Essays on Commodity Futures Markets

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by

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Abstract

This thesis investigates the asset pricing implications of different issues arising in the commodity futures market: the parameter uncertainty problem in commodity style integration, the role of investors' sentiment and the limited attention effect in the commodity futures market.

We review the mainstream long-short strategies in commodity futures markets and the theories underpin them in the first chapter.

In the second chapter, we solve the parameter uncertainty problem arising in commodity style integration by utilizing a Bayesian framework. Commodity style integration is appealing because by relying on a composite signal that combines multiple commodity characteristics, the integrated portfolio ought to capture a larger premium consistently over time. A key decision that a style-integration investor face is which criteria or model to use for determining the style weights at each portfolio formation time. By adopting a Bayesian framework, it is allowed that the investor to account for parameters uncertainty. Focusing on the allocation problem of a commodity futures investor that seeks exposure to the hedging pressure, term structure, momentum, skewness, and basis momentum styles, we assess a Bayesian integrated portfolio versus the naive equal-weight integrated (EWI) portfolio and other sophisticated integration approaches. The results suggest a Bayesian optimization approach outperforms the others according to diverse performance criteria. The findings are robust to transaction costs, variants of the

scoring schemes, longer ranking windows, and economic sub-periods analysis.

In the third chapter, we argue that the overall tone of recent news articles serves as a proxy for commodity futures investor sentiment. Studying a cross-section of commodities in the energy, agriculture, livestock, and metals sectors the findings indicate that media tone is able to predict subsequent commodity futures returns after controlling for well-known predictive signals such as hedging pressure, momentum, and roll yield inter alia. Sentiment-adjusted long-short portfolio allocation strategies significantly enhance the performance of traditional long-short commodity portfolios. Time-series and cross-sectional pricing tests suggest that the media tone has pricing ability over and above known commodity risk factors.

In the fourth chapter, we investigate the spillover effect of investors' attention from the equity market to the commodity market. We argue that investors' attention to a specific firm will spill to its related commodity futures market. This effect helps to construct a limited attention measure for commodity futures contracts. We show that the thus constructed measure is associated with higher returns of commodity futures in the future week, after adjusting for a battery of risk and characteristic benchmarks. Time-series and cross-sectional pricing tests suggest that the attention measure has pricing ability over and above known commodity risk factors.

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Chapter 1

Introduction

Over the past decade, commodity futures have attracted more attention from institutional investors. According to the Commodity Futures Trading Commission (CFTC), the fund inflows to various commodity futures indices from early 2000 to June 30, 2008 accounts for $200 billion (CFTC, 2008). Furthermore, commodities futures have increasingly been viewed as an alternative financial asset class for portfolio diversification. Specifically, commodity futures offer portfolio diversification benefits given their high expected returns with a low correlation with traditional asset classes such as equity and bonds. However, the source of the commodity futures premium is still under debate. Mainstream long-short strategies in commodity futures markets are based on signals such as roll yield, inventory levels, hedging pressure or past performance. We will review next the theories that underpin these signals.

1.1 Strategies Based on the Theory of Storage

The theory of storage, as put forward by Kaldor (1976), Working (1949), and Brennan (1976), states that commodity prices are driven by the cost of storage (transportation, warehousing and insurance costs). According to the theory, when commodity inventories are abundant, the commodity can be bought easy (relatively low price) in the spot market. Therefore, the benefit of holding the physical inventories (convenience yield) is low and the market is said to be in *contango* or with an upward-sloping term structure of commodity prices. The futures price of a contangoed contract is expected to decrease in value as maturity approaches. On the other hand, if the inventories are scarce, the term structure of futures prices slopes downward and markets are said to be in backwardation. In this scenario, the convenience yield to hold the physical inventories is higher than the cost of storage. The futures price of a backwardated asset is deemed to appreciate with maturity. Thus, a long position is likely to be profitable.

As the theory suggests, trading strategies based on the theory of storage shall use the roll yield and inventory levels as trading signals which capture the fundamentals of backwardation and contango. Specifically, a significant term structure premium is extracted by taking long positions in commodity futures with downward sloping future curves (higher basis) and simultaneous short positions in commodity futures with upward sloping future curves (lower basis) (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Koijen et al., 2018; Szymanowska et al., 2014).

Although the basis signal is widely used as a measure for convenience yield, Gu et al. (2019) argue that basis is determined not only by the convenience yield but also by other commodity-specific characteristics, most notably the "cost of carry", which includes both the interest rates (financing cost) and the storage cost. As a result, basis is a noisy proxy for the convenience yield with many confounding factors. Instead, they propose a purer measure, relative basis, which is defined as the difference between the prices of the first-nearby futures contract and second-nearby contract minus that between the prices of the second-nearby and the third-nearby contract. They argue that commodity specific characteristics that determine storage and financing costs are persistent over time. Thus, taking the difference between the short term and long term basis can get rid of elements from storage and financing costs, and therefore is a more precious measure for convenience yield.

1.2 Strategies Based on the Hedging Pressure Hypothesis

For a long history, commodity futures markets have been serving commodity producers to hedge their commodity price risk. One strand of literature that explains the source of risk premia of commodity futures is the longstanding normal backwardation theory of Keynes (1930), Hicks (1939) and Hirshleifer (1988). They posit that the commercial hedgers are on net short positions and need to offer positive risk premia to attract speculators to take the opposite position. This could be done by setting the futures price today below the expected maturity spot price of the futures contracts. This means the future prices are expected to rise when approaching maturity. Thus, the speculators in the long position will earn a positive risk premium for taking the risk transferred from the hedgers. Though the hedgers are in a net short position, they are not necessarily short. Cootner (1960) proposes the hedging pressure hypothesis which allows the net long hedgers. When hedgers are net long, the future prices should be set higher than the expected maturity spot price. Thus, by the theory, the hedging pressure premium is extracted by longing those commodities with the highest hedging pressure (short minus long hedgers positions over total hedgers positions) and shorting those commodities with the lowest hedging pres- sure; see e.g., Dewally et al. (2013), Basu and Miffre (2013).

1.3 Trend-Following Strategies

In equity markets, trend following strategies are popular and proved to be successful. Jegadeesh and Titman (1993) document that equities with the highest average return in the recent past outperform those with the worst past performance for up to 12 months. This strategy is referred to as cross-sectional momentum.

In the commodity futures market, the momentum strategy has been implemented by Miffre and Rallis (2007), Fuertes et al. (2010), Asness et al. (2013), and Bakshi et al. (2019). Momentum premium could be obtained by longing (shorting) those commodities with best (worse) past performance. The rationale for the positive average returns of the momentum strategy in the commodity market is still unclear. While many traditional risk factors fail to explain commodity momentum premium, possible explanations have been brought forward in both a behavioural and a rational pricing direction. From the behavioural perspective, Miffre and Rallis (2007), Shen et al. (2007), and Moskowitz et al. (2012) show that the momentum benefits will reverse beyond a year after portfolio formation. This can be explained as a sign of initial under-reaction and subsequent mean-reversion which supports the sentiment-based behavioural theories of Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999).

From the rational pricing perspective, it is argued that the momentum signals implicitly select commodities that other theories would choose as well. This has been shown by Miffre and Rallis (2007), Gorton et al. (2013), and Bianchi et al. (2015). Align with this argument, Bakshi et al. (2019) show that innovations in a commodity-based measure of speculative activity are positively related to the momentum factor.

A common feature of previous works is that they focus on the first nearby futures contract of different commodity futures markets. While this approach parallels the methodology of studies on the equity market, it does not exploit an important dimension of commodity futures markets: the term structure. This motivates Paschke et al. (2020) to implement the momentum strategy within individual futures curves by trading different maturities of the same commodity. The curve momentum strategy involves long–short fully collateralized positions in the first 2 nearby contracts of each commodity futures curve. The curve momentum signal is calculated using all excess return observations of the previous 12 months and open a long position in the nearby contract with the higher curve momentum signal and a short position in the other nearby. The curve momentum strategy offers a better risk-return trade-off than the conventional commodity momentum and carry strategies.

1.4 Strategies Focused on Tail Risk

Besides fundamental risk, market-wide higher moments are important indicators of market-wide risk which does not co-vary perfectly with volatility risk. For instance, Chang et al. (2013) show that stocks exposure to market skewness exhibit low returns on average. In commodity futures market, Fernandez-Perez et al. (2018) argues that systematically buying commodities with the most negative skewness and shorting commodities with the most positive skewness yield a Sharpe ratio of 0.78 which cannot be fully explained by the fundamentals of backwardation and contango.

The effect of downside risk has also been explored in the financial economics literature. Many studies have empirically tested the relationship between downside risk and equity returns in the US market. For instance, Ang et al. (2006) study the systematic downside risk measured by downside beta and motivate a role for this risk metric by relying on the disappointment utility function of Gul (1991). Atilgan et al. (2019) measure downside risk using value-at-risk and expected short-fall and uncover a negative relationship between these metrics and future equity returns. The authors name this phenomenon left-tail momentum and attribute it to the under-reaction of retail investors to negative price shocks. Following their study, we measure the commodity market downside risk by value-at-risk (VaR), specifically, the 1st and 99th percentile VaR. Downside risk premium could be obtained by longing/shorting commodity futures contracts that have high/low VaR1 and VaR99 signals.

1.5 Strategies Focused on Volatility/Liquidity Risk

As a modification to the term structure and momentum approaches, Boons and Prado (2019) proposes a strategy that uses the basis momentum as a signal for asset allocation. It is measured as the difference in momentum between first- and second-nearby future contracts. The resulting long-short basis-momentum portfolio generates a Sharpe ratio that is higher than that obtained on the standard basis or momentum strategies and cannot be explained by factors proposed by Szymanowska et al. (2014) and Bakshi et al. (2019). The authors argue that the basis-momentum predictability is related to volatility and liquidity risk. They find that nearby and spreading basis-momentum returns are increasing in lagged volatility. The evidence is therefore consistent with the interpretation that basis-momentum captures the returns to liquidity provision by speculators who absorb imbalances in the supply of and demand for futures contracts, with these returns increasing in volatility.

Aside from basis momentum, a widely used measure for liquidity is the one proposed by Amihud (2002). Marshall et al. (2012) and Szymanowska et al. (2014) have applied this measure in the commodity futures market. The trading signal is calculated as the daily price change per dollar volume on average over the past trading days in the last two months. The liquidity risk premium is obtained by longing/shorting the contracts with high/low liquidity measures.

1.6 Style Integration

We have discussed many trading styles based on different theories or perspectives. However, the performance of a standalone trading style could experience time-variation or cyclicality; namely, a successful style or factor may be gone or less useful over certain periods. A way to mitigate this problem is to construct a portfolio with exposure to multiple styles which can be cast as the "don't put all your eggs in the same basket" notion applied to style investing or the trading diversification idea. A recent and fast-growing literature has deployed style-integration through different approaches to determine the style weights. Brandt et al. (2009) formalize the idea of style-integration into an allocation framework and derive an optimization based integration approach where the style-weights are the result of maximizing the expected utility of the integrated portfolio. In the commodity futures market, Fernandez-Perez et al. (2019) define the style weights as proportional to the ability of each style (or factor) to explain the cross-sectional variation in excess returns of the assets. They reveal that the equally weighted portfolio integration is unrivalled in terms of risk-adjusted performance while it sustains a relatively low turnover, which echoes DeMiguel et al. (2009). A possible explanation is that the gain from optimal diversification is more than offset by estimation error.

In the first paper, we propose a Bayesian framework to solve the estimation error problem. Specifically, we incorporate economically motivated prior information into the widely used Brandt et al. (2009) integration approach. The resulting method, called Bayesian Optimal Integration (BOI) is confronted with the counterpart plain-vanilla approaches and with the challenging naive equal-weighted integration (EWI) approach. The BOI approach integrates out the unknown parameter space of mean returns and co-variance. The findings according to various portfolio evaluation criteria suggest that, in contrast with the other portfolios, the BOI portfolio that combines mean-variance utility maximization and Bayesian elements is able significantly to outperform the naive EWI portfolio.

1.7 Investors' Sentiment and Attention

The role of sentiment in asset pricing is the subject of a fast-growing behavioural finance literature that has by far focused predominantly on equities. However, the huge influx of capital into commodity futures since the early 2000s bears out the importance of studying the role of sentiment also in this asset class. The few papers that do so have largely focused on the intensity of internet searches (according to specific keywords) as a proxy for investor attention in general or for investor fear in particular, both of which are associated with the demand for information (Han et al., 2017a; Han et al., 2017b; Vozlyublennaia, 2014; Fernandez-Perez et al., 2020). Exceptions are Gao and Süss (2015) who study the role of sentiment on commodity prices through proxies such as the VIX and the Baker and Wurgler (2006) sentiment index inter alia, and Borovkova (2015) who conducts an event study to examine how commodity futures prices react to the news.

In the second paper of the thesis, we construct a weekly commodity sentiment measure that subsumes the tone of the recent news articles obtained by textual analysis algorithms. We then aggregate the media tone scores into a media-tone index that proxies the investor sentiment in the overall commodity market. Using a predictive regression analysis and a tactical portfolio allocation analysis, we verify the presence of the predictive elements of the media-tone measure and media-tone index. Both time-series and cross-sectional pricing tests confirm that the pricing ability of media tone is not a compensation for exposure to known risk factors.

Besides sentiment, limited investors' attention is another well-documented behavioural bias in the asset pricing literature. Traditional asset pricing theory assumes investors to pay sufficient attention to the asset. But, attention is a scarce resource (Kahneman, 1973). Investors have limited attention, especially when faced with the possibility of allocating their wealth to many alternative assets. Few investors will check whether the attributes of each of the assets satisfy their preferences and beliefs. However, when testing theories of attention, researchers face an important challenge: it is difficult to build a measure of investor attention that directly captures the limited attention effect as measures that reflect investor attention in previous literature are typically also associated with fundamental information.

In the third paper, we propose a novel measure of limited attention in the commodity futures market by utilizing the spillover effect of attention from the equity market to the commodity futures market. Specifically, when news of firms linked to a certain commodity sector arrives, investors' attention about those firms will transfer to the related commodity futures market. Then the corresponding commodity futures market will face more buying/selling pressure and should experience higher/lower returns in the subsequent weeks. Following this argument, we construct a weekly attention spillover variable for each commodity futures contract, computed as the average amount of firm-specific fundamental news within a week, which are news about firms' fundamentals. This measure excludes fundamental information from the commodity market and thus helps to identify the causal effect of limited attention effect in the commodity futures markets. We test the predictive ability of this novel measure of limited attention through a long-short commodity portfolio strategy. Both time-series and cross-sectional pricing tests confirm that the pricing ability of limited attention cannot be explained as exposure to well-known risk factors.

Chapter 2

A Bayesian Perspective on Style Investing: Exploiting Multiple Commodity Risk Premia

"*Probability is orderly opinion and inference from data is nothing other than the revision of such opinion in the light of relevant new information.*"– Eliezer S. Yudkowsky

2.1 Introduction

In line with the theory of storage (Brennan, 1976; Kaldor, 1976; Working, 1949) and the hedging pressure hypothesis (Cootner, 1960; Hirshleifer, 1988), long-short commodity portfolios or investment styles based on either a term-structure slope signal or a hedging pressure signal, respectively, as return predictors ought to capture a risk premium[1]. The term structure or carry premium is extracted by taking

[1]The theory of storage contends that commodity futures prices are driven by inventory levels and hence it associates a backwardated or downward-sloping futures curve with scarce inventories and a high convenience yield. The hedging pressure hypothesis states that there is a risk transfer

long positions in commodity futures with the most downward sloping forward curves and simultaneous short positions in the commodity futures with the most upward sloping forward curves (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Koijen et al., 2018; Szymanowska et al., 2014). The hedging pressure premium is extracted by longing the commodities with the largest hedgers' hedging pressure, defined as short minus long hedgers positions over total hedgers positions, and shorting those with the smallest hedgers' hedging pressure (Basu and Miffre, 2013; Dewally et al., 2013).

Another popular commodity style that has been associated with the inexorable backwardation versus contango phases is the trend-following or cross-sectional momentum strategy which captures a premium by simultaneously longing (shorting) the commodities with the best (worse) past performance (Asness et al., 2013; Fuertes et al., 2010; Miffre and Rallis, 2007). Echoing a large empirical literature on equities, recent evidence has been adduced in favour of a commodity skewness style; portfolios that are long (short) the commodities with the most negative (positive) skew capture a premium which has been rationalized in terms of investors' preferences for lottery-type payoffs (Fernandez-Perez et al., 2018). More recently, Boons and Prado (2019) put forward a basis-momentum style that captures a risk premia that is related to imbalances in the supply and demand of futures contracts that materialize when the market-clearing ability of speculators and intermediaries is impaired.

