1975F	COMEX	Dec-74	-0.0003	0.0550	-0.0217	6.2950
	Silver	SI	SI1963Q	COMEX	Jun-63	0.0004	0.0868	3.0628	16.7624
Livestock	Feeder Cattle	LC	LC1965J	CME	Nov-64	0.0032	0.0500	0.2669	2.2882
	Lean Hogs	LH	LH1966N	CME	Feb-66	0.0018	0.0775	0.6109	2.6162
	Pork Belly	PB	PB1962G	CME	Sep-61	-0.0027	0.1016	-0.0285	4.4280
Industrials	Copper	HG	HG1959V	COMEX	Jul-59	0.0061	0.0783	1.1347	4.4130
	Lumber	LB	LB1970H	CME	Oct-70	-0.0062	0.0853	-0.0071	3.6596
Softs	Cocoa	CC	CC1960H	ICE(US)	Jul-59	-0.0045	0.0684	0.4928	6.8867
	Cotton	CT	CT1960N	ICE(US)	Jul-59	0.0004	0.0689	0.1414	5.2869
	Coffee	KC	KC1973H	ICE(US)	Aug-73	-0.0005	0.1032	0.5792	4.9117
	Oats	O-	O-1959Z	CBOT	Jul-59	-0.0040	0.0843	0.7912	9.3094
	Orange Juice	JO	JO1963K	ICE(US)	Jan-76	0.0009	0.0900	0.7772	6.5740
	Sugar	SB	SB1961N	ICE(US)	Jan-61	-0.0030	0.1159	0.5318	4.7472
Grains	Corn	C-	C-1959U	CBOT	Jul-59	-0.0005	0.0874	0.3016	3.8175
	Rough Rice	RR	RR1986X	CBOT	Aug-86	-0.0068	0.0778	1.0328	3.0291
	Soybean	S-	S-1959U	CBOT	Jul-59	0.0017	0.0720	0.5569	8.0859
	Soybean Oil	BO	BO1959U	CBOT	Jul-59	0.0020	0.0829	0.6767	6.6665
	Soybean Meal	SM	SM1959Z	CBOT	Jul-59	0.0053	0.0859	0.8353	10.2260
	Wheat	W-	W-1959N	CBOT	Jul-59	-0.0053	0.0731	0.2315	5.2546
	Kansas Wheat	KW	KW1970H	KBOT	Jan-70	-0.0010	0.0737	0.3479	5.6256

Table 2 – Summary Statistics

This table reports summary statistics derived from the returns of momentum strategies and predictive variables featured in this study. All reported variables have been constructed using the full sample period August 1960 to December 2017. Data limitations of the CFNAI index restrict the beginning of the sample period to March 1967. The table reports arithmetic mean, standard deviation, median, *t*-statistic, minimum value, maximum value, skewness and kurtosis, as well as 10%, 25%, 75% and 90% percentile values for each variable.

Variable	Mean	Std. Dev	Median	*t*-statistic	Min	Max	Skew.	Kurt.	p10	p25	p75	p90
Panel A: Strategy Returns												
CS_{12}	0.0134	0.0652	0.0093	(5.38)	-0.2163	0.2181	0.1128	3.5332	-0.0653	-0.0266	0.0508	0.1010
TS_{12}	0.0099	0.0478	0.0080	(5.42)	-0.1907	0.1862	0.0391	4.1363	-0.0477	-0.0179	0.0379	0.0701
$H52_{12}$	0.0138	0.0574	0.0139	(6.29)	-0.1997	0.2297	0.1594	3.9505	-0.0530	-0.0202	0.0469	0.0820
$L52_{12}$	0.0107	0.0573	0.0064	(4.89)	-0.1667	0.2551	0.2297	3.8715	-0.0549	-0.0247	0.0462	0.0855
Panel B: Predictive Variables												
AVG	0.0003	0.0380	0.0004	(0.22)	-0.2324	0.1840	-0.1777	6.6493	-0.0421	-0.0214	0.0223	0.0422
CARRY	0.0095	0.0596	0.0076	(4.20)	-0.2507	0.2442	0.0952	4.0603	-0.0638	-0.0248	0.0449	0.0858
RD	0.0734	0.0256	0.0697	(75.76)	0.0090	0.2117	1.0541	5.4988	0.0447	0.0559	0.0868	0.1057
RD_{CARRY}	0.0000	0.0256	-0.0037	(0.00)	-0.0644	0.1415	1.0650	5.5909	-0.0285	-0.0178	0.0137	0.0320
RD_{AVG}	0.0000	0.0256	-0.0034	(0.00)	-0.0642	0.1351	1.0203	5.2867	-0.0282	-0.0177	0.0138	0.0333
CFNAI	-0.0020	1.0038	0.0600	-(0.05)	-5.1600	2.7600	-1.1398	6.7091	-1.1450	-0.4100	0.5700	1.0650

Table 3 - Strategy Performance Statistics

This tables presents the statistical summary of the returns derived from the benchmark, conventional momentum, timeseries momentum, 52-week high, and 52-week low strategies, over the sample period of August 1960 to December 2017. The table is presented over three panels. Panel A presents returns of portfolios formed on winner criteria basis (top tercile), panel B presents returns of portfolios formed on a loser basis (bottom tercile), and panel C presents returns of portfolios formed on a winner minus loser basis (top minus bottom tercile).

Strategy Returns 1960m8 to 2017m12

Panel A: Winners	**Cross-sectional momentum**	**Time-series momentum**	**52-week high**	**52-week low**	**Passive Long**
Annualized arithmetic mean	0.0801	0.0595	0.0885	0.064	0.0037
t-statistics	3.05	2.68	3.81	2.48	0.21
Annualized volatility	0.1954	0.1674	0.1761	0.1957	0.1316
Sharpe Ratio	0.4099	0.3552	0.5027	0.3271	0.0280
Skewness	-0.3655	-0.6438	0.0023	-0.2561	-0.1775
Kurtosis	5.430	6.925	6.474	5.012	6.659
Panel B: Losers					
Annualized arithmetic mean	-0.0945	-0.0548	-0.0767	-0.0642	0.0037
t-statistics	-3.72	-2.91	-3.28	-3.19	0.21
Annualized volatility	0.1904	0.1420	0.1772	0.1525	0.1316
Sharpe Ratio	-0.4964	-0.3857	-0.4327	-0.4211	0.0280
Skewness	0.1812	0.1547	0.3082	0.0986	-0.1775
Kurtosis	5.3080	5.6976	5.9970	5.0612	6.6586
Panel C: Winners - Losers					
Annualized arithmetic mean	0.1618	0.1193	0.1652	0.1282	0.0037
t-statistics	5.43	5.46	6.29	4.89	0.21
Annualized geometric mean	0.1366	0.1057	0.1457	0.1088	-0.0050
Annualized volatility	0.2259	0.1656	0.1989	0.1984	0.1316
Annualized downside volatility	0.1325	0.1043	0.1181	0.1138	0.0926
Skewness	0.1097	0.0362	0.1594	0.2297	-0.1775
Kurtosis	3.5292	4.1324	3.9505	3.8715	6.6586
Max monthly gain	0.2181	0.1862	0.2297	0.2551	0.1840
Max monthly loss	-0.2163	-0.1907	-0.1997	-0.1667	-0.2324
99%VaR (Cornish-Fisher)	0.2264	0.1692	0.2097	0.2087	0.1411
% of positive months	0.5864	0.6125	0.6323	0.5828	0.5078
Maximum Drawdown	-0.5877	-0.3581	-0.3441	-0.4452	-0.7644
Drawdown Length (months)	24	32	18	30	433
Max Run-up (consecutive)	0.7615	0.379	0.8599	0.5978	0.3577
Runup Length (months)	7	6	10	9	7
Max 12M rolling return	1.0724	0.6738	1.0451	0.7421	0.7102
Min 12M rolling return	-0.7375	-0.3466	-0.3280	-0.3845	-0.6329
Sharpe Ratio	0.7160	0.7205	0.8303	0.6462	0.0280
Sortino Ratio	1.3158	1.2089	1.5100	1.1954	0.0398