Individual factors can undergo time-variation or can be arbitraged away; namely, styles that have captured a sizeable premium over a period of time may temporarily weaken or wane (see e.g., Bhattacharya et al., 2017). One way to mitigate this

mechanism from hedgers or commercial traders (consumers or producers of the commodity) to speculators and thus, the futures price is set low (high) relative to the expected future spot price when hedgers are net short (long) so as to attract net long (short) speculation. The rise (fall) in the futures price as maturity approaches is the premium or compensation received by speculators for absorbing the net hedging demand.

problem is constructing a long-short portfolio with exposure to many styles, known as style-integrated portfolio. This is the old adage "don't put all your eggs in the same basket" applied to style investing that seeks to benefit from predictive-signal diversification. A key decision that a style-integration investor faces is the importance or weight to give to the styles at each portfolio re-balancing time t. With historical data on returns for each of the K standalone styles, the investor can estimate the style-weights, $\omega_{1,t}, ..., \omega_{K,t}$ that can be cast as "optimal" according to some performance or utility criteria. However, these optimized style-integrations (OIs) suffer from parameter estimation risk. Style-integration is thus an investment problem that remains open for a Bayesian study.

The present paper aims to contribute to the style-integration literature. First, we propose a novel Bayesian optimized style-integration (BOI) that allows the investor to determine the style-weights at each re-balancing time in a manner that accounts for parameter estimation risk. Specifically, we utilize a Bayesian framework that allows the investor to exploit prior information and beliefs into the style-weighing decision. Second, we document empirically the problem of an investor who seeks joint exposure to the basis, hedging pressure, momentum, skewness and basis-momentum factors to capture risk premia by exploiting a cross-section of 28 commodity futures contracts. This enables evidence to illustrate the merits of the proposed Bayesian perspective to style-integration vis-à-vis the challenging EWI and a battery of OIs.

The findings suggest that the commodity BOI portfolio is able to capture a significantly larger risk premia than the EWI portfolio, in contrast with the sophisticated OI portfolios, and in a relatively steady manner over time. These findings are not challenged by robustness tests that study the impact of considering transaction costs, longer rolling estimation windows or expanding windows in an attempt to reduce parameter estimation error in the sophisticated OI approaches, and alternative commodity scoring schemes within each style such as standardized signals, standardized rankings, simple binary buy-versus-sell signals or winsorized signals. Our findings speak to a recent literature on style-integration as a mean of capturing risk premia and to a long-standing literature on whether it is beneficial to deviate from the equal-weighted portfolio rule. In a comparison across style-integration methods, Fernandez-Perez et al. (2019) compare the naïve equal-weight style integration (EWI) rule and various sophisticated optimized integrations (OIs). The latter include the Brandt et al. (2009) approach where the style-weights maximize the expected power utility of the integrated portfolio. The evidence in Fernandez-Perez et al. (2019) suggests that the naïve EWI portfolio is unrivalled in terms of risk-adjusted performance by sophisticated style-integrated portfolios, a finding that echoes the DeMiguel et al. (2009) portfolio allocation conclusion "of the various optimizing models in the literature, there is no single model that consistently delivers a Sharpe ratio or a certainty-equivalent-return (CER) higher than that of the $1/N$ portfolio, which also has a very low turnover, which indicates that, out-of-sample, the gain from optimal diversification is more than offset by estimation error." Our study complements this literature by showing that once estimation error is dealt with using notions from Bayesian analysis, it is possible to extract a larger "alternative risk premia" or style-integrated premia that hinges on signal diversification.

Our paper complements also an extant literature that applies Bayesian principles to asset allocation and portfolio choice. Early theoretical studies examined optimal asset allocation and argued that parameter uncertainty should not be ignored (Brown, 1979; Jobson and Korkie, 1980; Klein and Bawa, 1976; Zellner and Chetty, 1965). These and other studies suggest using Bayesian principles to mitigate the sampling variability of the optimal portfolio weights due to the sample variability of the covariance matrix and especially the mean returns vector.

Although from the different viewpoint of commodity style-integration our article complements recent advances in Bayesian portfolio allocation rules (Bauder et al., 2021; Pástor and Stambaugh, 2000; Polson and Tew, 2000; Tu and Zhou, 2010). For instance, Pástor and Stambaugh (2000) study the portfolio choices of mean–variance–optimizing investors who use sample evidence to update prior beliefs centred on either the risk-based or characteristic-based pricing models.

The remainder of the paper is organized as follows. Section 2 presents the methodology. Section 3 describes the data and the properties of individual styles. Section 4 presents the comparison of style-integrated portfolios and robustness checks. A final section concludes.

2.2 Methodology

2.2.1 Asset Allocation Framework

This paper builds on the framework laid out in Fernandez-Perez et al. (2017) to conduct a structured study of alternative style-integration approaches. Let $k = 1, ..., K$ the set of standalone styles or factors under consideration by the commodity investor, and $i = 1, ..., N$ the cross-section of commodity futures contracts available. She can construct a style-integrated long-short portfolio at time t as dictated by the $N \times 1$ asset allocation vector $\mathbf{\Phi}_t$ given by

$$\mathbf{\Phi}_t \equiv \mathbf{\Theta}_t \times \boldsymbol{\omega}_t = \begin{pmatrix} \theta_{1,1,t} & \dots & \theta_{1,K,t} \\ \vdots & \ddots & \vdots \\ \theta_{N,1,t} & \dots & \theta_{N,K,t} \end{pmatrix} \begin{pmatrix} \omega_{1,t} \\ \vdots \\ \omega_{K,t} \end{pmatrix} = \begin{pmatrix} \varphi_{1,t} \\ \vdots \\ \varphi_{N,t} \end{pmatrix} \tag{2.2.1}$$

where $\mathbf{\Theta}_t$ is a $N \times K$ score matrix and $\boldsymbol{\omega}_t$ is a $K \times 1$ style-weights vector. The sign of the allocations indicates the futures position; a positive value $\phi_{i,t} \equiv \phi^L_{i,t} > 0$

(negative value $\phi^S_{i,t} < 0$) represents a long (short) position on the ith commodity futures contract at time t.

Following Brandt et al. (2009) and Barroso and Santa-Clara (2015) inter alia, we start by using the standardized-signals approach; namely, each column of Θ_t contains the predictive signals per style (standardized) with zero mean and unit standard deviation, i.e. $\theta_{i,k,t} \equiv \tilde{x}_{i,k,t} = (x_{i,k,t} - \bar{x}_{k,t})/\sigma^x_{k,t}$ where $x_{i,k,t}$ is the kth characteristic or observed signals for asset i at time t.

The commodity allocations $\tilde{\mathbf{\Phi}}_t = (\tilde{\phi}_{1,t}, ..., \tilde{\phi}_{N,t})$ are obtained through Equation 2.2.1 by combining commodity scores per style $\theta_{i,k,t}$ and style weights $\omega_{k,t}$. The normalized allocations $\tilde{\phi}_{i,t} = \phi_{i,t}/\sum_{i=1}^N |\phi_{i,t}|$ ensure 100% investment of the investor's mandate $\sum_{i=1}^N |\phi_{i,t}| = 1$. The style-integrated portfolio thus formed at time t is held for one month with excess return

$$R_{P,t+1} = \tilde{\mathbf{\Phi}}'_t \boldsymbol{R}_{t+1} = \sum_{i=1}^N \tilde{\phi}_{i,t} R_{i,t+1} \qquad (2.2.2)$$

where $\boldsymbol{R}_{t+1} \equiv (R_{1,t}, R_{2,t}, ..., R_{N,t})'$ is the $N \times 1$ vector of time t excess returns for the standalone styles, $R_{i,t} = ln(\frac{f^{front}_{i,t}}{f^{front}_{i,t-1}})$ with $f^{front}_{i,t}$ denoting the time t front-end futures contract price for the ith commodity. This procedure based on Equation 2.2.1 is iterated at portfolio time $t+1$ to obtain a new allocation vector $\tilde{\mathbf{\Phi}}_{t+1}$, and so forth. The framework encapsulated in Equation 2.2.1 nests not only many possible style integrations, but also any standalone style k (that we describe next) using a sparse vector $\boldsymbol{\omega}_t$ with the kth entry set at 1 and all other entries set at 0.

Broadly-speaking, two perspectives can be adopted to decide the weight or relative importance to assign to the styles at each portfolio formation (rebalancing) time: identical weights across styles which sidesteps estimation issues or time-varying, style-heterogeneous weights that are estimated from past data on returns for the styles. We discuss this aspect next.

2.2.2 Commodity Styles and Style-Integrations

Various commodity investment styles or factors have been suggested in the literature. Without loss of generality, in this paper we focus on the fairly well-known basis, momentum, hedging pressure, skewness, and basis-momentum styles. At each portfolio formation time, the corresponding long-short portfolio buys (sells) the commodity quintile which is expected to appreciate (depreciate) the most according to the predictive signal that underlies the style. The predictive signal for the term structure or carry style (Koijen et al., 2018) is the futures basis defined as the spread between spot and futures prices usually proxied by the difference in logarithmic prices between the front- and second-nearest maturity contract. The hedging pressure style is based on the net short positions of hedgers (or commercial traders) defined as the number of short minus long positions over total positions on average over the prior 12-months (Basu and Miffre, 2013). The momentum or past performance signal is the average past 12-month commodity futures return (Miffre and Rallis, 2007). The skewness portfolio exploits the degree of asymmetry of the commodity futures return distribution estimated with the Pearson coefficient of skewness using a year of daily data (Fernandez-Perez et al., 2018). Finally, the basis-momentum style (Boons and Prado, 2019) exploits the differential momentum between the first- and second-nearest futures contract along the term structure curve.

The simplest way to form a long-short style integrated portfolio that benefits from signal diversification is the EWI approach that assigns identical exposures to the K individual styles or commodity characteristics, $\boldsymbol{\omega}_t = \boldsymbol{\omega} = (1/K, ..., 1/K)$. The EWI has proven highly effective for several reasons (Fernandez-Perez et al., 2018). One is that EWI does not suffer from estimation error. Further, it reduces the possibility of data mining as it does not require a ranking of the K individual styles at each portfolio formation time using past data which entails choices such as the length of estimation window. Another is that it circumvents the perfect-foresight bias; namely, even assuming away parameter uncertainty, an "error" is incurred if the ranking of styles at month-end t by their past returns does not apply during the holding month $t+1$; in other words, if recent performance is not representative of prospective returns. Last but not least, the turnover of the EWI portfolio is typically low which lessens trading costs.

An investor seeking exposure to multiple risk factors can resort instead to optimized style-integration approaches (OIs) that are inspired from the portfolio allocation literature. We outline various OIs next. For this purpose, let N denote the number of commodity futures contracts available to form the style-integrated portfolio. Let the first two moments of their return distribution, $E_t(\boldsymbol{R}_{t+1})$ and $Var_t(\boldsymbol{R}_{t+1})$, be parameterized as $\boldsymbol{\mu}_t$ and $\boldsymbol{V}_t$, respectively, the $N \times 1$ vector of mean excess returns, and the $N \times N$ commodity covariance matrix. These parameters are estimated at each portfolio formation time t using a length-L window of past return data.

Mean-Variance Maximization (MV).

In the MV approach to style-integration the signal- or style-weights $\boldsymbol{\omega}_t$ are the time t solution of an optimization problem under a quadratic or mean-variance loss function

$$\begin{aligned} Max_{\omega_t}\ E_t[U_{P,t+1}] &= E_t[R_{P,t+1}] - \frac{1}{2}\gamma Var_t[R_{P,t+1}], \\ &= \boldsymbol{\Phi}_t'\boldsymbol{\mu}_t - \frac{\gamma}{2}\boldsymbol{\Phi}_t' V_t \boldsymbol{\Phi}_t \\ &= (\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)'\boldsymbol{\mu}_t - \frac{\gamma}{2}(\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)'\boldsymbol{V}_t(\boldsymbol{\Theta}_t\boldsymbol{\omega}_t) \end{aligned} \tag{2.2.3}$$

where $R_{P,t+1} = (\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)'\boldsymbol{R}_{t+1}$ is the style-integrated portfolio return from time t to $t+1$, and γ is the coefficient of relative risk aversion; as in Fernandez-Perez et al. (2018) and Brandt et al. (2009) inter alia, we adopt $\gamma = 5$. By solving the first-order maximization conditions, $\frac{\partial E_t[U(R_{P,t+1})]}{\partial \boldsymbol{\omega}_t}$, the MV optimized style-weights at time t are given by

$$\boldsymbol{\omega}_t = \frac{1}{\gamma}(\boldsymbol{\Theta}_t' \boldsymbol{V}_t \boldsymbol{\Theta}_t)^{-1} \boldsymbol{\Theta}_t' \boldsymbol{\mu}_t \tag{2.2.4}$$

As noted above, the commodity scores matrix $\boldsymbol{\Theta}_t$ multiplied by the optimized style-weight vector $\boldsymbol{\omega}_t$ gives the commodity allocations, Equation 2.2.1, which are normalized as $\tilde{\phi}_{i,t} = \phi_{i,t} / \sum_{i=1}^{N} |\phi_{i,t}|$ with $\sum_{i=1}^{N} |\tilde{\phi}_{i,t}| = 1$; we normalize $\phi_{i,t}$ likewise in all other OIs that follow.

MV Maximization with Shrinkage (MVshrinkage).

Forming a mean-variance efficient portfolio requires estimating the assets' covariance matrix. Let $\boldsymbol{V}_t$ denote the true $N \times N$ covariance matrix of commodity excess returns and $\hat{\boldsymbol{V}}_t$ the usual estimator or sample covariance matrix. When the number of assets is large (large dimension N), the usual covariance matrix estimator is typically not well-conditioned meaning that its inverse amplifies the estimation error, and may not even be invertible. Ledoit and Wolf (2004) propose a shrinkage covariance matrix estimator $\boldsymbol{S}_t$ that is both well-conditioned and more accurate than the usual covariance matrix estimator. Thus inspired, one can implement a mean-variance OI method with shrinkage covariance matrix to reduce estimation risk defined as

$$\boldsymbol{S}_t = (1-\lambda)\hat{\boldsymbol{V}}_t + \lambda \boldsymbol{I}_t \tag{2.2.5}$$

where $\boldsymbol{I}_t$ the $N \times N$ identity matrix, and $\lambda \in (0,1)$ is a tuning factor that measures the degree of shrinkage; $\boldsymbol{S}_t \approx \hat{\boldsymbol{V}}_t$ if $\lambda \to 0$, and $\boldsymbol{S}_t \approx \boldsymbol{I}_t$ if $\lambda \to 1$. Ledoit and Wolf (2004) show that the optimal shrinkage parameter conceptualized as the λ^* that minimizes the distance between the shrunk estimator of the covariance, $\boldsymbol{S}_t$, and the true covariance matrix $\boldsymbol{V}_t$, is given by

$$\lambda^* = max\{0, min\{\frac{\kappa}{T}, 1\}\} \tag{2.2.6}$$

where T is the estimation window length for $\hat{\boldsymbol{V}}_t$, and κ is a parameter that can be consistently estimated as detailed in Appendix 2.6.1. Finally, replacing the standard covariance estimator by $\boldsymbol{S}_t^*$ in the MV style-weights solution, Equation 2.2.4, the *MVshrinkage* style-weights are given by

$$\boldsymbol{\omega}_t = \frac{1}{\gamma}(\boldsymbol{\Theta}_t'\boldsymbol{S}_t^*\boldsymbol{\Theta}_t)^{-1}\boldsymbol{\Theta}_t'\boldsymbol{\mu}_t \tag{2.2.7}$$

For further details on the *MVshrinkage* style-weights estimation approach, see Appendix 2.6.1.