Strategy Returns 1960m8 to 1979m12

Panel A: Winners	**Cross-sectional momentum**	**Time-series momentum**	**52-week high**	**52-week low**	**Passive Long**
Annualized arithmetic mean	0.1860	0.1459	0.2076	0.1662	0.0606
t-statistics	4.28	4.04	4.99	3.59	2.04
Annualized volatility	0.1896	0.1592	0.1832	0.2043	0.1339
Sharpe Ratio	0.9814	0.9164	1.1334	0.8137	0.4521
Skewness	-0.1483	-0.0357	0.6844	-0.1051	0.7927
Kurtosis	3.5280	4.231	5.288	3.843	6.245
Panel B: Losers					
Annualized arithmetic mean	-0.0893	-0.0288	-0.0608	-0.033	0.0606
t-statistics	-1.71	-0.82	-1.47	-0.95	2.04
Annualized volatility	0.2227	0.1534	0.1825	0.1527	0.1339
Sharpe Ratio	-0.4012	-0.1876	-0.3332	-0.2163	0.4521
Skewness	0.3337	0.7053	0.9796	0.9468	0.7927
Kurtosis	5.744	7.320	8.092	7.174	6.245
Panel C: Winners - Losers					
Annualized arithmetic mean	0.2584	0.1742	0.2684	0.1993	0.0606
t-statistics	4.82	4.76	6.08	4.27	2.04
Annualized geometric mean	0.2310	0.1613	0.2501	0.1785	0.0518
Annualized volatility	0.2363	0.1613	0.1945	0.2056	0.1339
Annualized downside volatility	0.1435	0.1072	0.1060	0.1196	0.0762
Skewness	-0.0176	-0.1316	0.2075	0.0555	0.7927
Kurtosis	3.4176	4.9908	3.5931	3.5431	6.2454
Max monthly gain	0.1916	0.1749	0.2063	0.1963	0.1840
Max monthly loss	-0.2024	-0.1907	-0.1198	-0.1667	-0.1136
99%VaR (Cornish-Fisher)	0.2334	0.1709	0.2117	0.2073	0.1750
% of positive months	0.6695	0.6867	0.7382	0.6609	0.5184
Maximum Drawdown	-0.3547	-0.3232	-0.2908	-0.3258	-0.2938
Drawdown Length (months)	5	11	12	12	37
Max Run-up (consecutive)	0.7615	0.379	0.8599	0.5978	0.3577
Runup Length (months)	7	6	10	9	7
Max 12M rolling return	1.0724	0.6738	1.0451	0.7421	0.7102
Min 12M rolling return	-0.3666	-0.3466	-0.3280	-0.3776	-0.2409
Sharpe Ratio	1.0935	1.0802	1.3805	0.9692	0.4521
Sortino Ratio	2.0292	1.7616	2.8679	1.8272	0.8171

Table 3 – Strategy Returns (Cont.)

Strategy Returns 1980m1 to 1999m12

Panel A: Winners	**Cross-sectional momentum**	**Time-series momentum**	**52-week high**	**52-week low**	**Passive Long**
Annualized arithmetic mean	0.0047	0.0174	0.0267	0.0030	-0.0426
t-statistics	0.11	0.52	0.81	0.08	-1.71
Annualized volatility	0.1896	0.1493	0.1472	0.1740	0.1113
Sharpe Ratio	0.0247	0.1165	0.1813	0.0174	-0.3827
Skewness	-0.3590	-0.3509	0.3387	-0.0522	-0.4115
Kurtosis	4.5289	4.1581	5.7205	4.9057	3.4371
Panel B: Losers					
Annualized arithmetic mean	-0.1164	-0.0959	-0.1241	-0.1056	-0.0426
t-statistics	-3.18	-3.58	-3.43	-3.44	-1.71
Annualized volatility	0.1635	0.1197	0.1619	0.1374	0.1113
Sharpe Ratio	-0.7120	-0.8014	-0.7666	-0.7684	-0.3827
Skewness	0.0605	-0.2826	-0.0810	-0.1178	-0.4115
Kurtosis	3.7582	3.2903	5.0112	3.4476	3.4371
Panel C: Winners - Losers					
Annualized arithmetic mean	0.0949	0.1141	0.1508	0.1086	-0.0426
t-statistics	1.94	3.29	3.5	2.52	-1.71
Annualized geometric mean	0.0711	0.1022	0.1324	0.0904	-0.0488
Annualized volatility	0.2189	0.1553	0.1929	0.1926	0.1113
Annualized downside volatility	0.1339	0.0954	0.1198	0.1179	0.0807
Skewness	0.0671	0.0350	0.0220	0.2335	-0.4115
Kurtosis	3.8983	3.8443	4.4481	4.7403	3.4371
Max monthly gain	0.1721	0.1679	0.2297	0.2551	0.0836
Max monthly loss	-0.2102	-0.1371	-0.1997	-0.1636	-0.1079
99%VaR (Cornish-Fisher)	0.2169	0.1557	0.2013	0.2128	0.0849
% of positive months	0.5333	0.6125	0.6083	0.5583	0.4875
Maximum Drawdown	-0.5765	-0.296	-0.292	-0.4452	-0.6763
Drawdown Length (months)	24	22	30	30	229
Max Run-up (consecutive)	0.3779	0.3091	0.3968	0.3824	0
Runup Length (months)	3	7	5	7	0
Max 12M rolling return	0.4755	0.5220	0.5525	0.4590	0.2362
Min 12M rolling return	-0.7315	-0.2893	-0.2070	-0.3154	-0.4129
Sharpe Ratio	0.4336	0.7350	0.7817	0.5638	-0.3827
Sortino Ratio	0.7405	1.2605	1.3490	0.9684	-0.5175

Strategy Returns 2000m1 to 2017m12

Panel A: Winners	**Cross-sectional momentum**	**Time-series momentum**	**52-week high**	**52-week low**	**Passive Long**
Annualized arithmetic mean	0.0470	0.0102	0.0314	0.0207	-0.0086
t-statistics	0.97	0.23	0.7	0.43	-0.25
Annualized volatility	0.2023	0.1889	0.1908	0.2040	0.1468
Sharpe Ratio	0.2321	0.0541	0.1644	0.1014	-0.0583
Skewness	-0.5417	-1.1188	-0.7860	-0.6054	-0.9384
Kurtosis	7.8627	8.9208	6.8254	6.1042	7.1801
Panel B: Losers					
Annualized arithmetic mean	-0.0735	-0.0344	-0.0427	-0.0509	-0.0086
t-statistics	-1.71	-0.96	-0.96	-1.29	-0.25
Annualized volatility	0.1824	0.1515	0.1876	0.1674	0.1468
Sharpe Ratio	-0.4029	-0.2267	-0.2275	-0.3043	-0.0583
Skewness	-0.0682	-0.3254	-0.1395	-0.5174	-0.9384
Kurtosis	4.1294	4.2309	4.2938	3.8955	7.1801
Panel C: Winners - Losers					
Annualized arithmetic mean	0.1256	0.0617	0.074	0.0716	-0.0086
t-statistics	2.44	1.47	1.52	1.54	-0.25
Annualized geometric mean	0.1023	0.0461	0.0530	0.0527	-0.0197
Annualized volatility	0.2181	0.1780	0.2066	0.1964	0.1468
Annualized downside volatility	0.1208	0.1088	0.1262	0.1052	0.1160
Skewness	0.2879	0.2475	0.2977	0.4065	-0.9384
Kurtosis	3.2985	3.8183	3.9679	3.4964	7.1801
Max monthly gain	0.2181	0.1862	0.2045	0.1722	0.1172
Max monthly loss	-0.1313	-0.1400	-0.1588	-0.1463	-0.2324
99%VaR (Cornish-Fisher)	0.2229	0.183	0.2172	0.2053	0.1406
% of positive months	0.537	0.5278	0.5442	0.5256	0.5139
Maximum Drawdown	-0.4962	-0.3581	-0.3447	-0.4157	-0.6297
Drawdown Length (months)	33	32	90	33	92
Max Run-up (consecutive)	0.5093	0.2768	0.2334	0.3430	0.1748
Runup Length (months)	8	6	7	5	3
Max 12M rolling return	0.6113	0.4948	0.5423	0.6282	0.3330
Min 12M rolling return	-0.3835	-0.3195	-0.2809	-0.3845	-0.6329
Sharpe Ratio	0.5758	0.3468	0.3584	0.3647	-0.0583
Sortino Ratio	1.1016	0.5841	0.6069	0.7038	-0.0735

Figure 1 – Cumulative Returns

The figure below illustrates the log scaled cumulative returns of $1 dollar invested using the benchmark, conventional momentum, time-series momentum, 52-week high, and 52-week low momentum strategies. The figure plots cumulative returns, over four sample periods: August 1960 to December 2017; August 1960 to December 1979; January 1980 to December 1999, and January 2000 to December 2017.

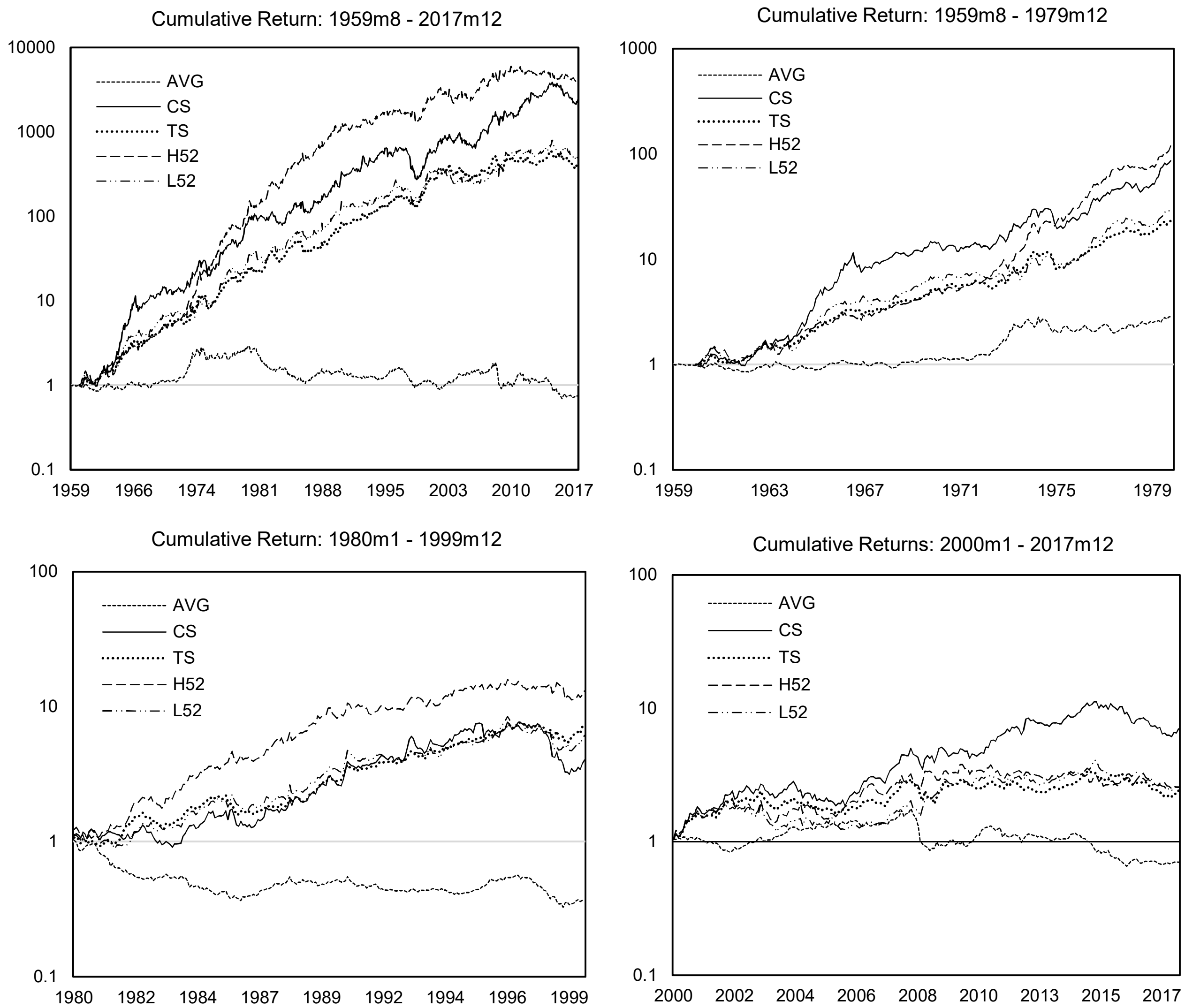


Figure 2 – 5 year rolling returns

The figure illustrates the rolling five year returns of conventional momentum, time-series momentum, 52-week high, and 52-week low momentum strategies. The horizontal broken line denotes the intersection of zero return. The diagonal line denotes the trend of returns over the full sample. The figures plot returns over the full sample period, from August 1965 to December 2017. Return data prior to August 1965 have been allocated to signal and rolling return generation.