Variance Minimization (MinVar)

The *MinVar* style-weights are the solution of an optimization problem where the focus is on the second moment or expected risk of the style-integrated portfolio (Fernandez-Perez et al., 2019). Thus, the style-integration investor solves at each time t the variance minimization problem

$$\begin{aligned} Min_{\boldsymbol{\omega}_t} E_t[(R_{P,t+1} - \bar{R}_P)^2] &= Var_t(R_{P,t+1}) \\ &= \boldsymbol{\Phi}_t'\boldsymbol{V}_t\boldsymbol{\Phi}_t \\ &= (\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)'\boldsymbol{V}_t(\boldsymbol{\Theta}_t\boldsymbol{\omega}_t) \end{aligned} \tag{2.2.8}$$

with first-order condition $\frac{\partial Var(R_{P,t})}{\partial \boldsymbol{\omega}_t} = 0$. The solution provides the *MinVar* style-weights

$$\boldsymbol{\omega}_t = \frac{(\boldsymbol{\Theta}_t'\boldsymbol{V}_t\boldsymbol{\Theta}_t)^{-1}\boldsymbol{\Theta}_t'\mathbb{1}}{\mathbb{1}'\boldsymbol{\Theta}_t(\boldsymbol{\Theta}_t'\boldsymbol{V}_t\boldsymbol{\Theta}_t)^{-1}\boldsymbol{\Theta}_t'\mathbb{1}} \tag{2.2.9}$$

with $\boldsymbol{\Theta}_t$ representing the $N \times K$ score matrix, Equation 2.2.1, and $\boldsymbol{V}_t$ the $N \times N$ commodity covariance matrix, respectively. Essentially, the *MinVar* style-integration approach reduces the dimensionality of the MV parameter space by focusing attention on the integrated portfolio risk.

Style-Volatility Timing (StyleVol).

Kirby and Ostdiek (2012) develop a portfolio allocation method which also focuses on variance minimization and assumes zero covariances across assets to reduce the parameter dimensionality. The resulting solution is to allocate wealth to each asset proportionality to the inverse of the asset's risk as measured by its past variance which is known as volatility timing. This approach has been adapted to style-integration by shifting the emphasis to the risk of each individual style (Fernandez-Perez et al., 2019). The weight assigned to the kth style at time t is

$$\omega_{k,t} = \frac{1/\sigma^2_{k,t}}{\sum_{k=1}^{K} 1/\sigma^2_{k,t}}, \ k = 1, ..., K \tag{2.2.10}$$

with $\sigma^2_{k,t}$ denoting the kth entry of the $K \times K$ style-covariance matrix $\boldsymbol{\Sigma}_t$. Thus, the more volatile a given style is, the less weight it receives in the style-integrated portfolio. The implicit assumption of the *SyleVol* integration approach is independence among the underlying styles.

Diversification-Ratio Maximization (MaxDiv)

Choueifaty and Coignard (2008) define the diversification ratio of a portfolio as the ratio of the aggregate individual assets' volatilities divided by the portfolio's volatility. Adapted to the present context the diversification ratio of the style-integrated portfolio can be defined as

$$D(\boldsymbol{\Phi}_t) = \frac{\boldsymbol{\Phi}_t' \boldsymbol{\Omega}_t}{\sqrt{\boldsymbol{\Phi}_t' \boldsymbol{V}_t \boldsymbol{\Phi}_t}} \tag{2.2.11}$$

where $\boldsymbol{\Phi}_t \equiv \boldsymbol{\Theta}_t\boldsymbol{\omega}_t$ is the commodity allocation vector, Equation 2.2.1, and $\boldsymbol{\Omega}_t = (\sigma_1^2, ..., \sigma_N^2)$ is the diagonal of the commodity excess return covariance matrix $\boldsymbol{V}_t$. Accordingly, the optimal *MaxDiv* style-weight vector $\boldsymbol{\omega}_t$ is obtained by solving the following maximization problem

$$Max_{\boldsymbol{\omega}_t} D(\boldsymbol{\omega}_t) = \frac{(\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)'\boldsymbol{\Omega}_t}{\sqrt{(\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)'\boldsymbol{V}_t(\boldsymbol{\Theta}_t\boldsymbol{\omega}_t)}} \tag{2.2.12}$$

As no closed-form solution exists for 2.2.12, one can obtain the *MaxDiv* weights $\boldsymbol{\omega}_t$ through the BFGS algorithm that belongs to the Quasi-Newton group of numerical optimization methods. To our best knowledge, the *MaxDiv* style-weights have not been utilized as yet in the literature.

Power Utility Maximization (PowerU)

Using quadratic (mean-variance) utility has the advantage of parsimony vis-à-vis power utility but the latter takes into account the higher moments of the return distribution of the integrated portfolio which can be important if returns are not Normally distributed. The *PowerU* style-weights are those that maximize the expected power utility of the style-integrated portfolio

$$Max_{\boldsymbol{\omega}_t}\ E_t[U(R_{P,t+1})] = E_t[\frac{(1+R_{P,t+1})^{1-\gamma}-1}{1-\gamma}] \tag{2.2.13}$$

where $R_{P,t+1} = \sum_{i=1}^N \tilde{\phi}_{i,t} R_{i,t+1}$ with $\tilde{\phi}_{i,t} = \phi_{i,t}/\sum_{i=1}^N |\phi_{i,t}| = \frac{\sum_{k=1}^K \theta_{i,k,t}\omega_k}{\sum_{i=1}^N |\sum_{k=1}^K \theta_{i,k,t}\omega_k|}$ the normalized ith asset allocation, and γ the coefficient of relative risk aversion as in Equation 2.2.3. The *PowerU* style-weights $\boldsymbol{\omega}_t$ can be obtained by solving 2.2.13 numerically via the BFGS algorithm. In the PowerU style-integration approach, as originally put forward by Brandt et al. (2009), the N asset allocations are defined as optimal deviations from the benchmark portfolio (e.g., value-weighted equity market portfolio) allocations denoted $\bar{\boldsymbol{\Phi}}_t$. The general style-integration structure, Equation 2.2.1, can be rewritten as $\boldsymbol{\Phi}_t = \bar{\boldsymbol{\Phi}}_t + \frac{1}{N}(\boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t)$ with $\boldsymbol{\omega}_t$ the *PowerU* style-weights, to nest the Brandt et al. (2009) parametric portfolio approach. The above optimization problem, Equation 2.2.13, is thus the Brandt et al. (2009) approach adapted to assets in zero-net-supply ($\bar{\phi}_{i,t} = 0$) such as futures or currencies, as implemented in Fernandez-Perez et al. (2018) and Barroso and Santa-Clara (2015), respectively.

Power Utility with Disappointment Aversion (PowerDA)

Constant relative risk aversion (CRRA) preferences cannot generate non-participation at any level of risk aversion, except in the presence of large transactions costs which would be implausible, especially in the case of futures contracts (Liu and Loewenstein, 2002). As a result, traditional portfolio choice models often predict large equity positions for most investors and fail to generate the observed cross-sectional variation in portfolio choice. A way to mitigate this problem is to incorporate loss aversion into the utility function.

Gul (1991) develops an axiomatic model of preferences which can generate disappointment aversion, and includes expected utility as a special case. Ang et al. (2005) extend this model for both the static and dynamic portfolio choice problems and show that it can robustly generate substantial cross-sectional variation in portfolio holdings, including optimal non-participation in the stock market. Inspired by their argument, Fernandez-Perez et al. (2019) implement an OI approach that incorporates disappointment aversion. Let the power utility function of the certainty equivalent return (CER), parameterized as δ, be given by

$$\frac{(1+\delta)^{1-\gamma}-1}{1-\gamma} = \frac{1}{K}\Big(\int_{-\infty}^{\delta} U(R_{P,t+1})dF(R_{P,t+1}) + A\int_{\delta}^{\infty} U(R_{P,t+1})dF(R_{P,t+1})\Big) \tag{2.2.14}$$

where $U(R_{P,t+1}) = \frac{(1+R_{P,t+1})^{1-\gamma}-1}{1-\gamma}$, with $R_{P,t+1} = R_{P,t} = \tilde{\boldsymbol{\Phi}}_t' \boldsymbol{R}_{t+1} = \boldsymbol{\omega}_t'(\boldsymbol{\Theta}_t' \boldsymbol{R}_{t+1})$ with $\boldsymbol{R}_{t+1}$ the $N \times 1$ vector of commodity futures excess returns. The scaling parameter K is defined as

$$K = Pr(R_{P,t+1} \leq \delta) + APr(R_{P,t+1} > \delta) \tag{2.2.15}$$

In this setting, the probability of losses (outcomes below the CER) and gains (or outcomes above the CER) are qualified by the disappointment aversion parameter $A \in [0,1)$. We employ $A = 0.6$ as Fernandez-Perez et al. (2019)[2]. The *PowerDA* style-weights $\boldsymbol{\omega}_t$ and CER value δ are obtained by solving simultaneously 2.2.14 and the following first-order condition

$$\frac{1}{A}E\Big[\frac{dU(R_{P,t+1})}{d\boldsymbol{\omega}_t'}\mathbb{1}_{\{R_{P,t+1}\leq\delta\}}\Big] + E\Big[\frac{dU(R_{P,t+1})}{d\boldsymbol{\omega}_t'}\mathbb{1}_{\{R_{P,t+1}>\delta\}}\Big] = 0 \tag{2.2.16}$$

where $\mathbb{1}$ is an indicator function. Appendix 2.6.2 provides details on the *PowerDA* implementation.

2.2.3 Bayesian Optimized Integration (BOI)

The purpose of this section is to design a Bayesian optimized style-integration (BOI) approach that incorporates Bayesian elements in order to account for estimation risk. The goal is to improve upon the challenging EWI that does not suffer from estimation risk and upon extant OIs that are contaminated by parameter estimation uncertainty.

As argued by DeMiguel et al. (2009), estimation risk is a source of uncertainty that lies behind the poor out-of-sample performance of the Markowitz's mean-variance (MV) portfolio allocation versus the naïve $1/N$ allocation. In the MV style-integration, the investor at time t chooses his style weights $\boldsymbol{\omega}_t$ so as to maximize the quadratic utility of his portfolio, Equation 2.2.3. The solution is given

[2]The disappointment aversion parameter value $A = 1$ gives rise to the CRRA preferences case.

the Equation 2.2.4 where $\boldsymbol{\mu}_t$ and $\boldsymbol{V}_t$ denote the first moments of $\boldsymbol{R}_t$. In order to implement the MV style-integration method, the investor ought to choose a length L for a past observation window to estimate $\hat{\boldsymbol{mu}}_t$ and $\hat{\boldsymbol{V}}_t$ giving the plug-in style weights $\hat{\boldsymbol{\omega}}_t = \frac{1}{\gamma}(\boldsymbol{\Theta}_t'\hat{\boldsymbol{V}}_t\boldsymbol{\Theta}_t)^{-1}\boldsymbol{\Theta}_t'\hat{\boldsymbol{\mu}}_t$. This approach can suffer from a low signal-to-noise ratio problem, namely, the utility $U(\hat{\boldsymbol{\omega}}_t)$ can deviate notably from the true utility $U(\boldsymbol{\omega}_t)$. In order to account for estimation risk, Zellner and Chetty (1965) proposed a Bayesian portfolio optimization solution that maximizes the expected utility under the predictive distribution which we adapt to the present purpose of style-integration. Let $\mathcal{F}_t$ denote the information set available at time t, and $U(\boldsymbol{\omega}_t)$ the utility of the style-weights $\boldsymbol{\omega}_t$ portfolio that is formed on N commodities with excess returns $\boldsymbol{R}_t$. The Bayesian optimized-integration (BOI) weights are defined as

$$\begin{aligned}\boldsymbol{\omega}_t^B &= argmax_{\boldsymbol{\omega}_t}\int_{-\infty}^{+\infty} U(\boldsymbol{\omega}_t)pr(\boldsymbol{R}_{t+1}|\mathcal{F}_t)d\boldsymbol{R}_{t+1} \\ &= argmax_{\boldsymbol{\omega}_t}\int_{-\infty}^{+\infty}\int_{\boldsymbol{\mu}_t}\int_{\boldsymbol{V}_t} U(\boldsymbol{\omega}_t)pr(\boldsymbol{R}_{t+1},\boldsymbol{\mu}_t,\boldsymbol{V}_t|\mathcal{F}_t)d\boldsymbol{\mu}_t d\boldsymbol{V}_t d\boldsymbol{R}_{t+1} \end{aligned} \tag{2.2.17}$$

with the predictive density $pr(\boldsymbol{R}_{t+1}|\mathcal{F}_t)$ obtained by integrating out the unknown parameters as

$$\begin{aligned}pr(\boldsymbol{R}_{t+1}|\mathcal{F}_t) &= \int_{\boldsymbol{\mu}_t}\int_{\boldsymbol{V}_t} pr(\boldsymbol{R}_{t+1},\boldsymbol{\mu}_t,\boldsymbol{V}_t|\mathcal{F}_t)d\boldsymbol{\mu}_t d\boldsymbol{V}_t \\ &= \int_{\boldsymbol{\mu}_t}\int_{\boldsymbol{V}_t} pr(\boldsymbol{R}_{t+1}|\boldsymbol{\mu}_t,\boldsymbol{V}_t,\mathcal{F}_t)pr(\boldsymbol{\mu}_t,\boldsymbol{V}_t|\mathcal{F}_t)d\boldsymbol{\mu}_t d\boldsymbol{V}_t\end{aligned} \tag{2.2.18}$$

where $pr(\boldsymbol{R}_{t+1}|\boldsymbol{\mu}_t,\boldsymbol{V}_t,\mathcal{F}_t)$ is the conditional probability, and $pr(\boldsymbol{\mu}_t,\boldsymbol{V}_t|\mathcal{F}_t)$ the posterior probability. Intentionally our BOI approach rests on the widely used mean-variance framework[3]. Accordingly, priors are required on the expected commodity excess returns vector $\boldsymbol{\mu}_t$ and corresponding covariance matrix $\boldsymbol{V}_t$ to obtain the

[3] The BOI approach proposed can be easily generalized to any non-quadratic utility.

posterior distribution. The prior for $\boldsymbol{V}_t$ is the inverse Wishart distribution which is a standard assumption for Bayesian estimation of a covariance matrix. A key idea behind the BOI proposed is that investors do not need directly to form a prior for $\boldsymbol{\mu}_t$. They can harness their beliefs (or information) on the past relative performance of the styles to form a prior for $\boldsymbol{\omega}_t$ which can next be mapped onto a prior for $\boldsymbol{\mu}_t$.

The MV style-integration solution establishes a one-to-one relation between the style-weight parameter vector $\boldsymbol{\omega}_t$ and the commodity return distribution mean vector $\boldsymbol{\mu}_t$ as

$$\boldsymbol{\mu}_t = \gamma \boldsymbol{V}_{\boldsymbol{\Theta}} \boldsymbol{\omega}_t \tag{2.2.19}$$

where $\boldsymbol{V}_{\boldsymbol{\Theta}} = (\boldsymbol{\Theta}_t')^{-1}(\boldsymbol{\Theta}_t' \boldsymbol{V}_t \boldsymbol{\Theta}_t)$. The BOI method that we propose uses priors for the style-weights $\boldsymbol{\omega}_t$ order to incorporate the investor's objective beliefs about the relative merit of the styles. Then we map the priors on the style-weights $\boldsymbol{\omega}_t$ into priors on the parameters of the commodity excess return distribution. Specifically, we begin by forming a Normal prior on $\boldsymbol{\omega}_t$

$$\boldsymbol{\omega}_t \sim N(\boldsymbol{\omega}_{t,0}, \frac{1}{\gamma} \boldsymbol{V}_{\boldsymbol{\Theta}}^{-1} \boldsymbol{V}_\mu) \tag{2.2.20}$$

where $\boldsymbol{V}_\mu$ is the variance of the prior of $\boldsymbol{\mu}_t$. Equation (2.2.20) says that the style-weight vector $\boldsymbol{\omega}_t$ is Normally distributed with prior mean $\boldsymbol{\omega}_{t,0}$ and covariance $\frac{1}{\gamma} \boldsymbol{V}_{\boldsymbol{\Theta}}^{-1} \boldsymbol{V}_\mu$ which represents the confidence about the prior. The prior distribution for $\boldsymbol{\omega}_t$ provides the prior distribution of $\boldsymbol{\mu}_t$ as

$$\boldsymbol{\mu}_t \sim N(\gamma \boldsymbol{V}_{\boldsymbol{\Theta}} \boldsymbol{\omega}_{t,0}, \boldsymbol{V}_\mu) \tag{2.2.21}$$

where the magnitude of $\boldsymbol{V}_\mu$ represents how close $\boldsymbol{\mu}_t$ is distributed around the prior mean or the degree of confidence on the prior mean. Following Tu and Zhou (2010), we adopt $\boldsymbol{V}_\mu = \frac{\boldsymbol{V}_t}{s^2}$ where s^2 is the average of the commodity return variances or diagonal elements of $\boldsymbol{V}_t$. Given the success of the naïve equal-weight rule in traditional portfolio allocation (DeMiguel et al., 2009) and in style-integration (Fernandez-Perez et al., 2019) we adopt $\boldsymbol{\omega}_{t,0} = 1/K$ as our informative prior for the style-weights mean, Equation (2.2.21). However, we should stress that any other informative prior that reflects the investor's beliefs or knowledge is feasible, e.g. an investor with diminished confidence on a given style k can set its prior to zero $\omega_{k,t,0} \approx 0$.

A history of commodity excess returns within a length-L observation window $\{R_{t-(L-1)}, \ldots, R_{t-1}, R_t\}$ can be used to update the above priors in order to obtain the posterior distribution $pr(\boldsymbol{\mu}_t, \boldsymbol{V}_t|\mathcal{F}_t)$ at time t. To obtain the posterior distribution, we resort to the Markov Chain Monte Carlo (MCMC) method widely used in Bayesian statistics. This method allows us to sample from the commodity return history which enables M simulated commodity excess return sequences $\{\boldsymbol{R}_{m,t-(L-1)}, \ldots, \boldsymbol{R}_{m,t-1}, \boldsymbol{R}_{m,t}\}_{m=1}^{M}$. These simulated returns are then inputs to approximate the first two moments of the stationary posterior distribution $pr(\boldsymbol{\mu}_t, \boldsymbol{V}_t|\mathcal{F}_t)$ using the Gibbs sampling algorithm which is one of the most popular MCMC methods (e.g., see Chen et al., 2012). In our empirical analysis below we employ $M = 10,000$ replications. Finally, with the posterior density at hand the MV portfolio optimization problem, Equation (2.2.3), is solved at each portfolio rebalancing time t to obtain the BOI style-weights $\boldsymbol{\omega}_t$. Further details on the BOI implementation are provided in Appendix .

2.3 Data and Empirical Results

2.3.1 Data

The empirical analysis is based on settlement prices, and open interest data for futures contracts on a cross-section of 28 commodities pertaining to various sectors: agriculture (cocoa, coffee, corn, cotton, frozen concentrated orange juice, oats, rough rice, soybeans, soybean meal, soybean oil, sugar 11, wheat and lumber), energy (PJM electricity, gasoline RBOB, heating oil, light sweet crude oil, natural gas of Henry hub and un-leaded gas), livestock (feeder cattle, frozen pork bellies, lean hogs, live cattle), and metal (high-grade copper, gold, palladium, platinum, silver 5000). Daily prices are obtained from *Refinitiv Datastream*. Open interest data is available weekly from the Commitment of Traders report of the U.S. Commodity Futures Trading Commission (CFTC). The sample period is January 1992 to December 2021.

As in Fernandez-Perez et al. (2018), the standalone styles and style-integrated portfolios are formed at month-end and held for one month. We carry out the usual rolling procedure; namely, futures returns are calculated using the price of the front-end futures contract up to the month preceding the maturity month when positions are rolled to the second-nearest contract.

2.3.2 Preliminary Data Analysis and Relative Performance of Styles

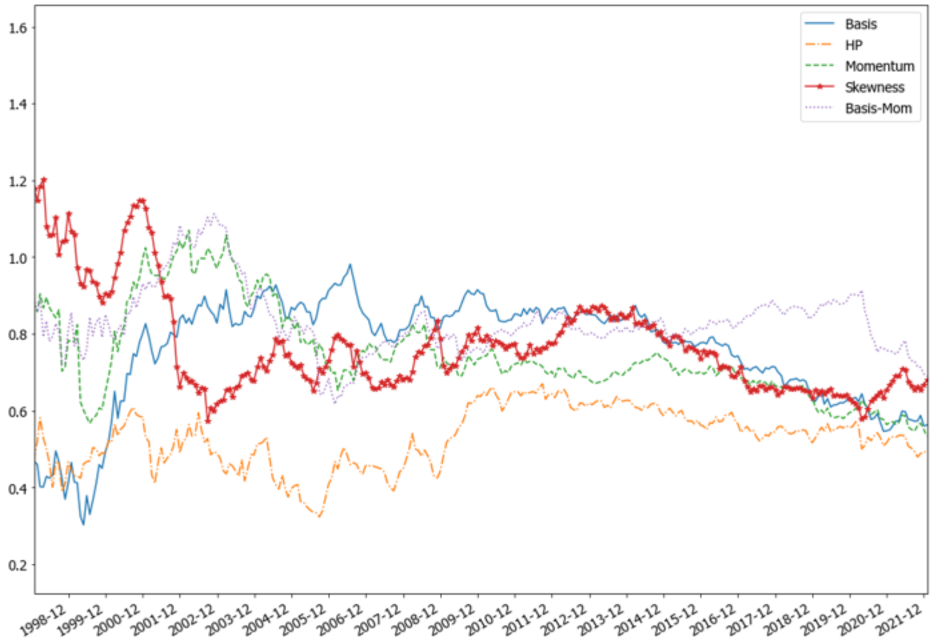
Table 2.1 summarizes the distribution of excess returns for the 28 commodity futures contracts and cross-correlations. The average excess return is generally insignificant over the sample period. Monthly returns show little evidence of predictability based on sample autocorrelations. Gasoline RBOB has the largest autocorrelation of 0.217. The distributions of returns are broadly symmetrical–exceptions with a large negative skew sugar, gasoline and platinum, and coffee with a positive skew. Some futures contracts exhibit the heavy-tailed property such as sugar, electricity, gasoline and platinum with kurtosis coefficient of 8.707, 6.829, 10.622 and 5.235, respectively. The average pairwise correlations of each commodity futures excess returns with the excess returns of the commodities in the same sector indicate that the within-group price dynamics is highly similar but far more independent across groups.

Table 2.2 summarizes the performance of the individual styles–basis, hedging pressure, momentum, skewness and basis-momentum – over the full sample period (Panel A), and over non-overlapping 6-year windows (Panel B), analogous to Fernandez-Perez et al. (2019).

According to the static analysis shown in Panel A, the reward-to-risk profiles suggested by the Sortino, Omega, and Sharpe ratios alongside the crash risk profiles (max drawdown, 99% VaR, and semi-deviation) endorse the skewness and basis-momentum portfolios. But this is not so over sub-periods as the skewness style ranks last in the second sub-period and the basis-momentum ranks almost last in the third sub-period. The fact that their relative performance is unstable–no individual style emerges as consistently superior–poses a challenge for investors in terms of choosing an individual style to adhere to. This motivates the notion of signal diversification that can be harnessed through a style-integration strategy; namely, style-integration may serve as hedge against individual style underperformance over specific periods.

Figure 2.1 plots the cumulative Sharpe ratio of the standalone styles. The first point in the graph is calculated from the monthly excess returns accrued over a 60-month investment window and the last point is based on returns until the end of the sample period. The graph confirms the instability in individual style rank-

Figure 2.1: Cumulative Sharpe ratios of standalone styles.



The figure plots the cumulative Sharpe ratio of long-short commodity futures portfolios or standalone styles based on the basis, hedgers' hedging pressure, momentum, skewness and basis-momentum signals as return predictors. The first feasible 60-month excess returns window is expanded by one month at a time. The analysis is based on commodity futures data from January 1992 to December 2021.

ings over time which calls for style-integration.

Next we examine the extent of overlap among the standalone styles. In order to provide a complete picture, Table 2.3 reports three different measures of (non)linear dependence. The widely used Pearson correlation (Panel A) suggests that the five styles are mildly overlapping. This is confirmed by the Spearman rank-order correlation (Panel B), and the Kendall correlation (Panel C) that additionally capture nonlinear relationships[4]. All three statistics concur in suggesting

[4]The Spearman correlation between two variables is the standard correlation between their rankings. While Pearson's correlation assesses linear relationships, Spearman's correlation captures monotonic (linear or not) relationships. Kendall's correlation is analogous to Spearman's correlation but outperforms it because it is more robust to outliers and has better small-sample properties.

that the premia captured by the five styles under consideration stems from different risk (or behavioural bias) sources. Thus, seeking to benefit from signal diversification, our representative investor pursues a style-integration strategy. Next, we compare various methods.

2.3.3 Style-integration Strategies

Table 2.4 reports summary statistics for the distribution of excess returns obtained with the various sophisticated optimized style-integrations (OIs) which include the new Bayesian approach (BOI), alongside the challenging EWI benchmark. Panel A reports the results over the entire sample period (static evaluation), and Panel B over non-overlapping 6-year sub-sample periods (dynamic evaluation). For now, all the style-integrations employ as entries of $\mathbf{\Theta}_t$, the score matrix $\mathbf{\Theta}_t$ in Equation 2.2.1, directly the standardized signals. This aspect of the style-integration methodology will be revisited below in robustness tests. Also for now, the estimation of the style-weight vector in the (B)OI strategies is carried out over 60-month rolling windows. Later in the robustness tests, this estimation window length L is expanded so as to re-assess the merit of BOI when the parameter uncertainty that affects OIs is lessened.

The easy-to-deploy EWI strategy stands out as very effective at extracting commodity risk premia. The EWI portfolio excess return of 8.0% p.a. surpasses each one of the standalone-style portfolios' excess returns ranging from 3.6% p.a. (Hedging Pressure) to 5.1% (Basis-Mom). On a risk-adjusted basis, the Sharpe ratio of the EWI portfolio at 0.815 represents a pervasive improvement in reward-to-risk: 40% gain in Sharpe ratio across all styles on average, and between 18% (Basis-Mom) and 65% (HP) individually. The Sharpe ratio gain of EWI versus the standalone styles is reiterated by the Sortino and Omega ratios. Last but not least, the EWI portfolio has a favourable crash risk profile vis-à-vis the standalone styles as suggested by the semi-deviation, maximum drawdown and 99% VaR measures. These findings overall confirm that predictive signal combination via an EWI long-short portfolio approach is fruitful.

The next issue to investigate is whether a sophisticated OI strategy can improve upon the style-integrated portfolio obtained with the naïve EWI strategy. Does a time-varying, heterogeneous (optimized) factor exposure deliver improvements versus the time-constant, equal exposure? Table 2.4 addresses this question by reporting summary statistics for the excess returns of the sophisticated OI portfolios outlined in Section 2.2.2, and the novel BOI portfolio developed in Section 2.2.3. The findings from our somewhat different set of styles specific to commodities and longer sample period are well aligned with the evidence in Fernandez-Perez et al. (2019).

It is noticeable that with a mean excess return of 5.2% p.a., Sharpe ratio of 0.588, maximum drawdown of -0.296 and 99% VaR of -0.058, the *PowerU* style-integration of Brandt et al. (2009) fails to outperform the EWI with corresponding values of 8.0% p.a., 0.815, -0.243 and -0.061. The naïve EWI portfolio is thus not only able to extract a larger commodity risk premium, but also exhibits a better crash risk. Introducing the disappointment aversion parameter $A = 0.6$ in the commodity style-integration with power utility (*PowerDA*) does not improve upon the baseline *PowerU* approach and hence, the EWI portfolio remains unchallenged [5]. Likewise, the OI method with focus on quadratic or mean-variance utility (MV), and the OIs that seek to reduce the dimensionality of the mean-variance parameter space (*MVshrinkage*, *MinVar*, and *StyleVol*) or employ a diversification ratio as objective function (*MaxDiv*) are also unable to challenge the naïve EWI approach. The style-integrated portfolios formed by the *MinVar*, *StyleVol* and *Max-*

[5] With a Sharpe ratio of 0.371, maximum drawdown of -0.225, and 99% VaR of -0.055 the *PowerDA* style-integrated portfolio deployed with larger disappointment aversion ($A = 0.2$) is still unable to outperform EWI. Additional performance measures for the latter are available from the authors.

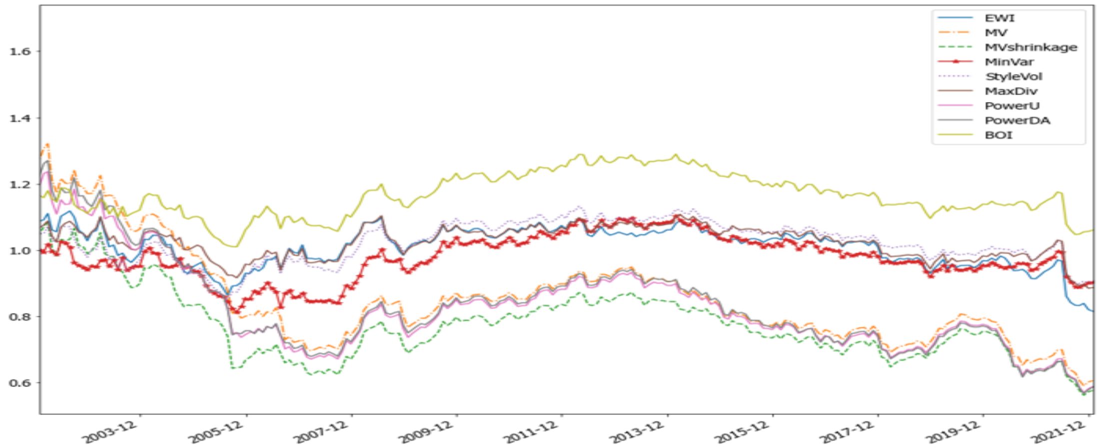
Div methods are quite competitive but not superior to the EWI portfolio. The p-values of the Ledoit and Wolf (2008) and Opdyke (2007) tests, $H_0 : SR_j SR_{EWI}$ vs $H_A : SR_j > SR_{EWI}$ clearly indicate that the reward-to-risk of each of the OI portfolios (denoted j) is either smaller or indistinguishable from that of the EWI portfolio.

By contrast, building on the fully parametric mean-variance setting but accounting for parameter estimation uncertainty through BOI delivers a style-integrated portfolio that outperforms all other OI portfolios and the challenging EWI portfolio as regards both the reward-to-risk and crash risk profiles. The small p-values of the Ledoit and Wolf (2008) and Opdyke (2007) tests, as shown in Table 2.4 panel A suggest at the 5% significance level or better that the Sharpe ratio of the BOI portfolio is superior to that of the naive EWI portfolio. This evidence based on a static (full sample) appraisal of portfolio performance is reinforced by the dynamic (non-overlapping 6-year rolling estimation windows) appraisal shown in Table 2.4, Panel B. The dynamic Sharpe ratio and the corresponding ranking of the EWI and OIs reiterates the superiority of the BOI approach. Thus, embedding an extant OI method into a Bayesian framework to account for estimation risk allows investors to harness multiple commodity factor exposures more efficiently to extract a sizeable risk premia consistently over time.