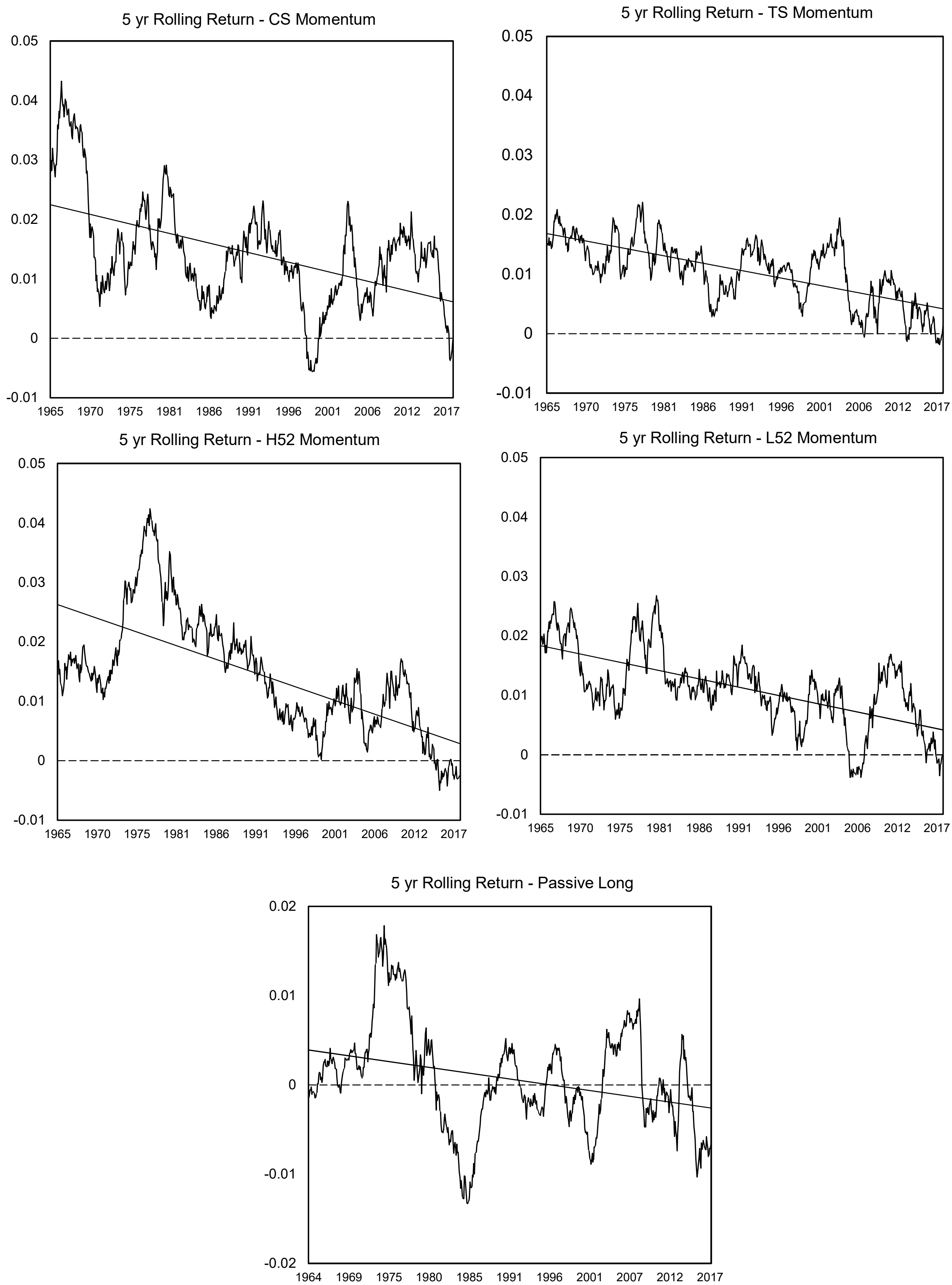


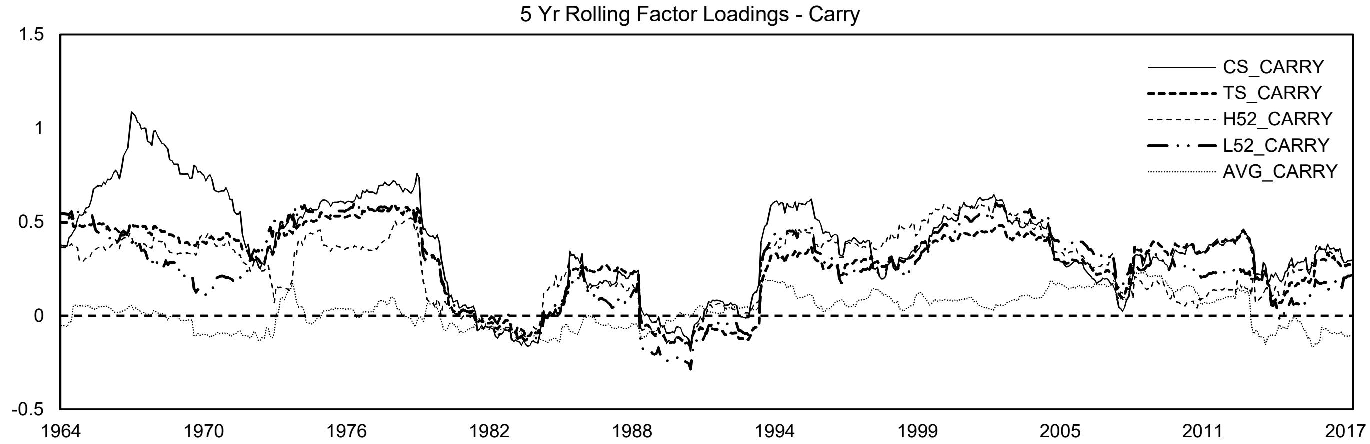
Table 4 - Correlation Matrix

This table presents a correlation matrix of the strategy and literary inspired risk-factors featured in this paper. The table is presented over two panels. Panel A presents strategy correlations, and panel B presents the factor correlations upon the benchmark, conventional momentum, timeseries momentum, 52-week high, and 52-week low strategies. Statistical significance is denoted by asterisks. One asterisk denotes significance at the 10% level, two asterisks denotes significance at the 5% level, and three asterisks denotes significance at the 1% level.

	Passive long	Cross-sectional momentum	Time-series momentum	52-week high	52-week low
Panel A: Strategy Correlations					
AVG	1				
CS	0.0955**	1			
TS	0.1198**	0.8079***	1		
H52	-0.0295	0.6312***	0.6532***	1	
L52	0.1878***	0.5727***	0.6295***	0.6885***	1
Panel B: Factor Correlations					
CARRY	0.0438	0.3362***	0.3642***	0.2833***	0.2853***
AVG	1	0.0955**	0.1198***	-0.0295	0.1878***
RD	0.0816**	0.0992***	0.1057***	0.1513***	0.1390***
RD_{CARRY}	0.0804**	0.0894**	0.0951**	0.1431***	0.1307***
RD_{AVG}	0.0000	0.0915**	0.0960**	0.1543***	0.1237***
CFNAI	0.1628***	0.0151	0.0246	0.0273	-0.0601

Figure 3 – Rolling factor loadings

The figure below illustrates the 5 year rolling factor loadings from a univariate OLS regression between August 1964 to December 2017. The horizontal broken line denotes the point of zero loading for each respective risk factor. The key in each figure denotes the line style for each factor loading.