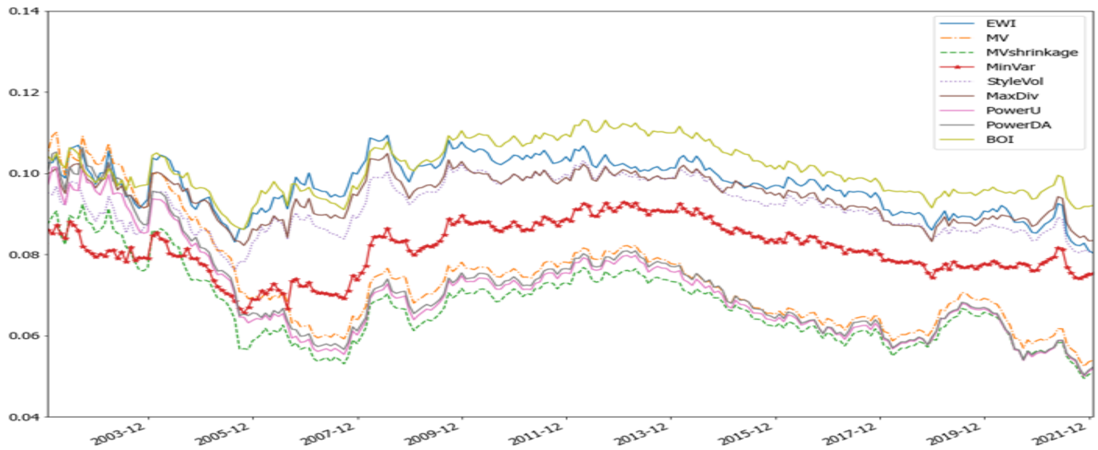
Further to illustrate the dynamic performance of the BOI portfolio vis-a-vis the competing EWI and OI portfolios, we plot in Figure 2.2 their cumulative Sharpe ratio, mean and volatility. The cumulative Sharpe ratio of the BOI portfolio, Panel A, surpasses rather steadily over time the Sharpe ratio of the naïve (non-parametric) EWI and competing sophisticated OI portfolios. This is the result of its superior ability to capture a risk premia as borne out by the larger mean excess return, Panel B, combined with relatively low risk (only the MinVar integrated portfolio has lower volatility), as shown in Panel C. The upshot is that the BOI

Figure 2.2: Performance of integrated strategies

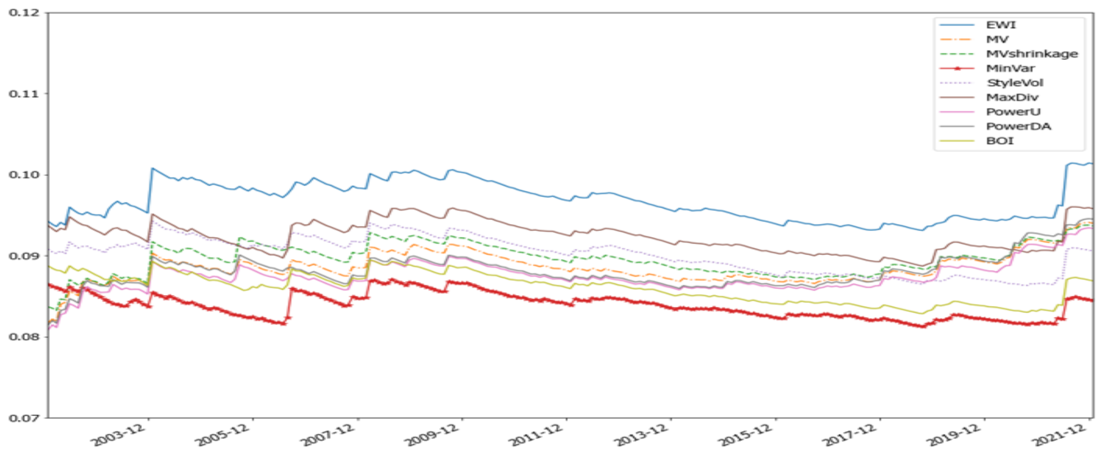
(a) Sharpe ratio



(b) Mean return



(c) Volatility



The figure plots the Sharpe ratio, annualized mean excess return and volatility of style-integrated portfolios based on their annualized monthly excess returns within expanding windows. The strategies are naïve equal-weights integration (EWI), and optimized integrations (OIs) formed according to mean-variance utility maximization (MV), mean-variance with shrinkage maximization (MVshrinkage), variance minimization (MinVar), style-volatility timing (StyleVol), diversification ratio maximization (MaxDiv), power utility maximization (PowerU), maximized power utility with disappointment aversion (PowerDA), and Bayesian optimized integration (BOI). The analysis is based on commodity futures data from January 1992 to December 2021.

approach benefits both from the sophistication of an optimized style-weighing approach (by contrast with the naïve EWI) and from an improved signal-to-noise ratio due to the Bayesian elements (by contrast with the OIs). The ability of BOI to improve the style-weights $\boldsymbol{\omega}_t$ decision leads to a more informative combination of sorting or predictive signals (basis, hedging pressure, momentum, skewness, and basis-momentum) and thus, to a more fruitful joint exposure to multiple factors.

2.4 Robustness Tests

In this section we deploy various robustness tests to ensure that the findings are not influenced by transaction costs, and survive variants of the OI methods, and longer estimation windows.

2.4.1 Turnover and Transaction costs

Trading intensity can erode the risk premium captured by investment styles due to trading costs. To study the role of trading costs, we calculate the portfolio turnover (TO) as

$$TO_j = \frac{1}{T-1} \sum_{t=1}^{T-1} \sum_{i=1}^{N} (|\tilde{\phi}_{j,i,t+1} - \tilde{\phi}_{j,i,t^+}|) \tag{2.4.1}$$

where $t = 1, \cdots, T$ denotes each of the month-end portfolio re-balancing times, $\tilde{\phi}_{j,i,t+1}$ is the ith commodity allocation weight at $t+1$ by the jth portfolio, while $\tilde{\phi}_{j,i,t^+} = \tilde{\phi}_{j,i,t} e^{R_{i,t+1}}$ is the actual portfolio weight right before the rebalancing at $t+1$ with $R_{i,t+1}$ denoting the monthly return of the ith commodity from month-end t to month-end $t+1$. The TO measure thus provides the average of all the trades incurred and embeds the mechanical evolution of the allocation weights due to within-month price dynamics. Figure 2.3, Panel A, shows the TOs. 2.3 Panel A.

The style-integrated portfolios are not more trading intensive than the standalone styles, even though potentially they invest in all N commodities whereas the latter invest, by construction, only in 40% of the N commodities. Among the standalone styles, the highest TO is exhibited by the basis portfolio and the lowest by the HP portfolio. Among the style-integrated portfolios, *MinVar* has the lowest TO followed by *MaxDiv* and *StyleVol*. Most importantly for the present purposes, in relative terms the BOI portfolio does not have a large TO which suggests prima facie that its superior performance will not be wiped out by transaction costs.
Next, using proportional trading costs of 3.3 bps (Locke & Venkatesh, 1997) and the more conservative 8.6 bps (Marshall et al., 2012), we calculate the net return of each portfolio and the corresponding net Sharpe ratio which is plotted in Figure 2.3, Panel B. We observe, first, that the erosion of performance due to transaction costs does not undermine the style-integrated portfolio proposition versus individual-style investing. Second, among the competing style-integrated portfolios, the BOI remains the one delivering the best reward-to-risk profile. Thus, altogether the findings endorse the BOI approach as highly efficient at signal diversification.

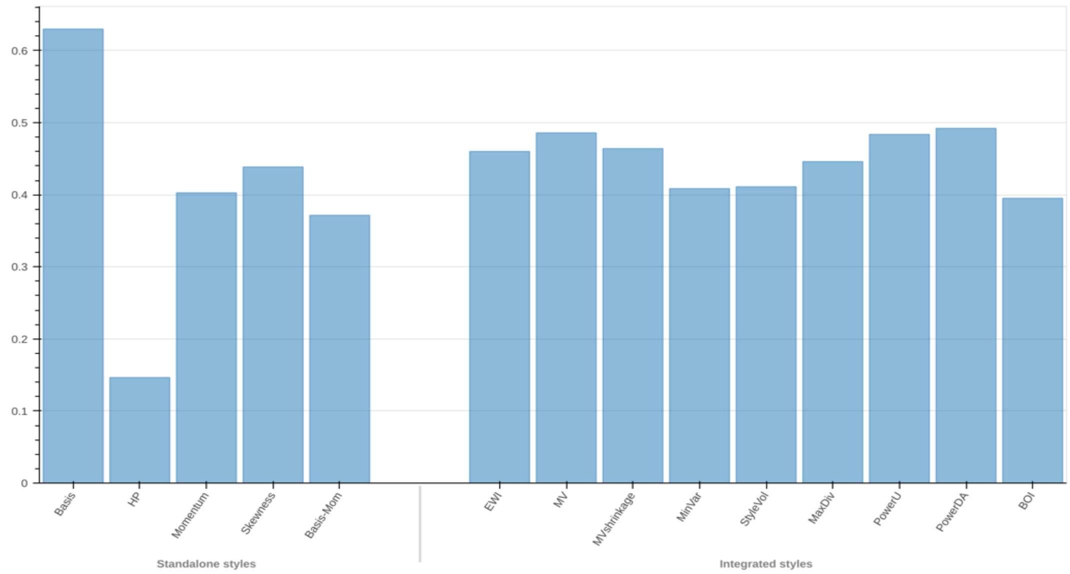
$$\tilde{R}_{P,t+1} = \sum_{i=1}^{N} \tilde{\phi}_{i,t} R_{i,t+1} - TC \sum_{i=1}^{N} |\tilde{\phi}_{i,t} - \tilde{\phi}_{i,t-1^+}| \tag{2.4.2}$$

2.4.2 Alternative Scoring Schemes

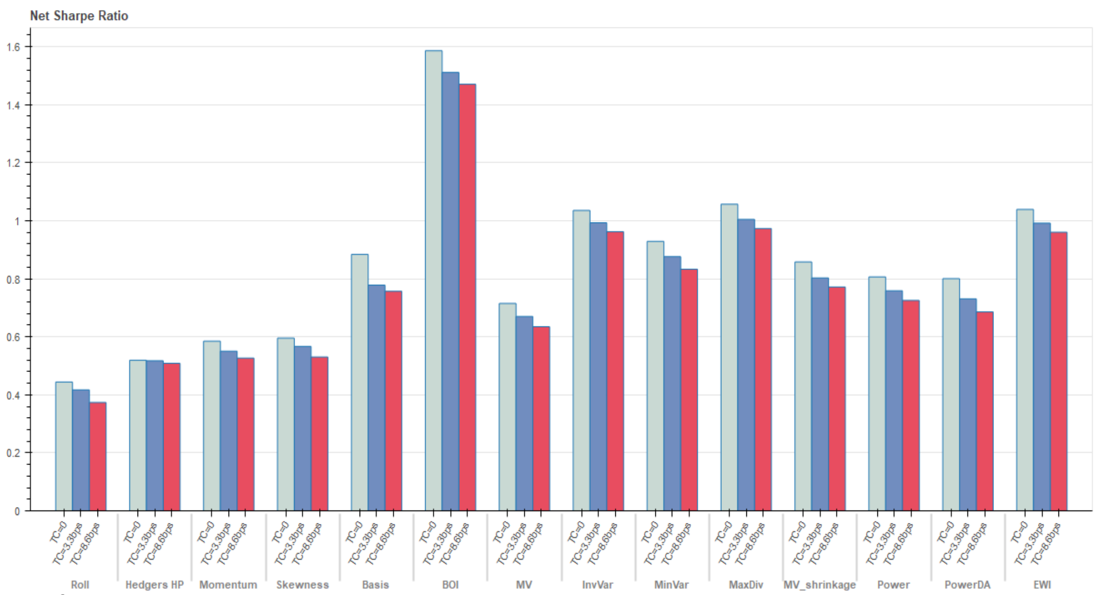
Thus far we have implemented the long-short portfolios using as entries of the score matrix $\mathbf{\Theta}_t$, Equation (2.2.1), the standardized signal $\theta_{i,k,t} \equiv \tilde{x}_{i,k,t} = (x_{i,k,t} - \bar{x}_{k,t})/\sigma^x_{k,t}$ with $x_{i,k,t}$ the kth characteristic or predictive signal for commodity i at time t. Now we consider three alternative score schemes that could mitigate the biases induced by outliers in the signal measurement.
As in Fernandez-Perez et al. (2019) we implement a score scheme with binary

Figure 2.3: Turnover and net Sharpe ratio of individual and integrated portfolios.

(a) Turnover



(b) Net Sharpe ratio



The figure reports the monthly turnover averaged over the entire sample period and the net Sharpe ratio of each long-short portfolio strategy using a lax trading cost estimate of 3.3 b.p. (Locke & Venkatesh, 1997) and a conservative 8.6 b.p. estimate (Marshall et al., 2012). The analysis is based on commodity futures data from January 1992 to December 2021.

short-versus-long entries $\theta_{i,k,t} \in \{-1, 1\}$, a standardized ranking scheme with $\theta_{i,k,t} \equiv \tilde{z}_{i,k,t} = (z_{i,k,t} - \bar{z}_{k,t})/^{z}_{k,t}$ where $z_{i,k,t} \in \{N, \ldots, 1\}$ is the ranking given to each commodity as candidate for a long position (N denotes top, and 1 denotes bottom) according to the kth predictive signal. As in DeMiguel et al. (2009) we implement a commodity scoring approach where each commodity characteristic or signal is winsorized cross-sectionally $\{x_{i,k,t}\}_{i=1}^{N}$; that is, we set as bottom (top) threshold the first (third) quartile minus (plus) three times the interquartile range, any observation outside those thresholds is shrank towards the corresponding threshold. Table 2.5 reports appraisal measures for the style-integrated portfolios implemented with the aforementioned scoring schemes. The earlier finding that the BOI method is unsurpassed by the challenging EWI benchmark and alternative OI methods remains unchanged. As a by-product, we observe that for most style-integrations the binary {-1,1} and standardized ranking scores deliver the largest reward-to-risk ratios by reducing the outlier effects in the signals.

2.4.3 Role of Estimation Window Length

Thus far we have relied on 60-month rolling windows of commodity excess returns $\{\boldsymbol{R}_{t-(60-1)}, \ldots, \boldsymbol{R}_t\}$ to estimate the style-weights $\boldsymbol{\omega}_t$. As the estimation sample widens the parameter uncertainty ought to decrease and hence, the merit of the BOI method versus extant OIs could be diluted and likewise, the superiority of the non-parametric EWI could diminish. To assess this conjecture, we deploy the BOI and competing OIs using: (i) recursive estimation windows starting from a 60-month length at the first portfolio formation time which is then expanded by one month at a time, and (ii) longer 120-month rolling estimation windows.

Figure 2.4 presents the cumulative risk-adjusted performance of the OI portfolios alongside the EWI. The BOI strategy still delivers long-short portfolios with the best Sharpe ratio (Panel A) which reflects the larger mean excess return (Panel

B) captured with lower risk (Panel C). Figure 2.5 graphs the cumulative performance of integrated portfolios with style-weights estimated with 120-month rolling windows. Since longer estimation windows ought to alleviate the parameter uncertainty problem, it is not surprising to see that the performance of some sophisticated OI portfolios such as *MaxDiv* and DeMiguel et al. (2009) through simulations, unfeasible large estimation windows of 3,000 months are needed to overcome estimation risk in a general portfolio allocation problem and outperform the $1/N$ benchmark.

2.5 Conclusion

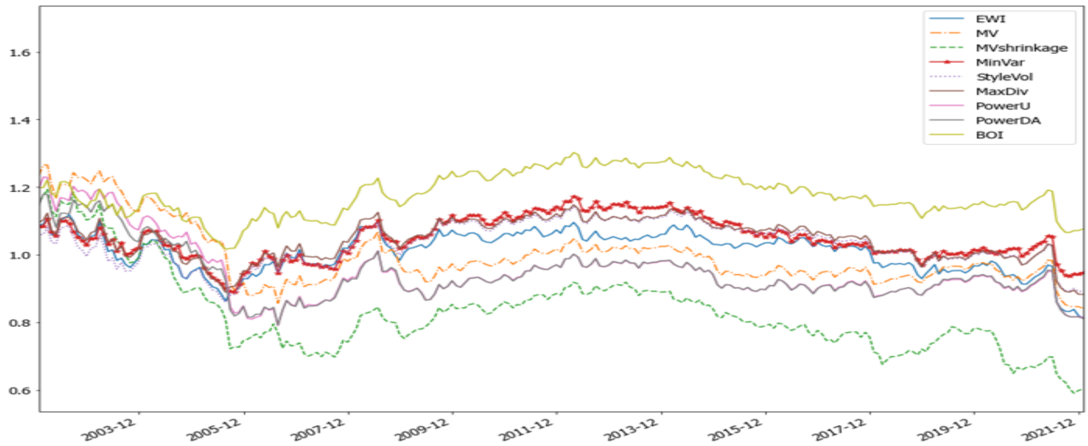
Commodity style-integration is an intuitive and clearcut proposition to capture a superior risk premium by forming a unique long-short portfolio with simultaneous exposure to lowly correlated factors. However, this factor diversification idea requires in practice choosing an appropriate blend of factor exposures at each portfolio rebalancing time. Extant strategies for this purpose are the equal-weights integration (EWI) that sets equal exposures constantly over time, and sophisticated style-integrations where the style-weights are the solution of an optimization problem. Echoing the portfolio allocation literature, the EWI strategy has proven very resilient vis-à-vis optimized integrations because it does not suffer from estimation risk.

This paper designs an optimized style-integration that incorporates Bayesian principles into a mean-variance framework to account for uncertainty in parameter estimation. Specifically, it maps the investor's prior beliefs and available information about the relative performance of the standalone styles onto priors on the commodity return mean and covariance parameters.