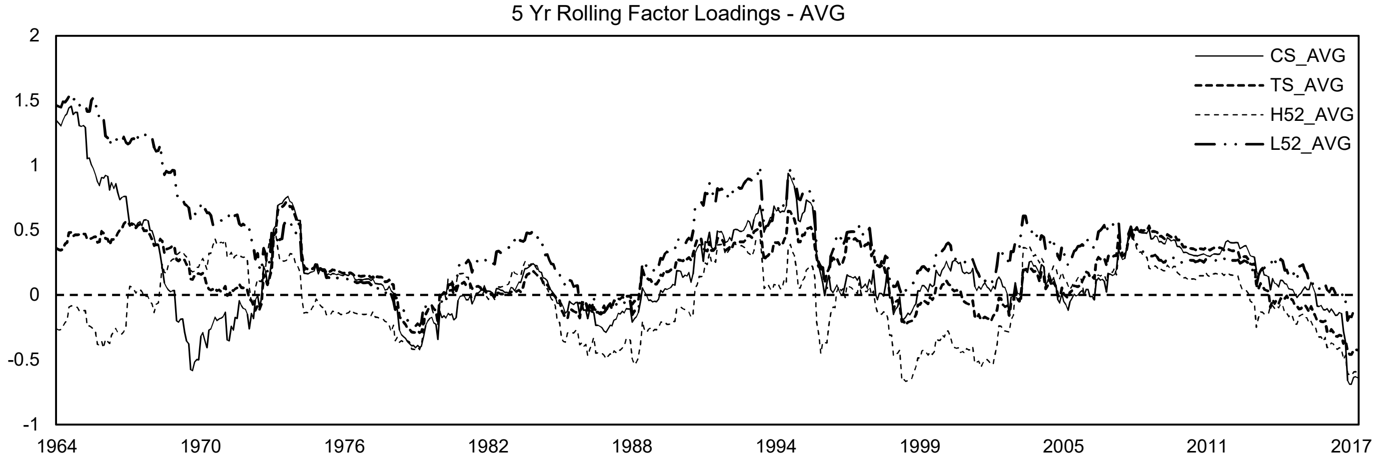


Figure 4 – Cooper et al. (2004) Market States

The figure below depicts the 36-month lagged market return signal of the Cooper et al. (2004) market state model, as well as a binary variable to denote the state of the market over time. The broken line denotes the point of zero return and divides the state of the market between 'up' and 'down'. The figure plots the state and return of the market from August 1962 to December 2017.

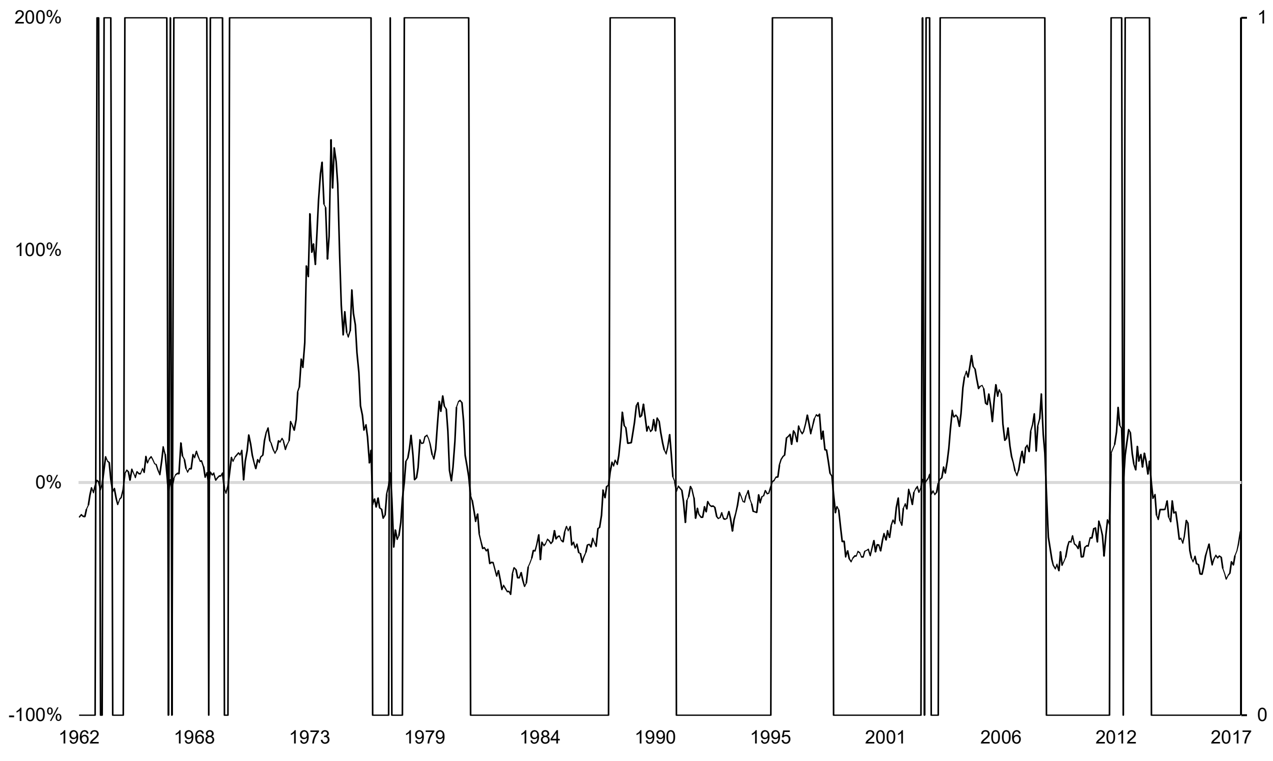


Table 5 – Cooper et al. (2004) Market States

This table reports summary statistics for strategy performance following 'up' and 'down' market states, following cooper et al. (2004) construction methodology. The table presents arithmetic mean of return, test static of the mean, and market state count for the benchmark (AVG), conventional momentum, timeseries momentum, 52-week high and 52-week low strategies. The table presents statistics of returns derived over the full sample period, over the first six months following 'up' and 'down' states, and over the first 12 months following 'up' and 'down' states. The table reports test-statistics for welch test of equal means, between 'up' and 'down' state performance within each panel. Statistical significance is denoted by asterisks. One asterisk denotes significance at the 10% level, two asterisks denotes significance at the 5% level, and three asterisks denotes significance at the 1% level. The reports summary performance from returns derived over the full sample period, August 1962 to December 2017, where the first 36-month of the sample period is attributed to signal generation.

	CS	CS (1-6)	CS (1-12)	TS	TS (1-6)	TS (1-12)	H52	H52 (1-6)	H52 (1-12)	L52	L52 (1-6)	L52 (1-12)	AVG	AVG (1-6)	AVG (1-12)
Following UP															
Arithmetic mean	1.68%	1.56%	1.49%	1.11%	1.01%	1.01%	1.15%	1.63%	1.66%	1.30%	1.16%	1.15%	0.57%	0.22%	0.16%
t-stat	4.57	9.61	12.08	4.24	9.24	12.36	5.02	13.19	17.65	4.06	9.41	12.24	2.71	2.08	1.89
States Count (n)	342	342	342	342	342	342	342	342	342	342	342	342	342	342	342
Following DOWN															
Arithmetic mean	1.09%	1.18%	1.23%	0.90%	0.99%	0.98%	1.63%	1.16%	1.14%	0.85%	0.99%	0.99%	-0.49%	-0.12%	-0.08%
t-stat	3.11	8.03	11.26	3.41	8.48	11.55	3.77	9.38	12.98	2.80	7.64	10.33	-2.38	-1.37	-1.18
States Count (n)	324	319	313	324	319	313	324	319	313	324	319	313	324	319	313
Welch Test of equal means (UP - Down = 0)															
t-stat	-1.17	-1.72	-1.58	-0.57	-0.13	-0.19	-1.08	-2.69	-4.05	-1.03	-0.96	-1.14	-3.60	-2.47	-2.22
p-Val	0.24	0.09	0.12	0.57	0.90	0.85	0.28	0.01**	0.00***	0.31	0.34	0.26	0.00***	0.01**	0.03**

Table 6 – RD Statistical Summary

This table presents a statistical summary of the RD, RD orthogonalized to CARRY (RD_{CARRY}) and RD orthogonalized to AVG (RD_{AVG}) across the full sample period August 1959 to December 2017. Panel A reports arithmetic mean, median, standard deviation and intertemporal correlation values. Panel B reports a statically summary of 3 and 6 month moving average expressions of RD, RD_{CARRY} RD_{AVG}. AC denotes the results of autocorrelation values in each variable between *t*-3 and *t*-6. Statistical significance in reported values are denoted by 1 (10% level), 2 (5% level), and 3 (1% level) asterisks.

Panel A: Monthly RD, RD_{CARRY} and RD_{AVG} Statistics

Variable	Mean	Median	Standard Deviation	*p*(1) (*t*,*t*-1)	*p*(2) (*t*,*t*-2)	*p*(3) (*t*,*t*-3)
RD	0.073	0.070	0.026	0.347***	0.279***	0.271***
RD_{CARRY}	0.000	-0.004	0.026	0.345***	0.276***	0.269***
RD_{AVG}	0.000	-0.004	0.026	0.347***	0.280***	0.267***

Panel B: 3 month and 6 month moving average statistics

Variable	Mean	Median	Standard Deviation	AC (*t*-3, *t*-6)
RD_{1-3}	0.0735	0.0719	0.0190	0.7697***
$RD_{CARRY,1-3}$	0.0001	-0.0013	0.0189	0.7677***
$RD_{AVG,1-3}$	0.0001	-0.0016	0.0189	0.7638***
RD_{1-6}	0.0736	0.0728	0.0164	0.7697***
$RD_{CARRY,1-6}$	0.0002	-0.0008	0.0164	0.7677***
$RD_{AVG,1-6}$	0.0002	-0.0008	0.0163	0.7638***

Figure 5 – Return Dispersion

This figure presents three line-charts depicting the timeseries of the values RD, RD orthogonalized to AVG and RD orthogonalized to CARRY, over the full sample period August 1959 to December 2017. The y-axis denotes the variable value while the x-axis denotes time. For the sake of uniformity, y-axis and x-axis values are reported at 0.05 and 4-year intervals, respectively.

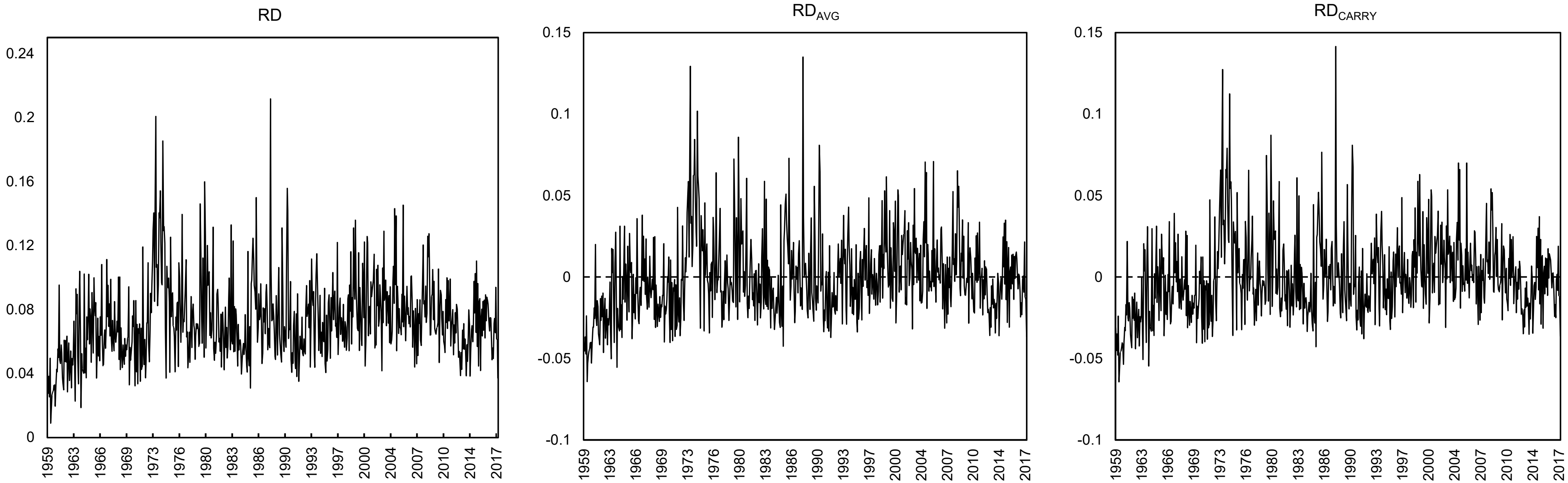


Table 7 – Predictive Regressions

This table presents a summary of the OLS multivariate regressions upon four momentum and one passive long commodity strategies. The table reports coefficient results, t-statistics (in parenthesis), ,adjusted R² values and p-values of *F*-statistics, to measure the fit of each regression. MOM_t denotes the dependant variable. RD_{term} denotes an intertemporal 3-month and 6-month moving average expression of RD, RD orthogonalized to CARRY (RD_{CARRY}) and RD orthogonalized to AVG (RD_{AVG}) at *t-5* and *t-1* respectively. $StRt_{t-36}$ denotes the 36-month return on the long-only market.