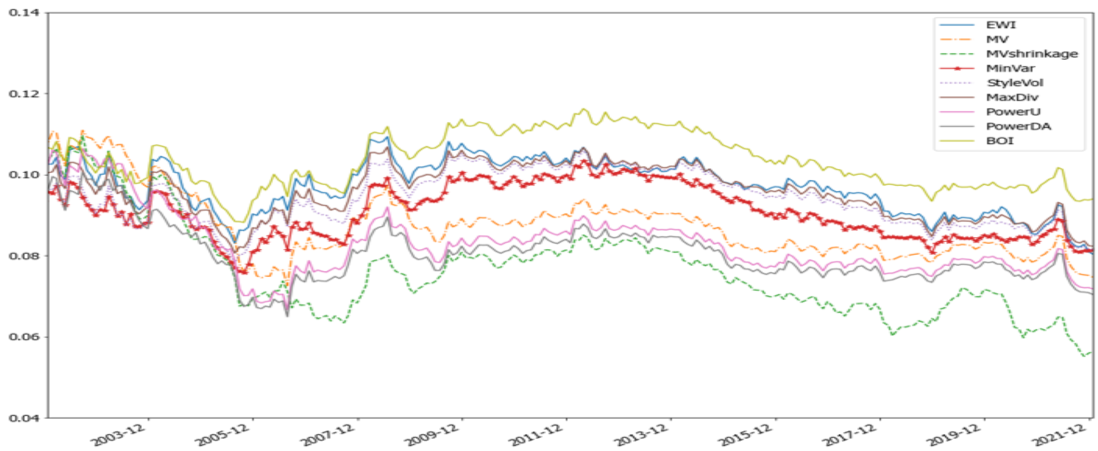
Using data on a cross-section of 28 commodities from January 1992 to December

Figure 2.4: Performance of integrated strategies using recursive sample

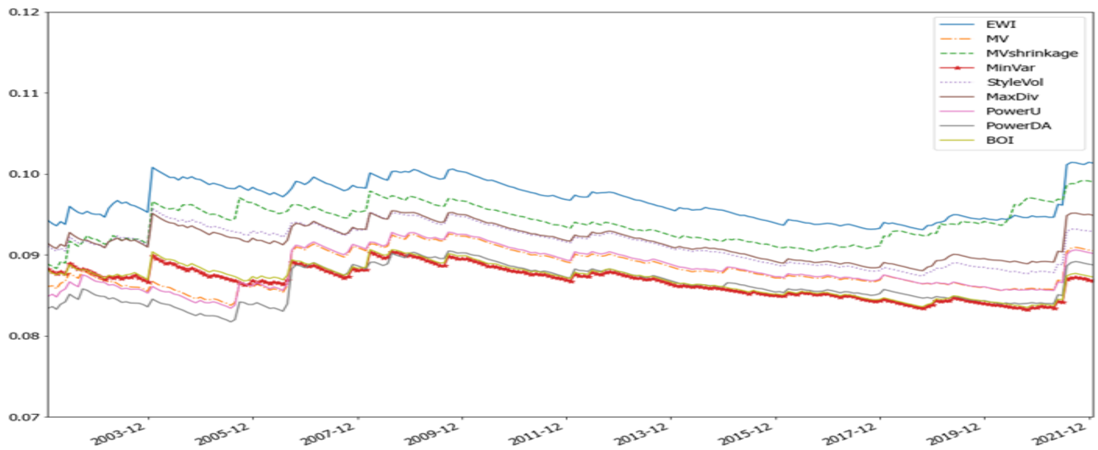
(a) Sharpe ratio



(b) Mean return



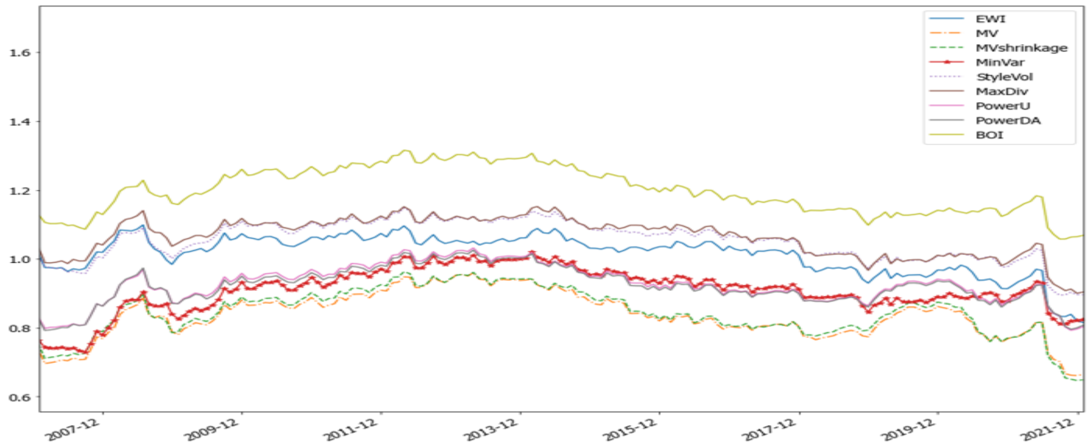
(c) Volatility



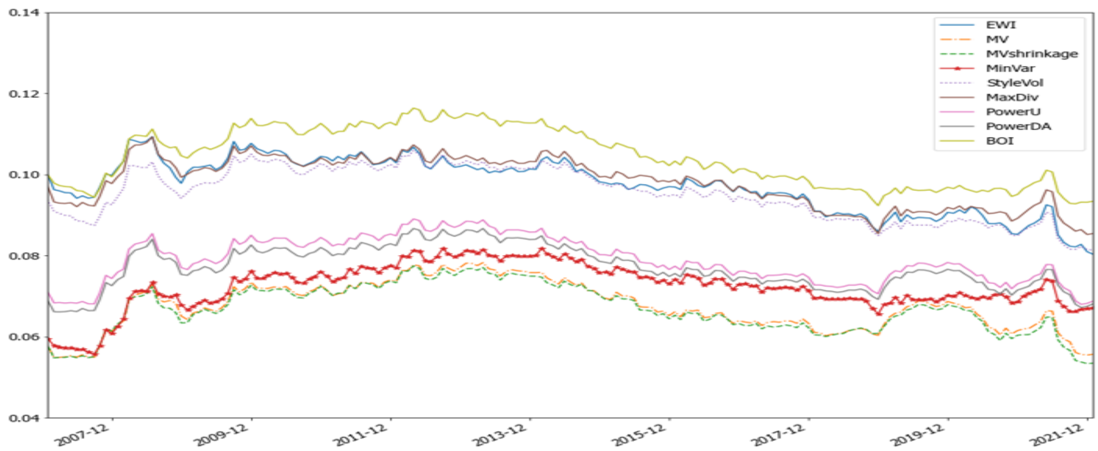
This figure plots the cumulative Sharpe ratio, mean excess return and volatility of the style-integrated portfolios with style-weights estimated at each month-end using recursive windows. The strategies are equal-weights integration (EWI), and optimized integrations (OIs) formed according to mean-variance utility maximization (MV), mean-variance with shrinkage maximization (MVshrinkage), variance minimization (MinVar), style-volatility timing (StyleVol), diversification ratio maximization (MaxDiv), power utility maximization (PowerU), maximized power utility with disappointment aversion (PowerDA), and Bayesian optimized integration (BOI). The analysis is based on commodity futures data from January 1992 to December 2021.

Figure 2.5: Performance of integrated strategies using 120 months window

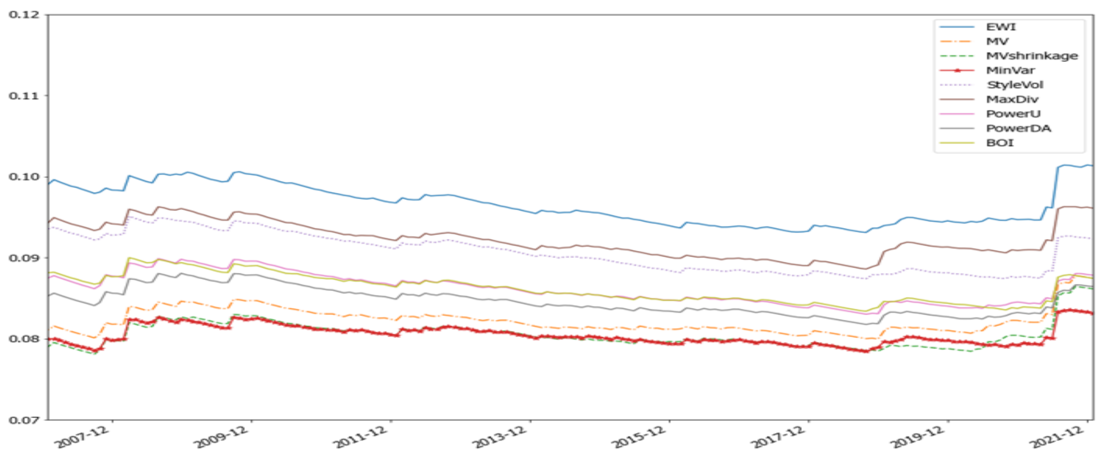
(a) Sharpe ratio



(b) Mean return



(c) Volatility



This figure plots the cumulative Sharpe ratio, mean excess return and volatility of the style-integrated portfolios with style-weights estimated at each month-end using 120-month rolling windows. The strategies are equal-weights integration (EWI), and optimized integrations (OIs) formed according to mean-variance utility maximization (MV), mean-variance with shrinkage maximization (MVshrinkage), variance minimization (MinVar), style-volatility timing (StyleVol), diversification ratio maximization (MaxDiv), power utility maximization (PowerU), maximized power utility with disappointment aversion (PowerDA), and Bayesian optimized integration (BOI). The analysis is based on commodity futures data from January 1992 to December 2021.

2021, and focusing on the carry, hedging pressure, momentum, skewness and basis-momentum styles, we confront the Bayesian optimized style-integration (BOI), with the EWI and various optimized integrations (OIs) inspired from the portfolio optimization literature.

The findings confirm the benefits of commodity style-integration, and reveal that it is important to deal with estimation risk. By contrast with the sophisticated OI portfolios, the BOI portfolio outperforms the EWI portfolio by extracting a significantly larger premia over time and offering an appealing crash risk profile. This finding stems from static and dynamic analyses, and survives trading costs, various commodity scoring schemes, and longer estimation windows. We conclude that the Bayesian approach to account for parameter uncertainty is an efficient way to diversify across commodity risk factors for premia extraction.

2.6 Appendix

2.6.1 Mean-Variance-with-Shrinkage Style Integration

Following Ledoit and Wolf (2003), the shrinkage estimator of the commodities covariance matrix $\boldsymbol{V}_t$ is a linear combination of the standard estimator $\hat{\boldsymbol{V}}_t$ and the identity matrix $\boldsymbol{I_N}$

$$\boldsymbol{S}_t = (1-\lambda)\hat{\boldsymbol{V}}_t + \lambda \boldsymbol{I_N} \tag{2.6.1}$$

where the parameter $\lambda \in (0,1)$ dictates the degree of shrinkage. Let $||Z||_F$ denote the Frobenius norm of the $N \times N$ symmetric matrix Z with entries $(z_{ij})_{i,j=1,..,N}$

defined as

$$||Z||_F = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} z_{ij}^2} \tag{2.6.2}$$

The optimal λ minimizes the expected Frobenius norm of the difference between the shrinkage estimator $\boldsymbol{S}_t$ and the true covariance matrix $\boldsymbol{V}_t$, i.e. $E(||\hat{\boldsymbol{S}}_t - \boldsymbol{V}_t||_F)$. Under the assumption that N is fixed and T tends to infinity, Ledoit and Wolf (2003) prove that the optimal value λ^* asymptotically behaves like a constant over T. This constant, called κ, can be written as

$$\kappa = \frac{\pi - \rho}{\gamma} \tag{2.6.3}$$

The optimal shrinkage parameter is given by

$$\lambda^* = max\{0, min\{\frac{\kappa}{T}, 1\}\} \tag{2.6.4}$$

where T is the length of the estimation window to obtain $\hat{\boldsymbol{V}}_t$. A consistent estimator of π is

$$\hat{\pi} = \sum_{i=1}^{N}\sum_{j=1}^{N}\hat{\pi}_{ij}, \text{ with } \hat{\pi}_{ij} = \frac{1}{T}\sum_{t=1}^{T}(R_{it} - \bar{R}_i)(R_{jt} - \bar{R}_j) - {\sigma_{ij}^2}^2 \tag{2.6.5}$$

where R_{it} is the excess return of the ith commodity, and σ_{ij}^2 is the ijth element of the standard covariance estimator $\hat{\boldsymbol{V}}_t$. A consistent estimator of ρ is given by

$$\hat{\rho} = \sum_{i=1}^{N}\hat{\pi}_{ii} + \sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\frac{\bar{\eta}}{2}\left(\sqrt{\frac{\sigma_{jj}^2}{\sigma_{ii}^2}}\hat{v}_{ii,ij} + \sqrt{\frac{\sigma_{ii}^2}{\sigma_{jj}^2}}\hat{v}_{jj,ij}\right) \tag{2.6.6}$$

where

$$\hat{v}_{ii,ij} = \frac{1}{T}\sum_{t=1}^{T}\{(R_{i,t} - \bar{R}_i)^2 - \sigma_{ii}^2\}\{(R_{i,t} - \bar{R}_i)(R_{j,t} - \bar{R}_j) - \sigma_{ij}^2\} \tag{2.6.7}$$

and

$$\bar{\eta} = \frac{2}{(N-1)N}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\eta_{ij} \tag{2.6.8}$$

with $\eta_{ij} = \frac{\sigma_{ij}^2}{\sqrt{\sigma_{ii}^2\sigma_{jj}^2}}$. Finally, a consistent estimator of γ is given by

$$\hat{\gamma} = \sum_{i=1}^{N}\sum_{j=1}^{N}(f_{ij} - \sigma_{ij}^2)^2 \tag{2.6.9}$$

where $f_{ij} = \bar{\eta}\sqrt{\sigma_{ii}^2\sigma_{jj}^2}$ with σ_{ii}^2 (commodity variance) representing the ith diagonal entry of $\hat{\boldsymbol{V}}_t$.

2.6.2 Disappointment Aversion Power Utility Style-Integration (*PowerU*).

Let $R_{p,t,s} = \boldsymbol{\Theta}_t\boldsymbol{\omega}_t\boldsymbol{R}_{t,s}$ denote the excess return of the style-integrated portfolio associated with the potential states s, and let $p_s \equiv pr(R_{P,t,s})$ denote the likelihood of this excess return. To solve equation (2.2.14) and (2.2.17) simultaneously, the concept of *quadrature* is used to approximate the certainty equivalent returns (CER) of the style-integrated portfolio, parameterized δ, as follows

$$(1+\delta)^{1-\gamma} = \frac{1}{K}\Big(\sum_{s:R_{P,t,s}\leq\delta} p_s R_{P,t,s}^{1-\gamma} + \sum_{s:R_{P,t,s}>\delta} A p_s R_{P,t,s}^{1-\gamma}\Big) \tag{2.6.10}$$

and the first-order-condition in (2.2.17) as

$$\sum_{s:R_{P,t,s}\leq\delta} p_s R_{P,t,s}^{-\gamma} exp(\boldsymbol{R}_{t,s}) + \sum_{s:R_{P,t,s}>\delta} A p_s R_{P,t,s}^{-\gamma} exp(\boldsymbol{R}_{t,s}) = 0 \tag{2.6.11}$$

Let the commodity futures excess return vector in any state s out of S possible states be denoted as $\boldsymbol{R}_{t,s}{}_{s=1}^{S}$ with probability weights $p_s{}_s^S = 1$. Assuming that the commodity futures excess return vector $\boldsymbol{R}_t \equiv (R_{1,t}, ..., R_{N,t})$ follows a multivariate Normal distribution: $\boldsymbol{R}_t \sim MVN(\boldsymbol{\mu}_t, \boldsymbol{V}_t)$, the vector of returns from the MVN distribution can be sorted from low to high across the S states. The certainty equivalent return δ^* corresponding to the optimal weights vector $\boldsymbol{\omega}_t^*$ (and style-integrated portfolio return $\boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*, \boldsymbol{R}_t)$ could lie within any interval

$$\begin{aligned}
&[\boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,1},\ \boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,2}),\\
&[\boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,2},\ \boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,3}),\\
&\vdots\\
&[\boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,N-1},\ \boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,N})
\end{aligned}$$

where $\boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*$ is the $N \times 1$ optimal allocation vector, Equation (2.2.1), and thus $R_{P,t,s}^* = \boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,s}$ is the excess return of the style-integrated portfolio associated with the potential state s. Suppose δ^* lies within $[\boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,i},\ \boldsymbol{\Theta}_t\boldsymbol{\omega}_t^*\boldsymbol{R}_{t,i+1})$, then $\boldsymbol{\omega}_t^*$ is the solution of the first-order condition

$$\sum_{s:R_{P,t,s}\leq\Theta_t\omega_t^*\boldsymbol{R}_{t,i}} p_s R_{P,t,s}^{*-\gamma} exp(\boldsymbol{R}_{t,s}) + \sum_{s:R_{P,t,s}>\Theta_t\omega_t^*\boldsymbol{R}_{t,i}} A p_s R_{P,t,s}^{*-\gamma} exp(\boldsymbol{R}_{t,s}) = 0 \tag{2.6.12}$$

Equation (2.6.12) can be interpreted as the first-order condition of a maximization problem with probabilities π_i that are linked with the original portfolio return probabilities as

$$\pi_i = \frac{(p_1, ..., p_i, Ap_{i+1}, ..., Ap_N)}{(p_1 + ... + p_i) + A(p_{i+1} + ... + p_N)} \tag{2.6.13}$$

The certainty equivalent return δ^* can thus be written as

$$\delta^* = \left(\sum_{s=1}^{N} (R^*_{P,t,s})^{1-\gamma} \pi_{is} \right) \tag{2.6.14}$$

The algorithm of bisection search can be used to find the optimal style-weight vector as follows:

1. Start with a guess of state i (for example, a value of 0.001 for the style-integrated portfolio return). Solve ω_t^* by equation (2.6.13).