$$MOM_t = \alpha + \beta_1 RD_{term} + \beta_2 StRt_{t-36} + e_t$$

6ma, t-1	α	β_1	β_2	$\bar{R}^2$	*p* > F
Panel A: RD					
CS_{12}	0.02	-0.38	0.02	0.75%	0.03
	(1.57)	-(2.09)	(2.34)		
TS_{12}	0.02	-0.30	0.01	0.76%	0.03
	(1.49)	-(2.22)	(1.58)		
$H52_{12}$	0.00	-0.13	0.02	0.89%	0.02
	(0.09)	-(0.88)	(2.36)		
$L52_{12}$	0.02	-0.25	0.01	0.18%	0.20
	(1.45)	-(1.56)	(1.19)		
AVG	-0.01	-0.21	0.02	2.99%	0.00
	-(0.96)	-(1.69)	(3.42)		
Panel B: RD_{CARRY}					
CS_{12}	-0.01	-0.39	0.02	0.76%	0.03
	-(0.7)	-(2.29)	(2.12)		
TS_{12}	0.00	-0.31	0.01	0.79%	0.03
	-(0.48)	-(2.28)	(1.59)		
$H52_{12}$	-0.01	-0.13	0.02	0.89%	0.02
	-(0.87)	-(0.89)	(2.36)		
$L52_{12}$	0.00	-0.26	0.01	0.20%	0.19
	-(0.02)	-(1.6)	(1.2)		
AVG	-0.02	-0.21	0.02	2.98%	0.00
	-(3.24)	-(1.68)	(3.42)		
Panel C: RD_{AVG}					
CS_{12}	-0.01	-0.41	0.02	0.85%	0.02
	-(0.7)	-(2.4)	(2.15)		
TS_{12}	0.00	-0.32	0.01	0.88%	0.02
	-(0.48)	-(2.39)	(1.6)		
$H52_{12}$	-0.01	-0.14	0.02	0.91%	0.02
	-(0.88)	-(0.94)	(2.37)		
$L52_{12}$	0.00	-0.25	0.01	0.18%	0.21
	(0.02)	-(1.54)	(1.16)		
AVG	-0.02	-0.21	0.02	3.03%	0.00
	-(3.25)	-(1.74)	(3.43)		

$$MOM_t = \alpha + \beta_1 RD_{term} + \beta_2 StRt_{t-36} + e_t$$

3ma, t-5	α	β_1	β_2	$\bar{R}^2$	*p* > F
Panel A: RD					
CS_{12}	0.02	-0.31	0.02	0.74%	0.03
	(1.37)	-(2.3)	(2.09)		
TS_{12}	0.01	-0.24	0.01	0.75%	0.03
	(1.22)	-(2.09)	(1.53)		
$H52_{12}$	0.00	-0.16	0.02	1.02%	0.01
	(0.22)	-(1.25)	(2.49)		
$L52_{12}$	0.02	-0.20	0.01	0.16%	0.22
	(1.28)	-(1.55)	(1.13)		
AVG	-0.02	-0.05	0.02	2.48%	0.00
	-(1.83)	-(0.44)	(3.05)		
Panel B: RD_{CARRY}					
CS_{12}	-0.01	-0.32	0.02	0.75%	0.03
	-(0.59)	-(2.33)	(2.09)		
TS_{12}	0.00	-0.25	0.01	0.77%	0.03
	-(0.38)	-(2.14)	(1.54)		
$H52_{12}$	-0.01	-0.17	0.02	1.03%	0.01
	-(0.95)	-(1.28)	(2.49)		
$L52_{12}$	0.00	-0.21	0.01	0.18%	0.21
	(0.08)	-(1.59)	(1.14)		
AVG	-0.02	0.05	0.02	2.47%	0.00
	-(2.92)	-(0.41)	(3.04)		
Panel C: RD_{AVG}					
CS_{12}	-0.01	-0.33	0.02	0.81%	0.03
	-(0.59)	-(2.4)	(2.1)		
TS_{12}	0.00	-0.25	0.01	0.80%	0.03
	-(0.37)	-(2.15)	(1.52)		
$H52_{12}$	-0.01	-0.17	0.02	1.04%	0.01
	-(0.95)	-(1.3)	(2.49)		
$L52_{12}$	0.00	-0.20	0.01	0.17%	0.21
	(0.11)	-(1.57)	(1.11)		
AVG	-0.02	-0.06	0.02	2.49%	0.00
	-(2.94)	-(0.49)	(3.06)		

Table 8 – RD regressions

This table presents a summary of OLS regression results between dependant variable, CFNAI at time *t* and demeaned RD from time *t* to time *t-3.* *T*-statistic values of coefficients are denoted in parentheses.

$$CFNAI_t = \alpha_t + \beta_1(10RD-\overline{X}) + e_t$$

	α	β_1	R^2	$p > F$
Panel A: RD_t				
t	0.011	-0.458	1.30%	0.00
	(0.15)	-(2.23)		
t-1	0.009	-0.409	1.03%	0.01
	(0.13)	-(1.84)		
t-2	0.011	-0.446	1.22%	0.01
	(0.15)	-(1.78)		
t-3	0.010	-0.417	1.07%	0.01
	(0.14)	-(1.58)		
Panel B: $RD_{3,t}$				
t	0.019	-0.774	1.86%	0.00
	(0.27)	-(2.05)		
t-1	0.022	-0.863	2.32%	0.00
	(0.32)	-(2.17)		
t-2	0.022	-0.836	2.18%	0.00
	(0.32)	-(1.89)		
t-3	0.023	-0.882	2.42%	0.00
	(0.34)	-(1.79)		
Panel C: $RD_{6,t}$				
t	0.033	-1.237	3.38%	0.00
	(0.5)	-(2.02)		
t-1	0.032	-1.225	3.32%	0.00
	(0.49)	-(1.87)		
t-2	0.033	-1.247	3.44%	0.00
	(0.5)	-(1.85)		
t-3	0.033	-1.255	3.49%	0.00
	(0.49)	-(1.87)		

Table 9 – Logit Regressions

This table reports the results of two sets of logit regressions based upon RD and the CFNAI over two panels. The table reports intercept, beta coefficients, McFadden R² and log likelihood results. Both panels have been constructed using an inter-temporal independent variable β_1 between *t* and *t-6*. *T*-statistics of coefficient values are presented in parentheses. The table reports results derived from 610 monthly observations from the earliest available start date of the CFNAI, March 1967 to December 2017. Decile, quartile and quintile binary values are constructed using 10% (< -1.149), 20% (< -0.558) 25% (< -0.410) percentile extremes of CFNAI; and 90% (> 0.106), 80% (> 0.092), and 75% (> 0.087) percentile extreme values of RD.