2. Compute the CER of the style-integrated portfolio δ^* by equation (2.6.14).

3. If $\delta^* \in [\boldsymbol{\Theta}_t \boldsymbol{\omega}_t^* \boldsymbol{R}_{t,i},\ \boldsymbol{\Theta}_t \boldsymbol{\omega}_t^* \boldsymbol{R}_{t,i+1})$ then $\boldsymbol{\omega}^*$ is the optimal style-weight vector at time t and the algorithm ends. If δ^* is instead larger (smaller) than the above upper (lower) bound, we go back to step 1 and search within the upper (lower) half of the state space, and so on.

2.6.3 Bayesian Style Optimal Integration Implementation

Let the random variable $\boldsymbol{R}_t$ denote the $N \times 1$ vector of commodity future excess returns with mean vector $\boldsymbol{\mu}_t$ and covariance matrix $\boldsymbol{V}_t$. Investors can form objective-based priors for $\boldsymbol{\mu}_t$ as $\boldsymbol{\mu}_t \sim N(\gamma \boldsymbol{V}_{\boldsymbol{\Theta}} \boldsymbol{\omega}_{t,0}, \sigma_\rho^2(\frac{1}{s^2}\boldsymbol{V}_t))$ where $N(.)$ is the Gaussian density, and $\boldsymbol{V}_{\boldsymbol{\Theta}}$ is a direct function of $\boldsymbol{V}_t$ given by $\boldsymbol{V}_{\boldsymbol{\Theta}} = (\boldsymbol{\Theta}_t')^{-1}(\boldsymbol{\Theta}_t' \boldsymbol{V}_t \boldsymbol{\Theta}_t)$ with $\boldsymbol{\Theta}_t$ the commodity score matrix in Equation (2.2.1). Thus, the prior for $\boldsymbol{\mu}_t$ is determined by the equal style-weight scheme $\boldsymbol{\omega}_{t,0} = 1/K$ and inverse Wishart distribution $\boldsymbol{V}_t \sim IW(\boldsymbol{\Lambda}_0^{-1})$ where the scale matrix $\boldsymbol{\Lambda}_0$ is usually the identity matrix. As it is seldom possible to obtain a closed-form expression for the posterior density of the parameters (leaving aside the special case where the posterior and prior densities are in the same parametric family of densities) we utility the Markov Chain Monte Carlo (MCMC) method to approximate the posterior distribution by simulation. The investor obtains the posterior distribution $pr(\boldsymbol{\mu}_t, \boldsymbol{V}_t|\mathcal{F}_t)$. The method unfolds in three steps: (1) Using a Markov chain generate $M + M_0$ sequences of commodity excess returns $\{\boldsymbol{R}_{t-(L-1)}, ..., \boldsymbol{R}_{t-1}, \boldsymbol{R}_t\}_{m=1}^{M}$ from the priors; we use $M = 10,000$ and $M_0 = 2,000$; (2) discard the first M_0 "burn-in" samples to ensure the Markov chain has converged; (3) use the remaining M return samples to obtain the mean and covariance parameters that approximate the posterior distribution, namely, $(\boldsymbol{\mu}_t, \boldsymbol{V}_t)_M$.

These steps can be directly performed using the PyMC3 package of Python. After setting the priors of $\boldsymbol{\mu}_t$ and $\boldsymbol{V}_t$, and the observed commodity future returns from $t - 60$ to t as input, $\{\boldsymbol{R}_{t-(L-1)}, ..., \boldsymbol{R}_{t-1}, \boldsymbol{R}_t\}$, the package generates the posterior density $(\boldsymbol{\mu}_t, \boldsymbol{V}_t)_M$ using the MCMC algorithm known as Gibbs sampling. This posterior is then used to solve the mean-variance optimization problem, Equation (2.2.3), to derive the BOI style-weights $\boldsymbol{\omega}_t^{BOI}$.

Table 2.1: Summary Statistics for Commodity Future Returns.

Sector	Commodities	Mean	StDev	AR(1)	Skew	Kurt		Average Correlations				Obs	First obs	Last obs
								Agriculture	Energy	Livestock	Metal		YYYYMM	YYYYMM
Agriculture	Cocoa (ICE)	-0.054	(-0.267)	0.293	-0.203	0.152	0.727	0.372	0.074	-0.057	0.212	360	199201	202112
	Coffee (ICE)	-0.116	(-0.845)	0.357	-0.046	0.657	1.744	0.450	0.026	-0.039	0.252	360	199201	202112
	Corn (CBOT)	-0.107	(-1.513)	0.261	0.021	-0.125	0.846	0.743	0.156	-0.021	0.241	360	199201	202112
	Cotton (ICE)	-0.077	(-0.725)	0.276	-0.023	-0.079	0.541	0.529	0.113	0.029	0.272	360	199201	202112
	Oat (CBOT)	-0.063	(-0.263)	0.311	0.014	0.128	0.853	0.611	0.150	0.062	0.195	360	199201	202112
	Orange juice (NYMEX)	-0.115	(-1.300)	0.308	-0.130	0.004	0.288	0.361	0.050	0.052	0.125	360	199201	202112
	Rough rice (CBOT)	-0.138	(-2.085)	0.265	-0.042	0.345	2.448	0.404	0.009	-0.025	0.067	360	199201	202112
	Soyabean meal (CBOT)	0.064	(2.024)	0.274	-0.048	-0.013	1.379	0.680	0.116	-0.062	0.153	360	199201	202112
	Soyabean oil (CBOT)	-0.062	(-0.758)	0.240	-0.079	-0.321	2.187	0.674	0.129	0.078	0.281	360	199201	202112
	Soyabeans (CBOT)	0.008	(0.848)	0.239	-0.060	-0.509	1.442	0.795	0.138	0.000	0.251	360	199201	202112
	Sugar (ICE)	-0.093	(-0.399)	0.339	0.143	-1.139	8.707	0.361	0.059	-0.005	0.180	360	199201	202112
	Wheat (CBOT)	-0.142	(-2.268)	0.288	-0.068	0.174	1.125	0.641	0.114	0.045	0.221	360	199201	202112
	Lumber (CME)	-0.133	(-1.409)	0.325	0.029	0.155	0.602	0.331	0.027	0.093	0.165	360	199201	202112
Energy	Crude oil (NYMEX)	-0.033	(-0.228)	0.311	0.173	-0.445	1.105	0.199	0.797	0.097	0.314	360	199201	202112
	Electricity (NYMEX)	-0.213	(-2.006)	0.373	0.180	0.105	6.829	0.069	0.552	0.049	0.090	360	199201	202112
	Heating oil (NYMEX)	0.006	(0.809)	0.320	0.098	-0.013	1.751	0.160	0.846	0.096	0.271	360	199201	202112
	Natural gas (NYMEX)	-0.257	(-1.748)	0.480	0.052	-0.021	0.798	0.075	0.743	0.046	0.087	360	199201	202112
	RBOB (NYMEX)	-0.006	(-0.545)	0.251	0.217	-1.297	10.622	0.286	0.492	0.054	0.374	141	200510	202112
	Unleaded gas (NYMEX)	0.048	(1.701)	0.274	0.001	0.445	5.060	-0.006	0.661	0.066	0.085	180	199201	200701
Livestock	Feeder cattle (CME)	0.011	(0.734)	0.140	0.040	-0.354	0.927	-0.075	0.051	0.604	0.018	360	199201	202112
	Frozen pork bellies (CME)	-0.035	(0.246)	0.312	-0.173	0.172	2.873	0.116	0.057	0.724	0.072	234	199201	201107
	Lean hogs (CME)	-0.087	(-0.981)	0.288	-0.045	-0.191	1.520	-0.028	0.125	0.803	-0.033	360	199201	201507
	Live cattle (CME)	0.057	(2.296)	0.154	-0.020	-0.484	3.280	0.045	0.015	0.602	0.041	360	199201	202112
Metal	Copper (COMEX)	0.009	(0.723)	0.256	0.107	-0.543	4.841	0.335	0.259	0.056	0.661	360	199201	202112
	Gold (COMEX)	0.013	(0.941)	0.155	-0.110	-0.027	1.440	0.242	0.130	-0.024	0.698	360	199201	202112
	Palladium (NYMEX)	0.040	(1.343)	0.328	-0.010	-0.302	2.444	0.241	0.186	0.047	0.742	360	199201	202112
	Platinum (NYMEX)	0.010	(0.747)	0.211	0.076	-1.072	5.235	0.351	0.231	0.021	0.834	360	199201	202112
	Silver (COMEX)	-0.014	(0.550)	0.281	-0.075	-0.251	1.272	0.271	0.127	-0.023	0.796	360	199201	202112

The table reports for 28 commodities the annualized mean and standard deviation of excess returns or change in month-end logarithmic futures prices, first-order autocorrelation, skewness, kurtosis, and the average pairwise correlation between the excess returns of the commodity at hand and the commodities within each sector. Newey-West robust t-statistics for the significance of the mean excess returns are reported in parentheses. Exchanges are reported in brackets. All contracts are quoted in US dollars.

Table 2.2: Performance of Individual Commodity Styles

	Basis	HP	Momentum	Skewness	Basis-Mom
Panel A: Static portfolio evaluation					
Mean	0.043	0.036	0.044	0.047	0.051
	(3.030)	(2.784)	(3.001)	(3.343)	(3.757)
StDev	0.081	0.078	0.088	0.072	0.077
Semi-deviation	0.221	0.224	0.247	0.192	0.216
Skewness	0.270	0.076	-0.081	0.091	-0.211
Skewtest	2.097	0.597	-0.636	0.720	-1.648
Kurtosis	0.448	0.436	0.519	0.284	1.513
Kurttest	1.664	1.631	1.855	1.183	3.823
JB test	0.025	0.203	0.109	0.426	0.000
AR1	-0.011	-0.023	0.040	0.044	0.042
Max Drawdown	-0.248	-0.140	-0.189	-0.209	-0.259
99% VaR	-0.051	-0.049	-0.055	-0.044	-0.047
Sharpe ratio	0.563	0.495	0.533	0.680	0.689
Sortino ratio	0.943	0.788	0.869	1.160	1.124
Omega ratio	1.533	1.440	1.488	1.663	1.696
Panel B: Dynamic Sharpe ratio (style ranking)					
Jan 1992 - Dec 1997	0.468(5)	0.476(4)	0.876(3)	1.178(1)	0.892(2)
Jan 1998 - Dec 2003	1.256(1)	0.544(4)	0.996(2)	0.291(5)	0.937(3)
Jan 2004 - Dec 2009	0.907(1)	0.837(3)	0.393(5)	0.902(2)	0.482(4)
Jan 2010 - Dec 2015	0.324(4)	0.279(5)	0.552(3)	0.664(2)	1.012(1)
Jan 2016 - Dec 2021	-0.129(5)	0.274(3)	-0.096(4)	0.440(1)	0.278(2)

This table summarizes the performance of five styles or long-short portfolios formed according to different commodity futures return predictors (as sorting signals): basis defined as log futures price difference between front- and second-nearest contract, hedging pressure or net hedgers' short positions over total positions, momentum or past-year average return, Pearson coefficient of skewness of the commodity futures return distribution estimated with past-year daily returns, and basis-momentum or differential momentum between front- and second-nearest contracts. Mean and standard deviation are annualized. Panel A reports statistics over the full sample period January 1992 to December 2021. Panel B reports Sharpe ratios over 6-year non-overlapping sub-periods and corresponding style ranks in parenthesis with 1 denoting top risk-adjusted performance.

Table 2.3: Dependence between Individual Commodity Investment Styles

Panel A: Pearson correlation	Basis	HP	Momentum	Skewness	Basis-Mom
Basis	1.000	0.162	0.416	0.150	0.263
HP		1.000	0.240	0.071	0.124
Momentum			1.000	-0.046	0.322
Skewness				1.000	-0.146
Basis-Mom					1.000
Panel B: Spearman rank-order corr.	**Basis**	**HP**	**Momentum**	**Skewness**	**Basis-Mom**
Basis	1.000	0.179	0.343	0.101	0.317
HP		1.000	0.173	0.090	0.029
Momentum			1.000	-0.088	0.303
Skewness				1.000	-0.124
Basis-Mom					1.000
Panel C: Kendall correlation	**Basis**	**HP**	**Momentum**	**Skewness**	**Basis-Mom**
Basis	1.000	0.126	0.240	0.069	0.223
HP		1.000	0.120	0.062	0.021
Momentum			1.000	-0.061	0.217
Skewness				1.000	-0.086
Basis-Mom					1.000

The table reports measures of dependence between the monthly excess returns of the standalone styles. Panel A reports the Pearson correlation (linear dependence). Panels B and C reports the non-parametric Spearman rank-order correlation and Kendall correlation, respectively, that capture linear and nonlinear dependence. The sample period is January 1992 to December 2021.

Table 2.4: Performance of Integrated Commodity Styles

		Optimized Style-Integrations (OI)							
	EWI	MV	MVshrinkage	MinVar	StyleVol	MaxDiv	PowerU	PowerDA	BOI
Panel A: Static portfolio evaluation									
Mean	0.080	0.054	0.051	0.075	0.082	0.083	0.052	0.052	0.092
StDev	0.101	0.094	0.094	0.084	0.102	0.096	0.093	0.094	0.087
Semi-deviation	0.272	0.258	0.258	0.209	0.275	0.248	0.258	0.262	0.212
Max Drawdown	-0.243	-0.297	-0.287	-0.158	-0.255	-0.219	-0.296	-0.296	-0.174
99% VaR	-0.061	-0.058	-0.058	-0.050	-0.062	-0.057	-0.058	-0.059	-0.051
Sharpe Ratio (SR)	0.815	0.606	0.577	0.904	0.823	0.886	0.588	0.587	1.060
Sortino ratio	1.393	1.012	0.960	1.677	1.400	1.566	0.976	0.970	1.987
Omega ratio	1.900	1.599	1.563	2.041	1.918	2.023	1.576	1.574	2.309
DSR (gain versus EWI)		0.286	0.257	0.584	0.503	0.566	0.268	0.266	0.740
Ledoit-Wolf test p-value		0.883	0.931	0.222	0.383	0.128	0.902	0.901	0.005
Opdyke test p-value		0.199	0.128	0.888	0.915	0.774	0.173	0.101	0.042
Panel B: Dynamic Sharpe ratio (style ranking)									
Jan 1992 - Dec 1997	1.108(7)	1.296(3)	1.107(8)	1.293(4)	1.103(9)	1.265(6)	1.278(5)	1.300(2)	1.373(1)
Jan 1998 - Dec 2003	0.999(4)	1.000(3)	0.860(8)	0.671(9)	1.002(2)	0.902(7)	0.923(6)	0.931(5)	1.005(1)
Jan 2004 - Dec 2009	1.115(2)	0.378(9)	0.464(6)	1.058(5)	1.113(3)	1.076(4)	0.411(7)	0.398(8)	1.314(1)
Jan 2010 - Dec 2015	0.979(4)	0.513(9)	0.604(6)	1.042(3)	0.977(5)	1.055(2)	0.547(8)	0.558(7)	1.180(1)
Jan 2016 - Dec 2021	0.193(5)	0.116(6)	0.089(7)	0.496(2)	0.194(4)	0.381(3)	0.081(8)	0.072(9)	0.583(1)

The table reports summary statistics for the excess returns of the equal-weight style integrated (EWI) portfolio and optimized style-integrated (OI) portfolios with the style-weight vector determined at each portfolio rebalancing time by quadratic utility maximized weights (mean variance; MV), mean-variance with shrinkage maximization (MVshrinkage), variance minimization (MinVar), style-volatility timing (StyleVol), diversification-ratio maximization (MaxDiv), power utility maximization (PowerU), maximization of power utility with disappointment aversion (PowerDA), and Bayesian optimized integration (BOI). The length of the rolling estimation window for the style-weights is 60 months and the style-integrations are based on a matrix $\mathbf{\Theta}_t$ in Equation (2.2.1) with standardized signals as commodity scores. Mean and standard deviation are annualized. The hypotheses for the Ledoit and Wolf (2008) and Opdyke (2007) tests are $H_0 : SR_i - SR_{EWI} \leq 0$ versus $H_A : SR_i - SR_{EWI} > 0$ where i is each of the OI strategies. Panel A reports statistics over the full sample period January 1992 to December 2021. Panel B reports Sharpe ratios over 6-year non-overlapping sub-periods and corresponding style-integrated portfolio ranks in parentheses.