	α	β_1(RD)	McFadden R^2	Log Likelihood		α	β_1(CFNAI)	McFadden R^2	Log Likelihood
	Panel A: Dependant variable $CFNAI_t$					*Panel B: Dependant variable RD_t*			
Quartile									
t	-1.246	0.424	0.63%	-338.12	t	-1.087	0.424	0.60%	-355.92
	-(10.92)	(2.09)				-(10.12)	(2.09)		
t-1	-1.310	0.625	1.39%	-335.25	t-1	-1.099	0.445	0.66%	-354.41
	-(11.26)	(3.11)				-(10.2)	(2.19)		
t-2	-1.282	0.553	1.08%	-336.03	t-2	-1.107	0.484	0.78%	-353.66
	-(11.11)	(2.74)				-(10.25)	(2.38)		
t-3	-1.201	0.302	0.31%	-338.34	t-3	-1.005	0.112	0.04%	-355.98
	-(10.64)	(1.47)				-(9.54)	(0.535)		
t-4	-1.163	0.182	0.11%	-338.74	t-4	-1.024	0.196	0.12%	-355.36
	-(10.4)	(0.88)				-(9.66)	(0.94)		
t-5	-1.211	0.349	0.40%	-337.41	t-5	-1.000	0.073	0.02%	-354.44
	-(10.68)	(1.706)				-(9.47)	(0.35)		
t-6	-1.157	0.176	0.11%	-338.19	t-6	-0.996	0.070	0.02%	-354.13
	-(10.34)	(0.85)				-(9.44)	(0.33)		
Quintile									
t	-1.555	0.665	1.36%	-301.08	t	-1.420	0.665	1.30%	-317.00
	-(12.87)	(2.95)				-(12.42)	(2.95)		
t-1	-1.495	0.455	0.62%	-303.13	t-1	-1.391	0.521	0.78%	-317.15
	-(12.6)	(1.98)				-(12.26)	(2.28)		
t-2	-1.509	0.518	0.81%	-302.33	t-2	-1.441	0.723	1.55%	-314.44
	-(12.67)	(2.27)				-(12.5)	(3.22)		
t-3	-1.465	0.356	0.37%	-303.44	t-3	-1.313	0.204	0.11%	-318.79
	-(12.45)	(1.53)				-(11.83)	(0.86)		
t-4	-1.437	0.256	0.19%	-303.78	t-4	-1.361	0.421	0.50%	-317.30
	-(12.32)	(1.08)				-(12.08)	(1.82)		
t-5	-1.490	0.471	0.66%	-302.11	t-5	-1.320	0.211	0.12%	-317.00
	-(12.55)	(2.04)				-(11.85)	(0.88)		
t-6	-1.392	0.079	0.02%	-303.85	t-6	-1.330	0.264	0.19%	-316.52
	-(12.07)	(0.33)				-(11.89)	(1.12)		
Decile									
t	-2.327	0.849	1.43%	-195.57	t	-2.175	0.869	1.32%	-212.48
	-(15.4)	(2.48)				-(15.42)	(2.53)		
t-1	-2.258	0.467	0.40%	-197.47	t-1	-2.173	0.867	1.31%	-212.37
	-(15.35)	(1.25)				-(15.41)	(2.53)		
t-2	-2.216	0.184	0.06%	-197.99	t-2	-2.191	0.980	1.74%	-211.34
	-(15.32)	(0.46)				-(15.41)	(2.92)		
t-3	-2.153	-0.397	0.17%	-197.62	t-3	-2.230	1.200	2.74%	-209.06
	-(15.25)	-(0.82)				-(15.43)	(3.68)		
t-4	-2.173	-0.163	0.03%	-197.81	t-4	-2.228	1.194	2.74%	-208.95
	-(15.27)	-(0.36)				-(15.41)	(3.67)		
t-5	-2.233	0.353	0.20%	-197.38	t-5	-2.269	1.398	3.94%	-206.26
	-(15.3)	(0.912)				-(15.42)	(4.41)		
t-6	-2.189	0.024	0.00%	-197.66	t-6	-2.267	1.396	3.93%	-206.16
	-(15.25)	(0.056)				-(15.41)	(4.4)		

Appendix 1 – Strategy performance sorted by macroeconomic variables

The table reports arithmetic mean and test-statics of strategy return using a variety of binary conditioned macroeconomic sorting variables, including TED spread, OVX index, VIX index, US recession probability, US industrial production and Term premium. The table reports results over three panels. Panel A reports strategy returns derived using the lower quantile (Q1) of each sorting variable. Upper and lower quantile breakpoints have been constructed using the full sample median of the macroeconomic variable. Panel B reports strategy returns derived using the upper quantile (Q2) of the sort variable. Panel C reports the welch test p-value for difference in mean between the mean returns reported in panels A and B. Statistical significance is denoted by asterisks. One asterisk denotes significance at the 10% level, two asterisks denotes significance at the 5% level, and three asterisks denotes significance at the 1% level.

		CS	TS	H52	L52	AVG
Panel A: Q1 (Lower Quantile)						
TED						
	mean return	1.12%	0.74%	0.93%	0.84%	0.17%
	t-stat	2.27	2.03	2.18	2.08	0.66
OVX						
	mean return	1.10%	0.16%	0.29%	0.46%	1.16%
	t-stat	1.40	0.26	0.45	0.82	2.34
VIX						
	mean return	1.13%	0.98%	0.64%	0.88%	0.53%
	t-stat	2.30	2.49	1.41	2.10	1.96
US Recession Prob.						
	mean return	1.14%	0.95%	1.27%	0.81%	0.37%
	t-stat	3.46	3.73	4.16	2.64	1.85
US Industrial Prod						
	mean return	1.01%	0.82%	1.15%	0.92%	-0.21%
	t-stat	2.87	3.09	3.47	2.99	-1.00
Term Premium						
	mean return	1.16%	0.82%	1.38%	1.00%	-0.10%
	t-stat	3.33	3.21	4.19	3.03	-0.54
Panel B: Q2 (Higher Quantile)						
TED						
	mean return	0.85%	0.66%	0.53%	0.61%	-0.25%
	t-stat	1.92	1.90	1.30	1.45	-0.87
OVX						
	mean return	0.62%	0.44%	0.18%	0.80%	-1.96%
	t-stat	0.79	0.61	0.25	1.05	-2.93
VIX						
	mean return	0.61%	0.32%	0.42%	0.31%	-0.77%
	t-stat	1.21	0.87	0.98	0.69	-2.50
US Recession Prob.						
	mean return	1.15%	0.90%	1.46%	1.06%	-0.33%
	t-stat	2.94	2.99	4.08	3.09	-1.33
US Industrial Prod						
	mean return	1.68%	1.17%	1.60%	1.21%	0.27%
	t-stat	4.81	4.67	5.60	3.92	1.35
Term Premium						
	mean return	1.54%	1.17%	1.37%	1.13%	0.17%
	t-stat	4.33	4.51	4.75	3.97	0.77
Panel C: Test for equality (Q2 - Q1 = 0) Welch test						
TED		0.64	0.88	0.50	0.69	0.28
OVX		0.67	0.76	0.91	0.72	0.00***
VIX		0.46	0.21	0.72	0.35	0.00***
US Recession Prob.		0.98	0.90	0.68	0.59	0.03**
US Industrial Prod		0.18	0.34	0.31	0.51	0.09*
Term Premium		0.45	0.34	0.98	0.77	0.35