Table 2.5: Performance of Alternative Scoring Schemes

		Optimized Style-Integrations (OI)							
	EWI	MV	MVshrinkage	MinVar	InvVar	MaxDiv	PowerU	PowerDA	BOI
Panel A: Binary scores									
Mean	0.079	0.055	0.052	0.076	0.078	0.078	0.055	0.054	0.094
StDev	0.076	0.072	0.071	0.075	0.076	0.076	0.072	0.072	0.074
semi StDev	0.186	0.195	0.195	0.187	0.187	0.189	0.194	0.196	0.175
Max Drawdown	-0.097	-0.159	-0.136	-0.115	-0.101	-0.105	-0.150	-0.151	-0.089
99% VaR	-0.044	-0.044	-0.044	-0.044	-0.044	-0.045	-0.044	-0.044	-0.042
Sharpe Ratio (SR)	1.040	0.786	0.744	1.012	1.034	1.028	0.787	0.770	1.243
Sortino ratio	1.938	1.327	1.245	1.862	1.914	1.904	1.340	1.299	2.420
Omega ratio	2.196	1.798	1.741	2.145	2.184	2.173	1.808	1.793	2.555
DSR (versus EWI)		-0.254	-0.296	-0.028	-0.005	-0.012	-0.253	-0.270	0.203
Ledoit-Wolf test		0.961	0.982	0.630	0.570	0.577	0.963	0.972	0.000
Opdyke test		0.130	0.072	0.839	0.963	0.924	0.130	0.103	0.045
Panel B: Standardized rankings									
Mean	0.084	0.067	0.059	0.083	0.084	0.082	0.068	0.067	0.099
StDev	0.083	0.083	0.083	0.081	0.083	0.082	0.083	0.083	0.081
semi StDev	0.209	0.219	0.224	0.201	0.207	0.207	0.216	0.216	0.195
Max Drawdown	-0.129	-0.197	-0.258	-0.151	-0.130	-0.169	-0.171	-0.185	-0.140
99% VaR	-0.049	-0.050	-0.051	-0.047	-0.049	-0.048	-0.050	-0.050	-0.046
Sharpe Ratio (SR)	1.009	0.824	0.733	1.033	1.017	1.006	0.836	0.824	1.204
Sortino ratio	1.846	1.434	1.245	1.909	1.863	1.829	1.471	1.446	2.305
Omega ratio	2.168	1.889	1.748	2.263	2.189	2.205	1.907	1.891	2.565
DSR (versus EWI)		-0.185	-0.276	0.024	0.008	-0.003	-0.173	-0.185	0.196
Ledoit-Wolf test		0.919	0.984	0.375	0.385	0.516	0.910	0.922	0.000
Opdyke test		0.252	0.073	0.860	0.945	0.979	0.281	0.243	0.037
Panel C: Winsorized signals									
Mean	0.072	0.061	0.052	0.074	0.072	0.072	0.062	0.061	0.086
StDev	0.075	0.077	0.076	0.074	0.075	0.074	0.076	0.077	0.074
semi StDev	0.186	0.201	0.205	0.182	0.185	0.183	0.199	0.200	0.174
Max Drawdown	-0.167	-0.170	-0.171	-0.162	-0.162	-0.171	-0.173	-0.171	-0.151
99% VaR	-0.044	-0.046	-0.047	-0.044	-0.044	-0.044	-0.046	-0.046	-0.042
Sharpe Ratio (SR)	0.961	0.812	0.701	1.003	0.974	0.976	0.823	0.811	1.166
Sortino ratio	1.776	1.420	1.192	1.855	1.803	1.809	1.445	1.423	2.258
Omega ratio	2.078	1.854	1.694	2.178	2.109	2.130	1.862	1.846	2.439
DSR (versus EWI)		-0.149	-0.260	0.042	0.013	0.015	-0.138	-0.150	0.205
Ledoit-Wolf test		0.881	0.978	0.252	0.261	0.383	0.875	0.889	0.000
Opdyke test		0.323	0.072	0.735	0.904	0.902	0.357	0.311	0.019

The table summarizes the excess returns of the nine style-integrated portfolios based on a score matrix $\mathbf{\Theta}_t$ in Equation (2.2.1) with binary entries (-1,+1) in Panel A, standardized rankings in Panel B and cross-sectionally winsorized signals in Panel C. The length of rolling windows for the style-weight estimation is 60 months. Mean and standard deviation are annualized. p-values are reported for the Ledoit and Wolf (2008) and Opdyke (2007) tests $H_0 : SR_i - SR_{EWI} \leq 0$ versus $H_A : SR_i - SR_{EWI} > 0$ where i denotes an OI strategy. The sample period is January 1992 to December 2021.

Chapter 3

On the Information Content of Media Tone in Commodity Futures Markets: What does it tell us?

3.1 Introduction

The asset pricing role of investor sentiment has been the subject of a burgeoning literature. Advances in data science in the recent decade have opened the possibility to access novel data sources such as newspaper articles, internet search queries, and posts on social media to characterize the information environment and its impact on financial markets. In a seminal paper, Tetlock (2007) provides evidence that media tone obtained from an automated content analysis to the Wall Street Journal (WSJ) *Abreast of the market* column predicts U.S. stock price changes. Specifically, pessimistic tone is associated with subsequent falling market prices and a reversal to fundamentals. If the column reveals new information then a complete reversal should not be observed. If the column contains stale information then media pessimism should not be able to predict falling prices. On this basis, Tetlock argues that negative media tone acts as a proxy for investors' mindset or sentiment that contains pricing information over and above fundamentals. Subsequent studies have also mainly focused on equities as the main asset class.

Commodities provide three benefits to investors' portfolios of stocks and bonds: protection against inflation, diversification and sizeable risk premia. In fact, with the development of commodity futures indexes and investment vehicles that benchmark against these indices, commodities have evolved as an asset class since the 1990s. Seeking to understand whether and how commodity prices respond to the tone of commodity-related news can not only be fruitful towards designing new trading strategies, or refining traditional allocations, that may capture larger risk premia, but it can also provide asset pricing insights in commodity futures markets.

The goal of this paper is to quantify the role of commodity media tone in commodity markets. For this purpose, the paper adopts a purely statistical (predictive regressions) framework, an economic (tactical portfolio allocation) framework, and an asset pricing framework.

Through textual analysis algorithms applied to news articles, we begin by constructing a media-tone signal for each commodity and aggregate it into a media-tone index as proxy for overall market sentiment. This commodity sentiment index is highly positively correlated with widely-used sentiment proxies in the finance literature such as the VIX, Baker and Wurgler (2006) sentiment index, and the Michigan Consumer Sentiment Index.

Predictive regressions in a panel setting using the commodity-specific media tone signals, and in a time-series framework using the aggregate commodity market media-tone both reveal that media tone has predictive content for commodity price movements. Expanding this regression framework to accommodate nonlinearities, we document that pessimistic media tone has stronger predictive content than optimistic media-tone. Consistent with this finding, the results further suggest that the predictive ability of media tone exacerbates during crisis stages of the business cycle. These findings are relevant for investors' market timing.

Third, we find that embedding commodity-specific media tone in traditional tactical allocations such as, for instance, those carried out according to roll-yield and hedging pressure signals enables portfolios with more favourable reward-to-risk profiles. In addition to these significant larger premia captured by media tone-adjusted long-short portfolios, time-series and cross-sectional tests confirm that there is pricing ability in media tone beyond compensation for exposure to traditional commodity risk factors. The pricing findings lend support to traditional theories while not ruling out the presence of investors' behavioural biases.

The paper expands a sparse literature on the role of investors' psychology in commodity markets. A few papers use internet search volume as a proxy for the demand of information revealing investor attention or fear (Fernandez-Perez et al., 2020; Han et al., 2017a; Han et al., 2017b; Vozlyublennaia, 2014). Gao and Süss (2015) studies the role on commodity prices of market sentiment proxies such as the CBOE's volatility index (VIX) also know as "fear gauge" or "gear index" and the Baker and Wurgler (2006) sentiment index. We instead construct a sentiment proxy from commodity media tone and study if it can predict commodity returns.

The paper speaks to a rapidly growing literature that applies textual analysis to news articles or internet posts in social media to quantify the information environment and investigates its relation with financial markets in order to test behavioural finance theories. De Long et al. (1990) formulate a model where noise traders driven by investor sentiment coexist with rational investors. Their model suggests that pessimistic sentiment temporarily influences stock prices. Tetlock (2007) hypothesizes that newspapers tone can proxy investor sentiment and provides supportive evidence to suggest specifically that the WSJ *Abreast of the market* column reveals traders' moods and expectations which are channeled into prices via trading activity. In the words of Tetlock (2015) "even when there is no causal channel, media content can be a useful window into investors and managers' beliefs." Subsequent studies have documented that investor sentiment proxied by the linguistic content of media reports or internet postings on social networks has predictive content for stock market activity (e.g., Garcia, 2013; Bollen et al., 2011; Karabulut, 2013). We expand this literature by focusing our analysis on commodity media tone. Our finding that pessimistic media-tone on commodities has stronger predictive ability than optimistic tone is consistent with prospect (or loss-aversion) theory and echoes a parallel literature which contends that negative information has a stronger psychological impact and is more thoroughly processed by individuals than positive information (e.g., Baumeister et al., 2001; Rozin and Royzman, 2001).

The remainder of the paper is organized as follows. Section 2 presents the data and our media tone measures. Section 3 explores the explanation power of the media tone measures. Section 4 contains the in-sample predictive regression analysis and robustness checks. Section 5 shows the out-of-sample test. Section 6 explains the sources of predictability contained in our media tone measures. A final section concludes.

3.2 Data and Media-Tone Measure

3.2.1 Commodities Sample

This research employs data on a cross-section of 28 commodity futures contracts comprising 17 agricultural (4 cereal grains, 4 oilseeds, 4 meats, 5 miscellaneous other softs), 6 energy, and 5 metals (1 base, 4 precious). For each of the commodities, end-of-day futures settlement prices and daily dollar trading volume are obtained from *Refinitiv Datastream*, and open interest data from the *Commitment of Traders Report of the Commodity Futures Trading Commission*. The observations are sampled at the weekly frequency from January 1, 2000 to July 31, 2019. Excess returns are calculated as $ln(F^{T1}_{i,t}/F^{T1}_{i,t-1})$.

3.2.2 Data from Ravenpack

The paper employs sentiment scores for commodity articles (or "news events") published in the following financial newspapers/magazines: Dow Jones Financial Wires, Wall Street Journal, Barron's and Marketwatch. The article-specific event sentiment scores (ESS) are constructed by the data analytics provider *Ravenpack* using textual analysis algorithms. A comprehensive sample of ESS data is obtained from the *Wharton Research Data Services (WRDS) Ravenpack* section. The sentiment of each news article is encapsulated in its ESS ranging between 0 and 100; a value of 50 means neutral sentiment, values above 50 are given to articles with the overall positive (or optimistic) sentiment, and values below 50 represent negative sentiment. Table 3.1 is an example of the dataset: The news is recorded in

Table 3.1: Ravenpack Dataset Example

RP_ENTITY_ID	ENTITY_TYPE	ENTITY_NAME	POSITION_NAME	RELEVANCE	ESS	AES	AEV	ENS	ENS_SIMILARITY_GAP	RPNA_DATE_UTC	RPNA_TIME_UTC	TIMESTAMP_UTC
120B6A	CMDT	Rough Rice		100	50	43	79	18	0.05951	20190801	32:30.7	32:30.7
120B6A	CMDT	Rough Rice		33		43	79			20190801	07:44.6	07:44.6
120B6A	CMDT	Rough Rice		12		43	79			20190801	35:57.6	35:57.6
120B6A	CMDT	Rough Rice		14		43	79			20190801	16:10.1	16:10.1
120B6A	CMDT	Rough Rice		100	50	43	79	13	0.23396	20190801	09:24.8	09:24.8
120B6A	CMDT	Rough Rice		100	50	43	79	10	0.03128	20190801	54:27.7	54:27.7

milliseconds. Our data sample starts from Jan 01, 2000 which is the earliest date that can be tracked in Ravenpack to July 31, 2019. We extract from RavenPack the following variables.

- *ENTITY_NAME* indicates the name of a certain commodity product.

- *Event Sentiment Score (ESS)* is a value ranging from 0 (negative) to 100 (positive) where 50 represents an article with a neutral tone. It is available for each article that measures the media tone of a given commodity.

- *Relevance* is an index provided by RavenPack that indicates the relevance of a news article to a given commodity product. This takes values ranging from 0 (least relevant) to 100 (most relevant). If the type of the article can be identified and the commodity product plays an important role in the main context of the story – e.g. the price of this product is rising – then the Relevance score is 100. If the commodity is mentioned but plays an unimportant role, then it gets a low Relevance score.

- *ENS* is the *event novelty score* which represents how novel a story is within the 24-hour time window. Any two stories that match the same event for the same entities will be considered similar according to ENS.

- *RP_STORY_EVENT_COUNT* represents the total entity records published by RavenPack per news story. It works as a proxy for media coverage.

We will use the above-mentioned variables to build up our media-tone measure. von Beschwitz et al. (2020) verify the appropriateness of the threshold by examining the response of stock prices to articles with different relevance scores. RavenPack recommends "filtering for Relevance greater than or equal to 90 as this helps reduce noise in the signal." Thus, in this study, we focus on news that has $RELEVANCE$ score higher than 90.

3.2.3 Commodity-specific Media Tone Equation

As in Borovkova (2015), the paper assumes that the impact of media tone or sentiment on commodity prices decays with the staleness of the news[1]. Accord-

[1]Tetlock (2011) also establishes in equity markets that the extent of the investor reaction to media tone decreases with the staleness of the news.

ingly, an exponentially weighted average of daily ESSs is used to calculate a novel commodity-specific sentiment score. Let i denote the commodity at hand and t the sample week; In this paper, without loss of generality t denotes the Monday of each week. Suppose that as of the Monday of week t the ith commodity has received recent (past 7 days) coverage by articles published, respectively, on the Monday, and on the preceding Sunday and Friday. The media-tone score $0 \leq MedTone_{i,t} \leq 100$ is calculated as follows

$$MedTone_{i,t} = \frac{0.9^0 * ESS_{Mon,i} + 0.9^1 * ESS_{Sun,i} + 0.9^3 * ESS_{Fri,i}}{0.9^0 + 0.9^1 + 0.9^3} \tag{3.2.1}$$

where $ESS_{Mon,i}$ is the sentiment score for the specific article about the ith commodity published on Monday, and so forth; and 0.9 is the decay factor adopted by Borovkova (2015). Among various robustness checks, the authors consider an alternative media-tone score defined as an equally-weighted average of the ESSs.

Table 3.2 presents summary statistics for the commodity futures excess returns and media tone (mean, standard deviation, first-order autocorrelation, and Ljung-Box test statistic for the null hypothesis that the first four autocorrelations are jointly zero). Weekly excess returns show little evidence of predictability based on sample autocorrelations; the Ljung-Box test is only able to reject the null hypothesis of no autocorrelation up to order 4 for live cattle, cocoa, coffee and gasoline RBOB. The weekly MedTone signal, as defined in Equation (3.2.1), shows variability over time and although more highly autocorrelated than the excess returns, the null hypothesis of zero autocorrelation up to week four is also generally not rejected.

Table 3.2: Summary Statistics for ESS

			First obs	Last obs	Excess return					Media Tone				
Commodity	**Sub-sector**	**Exchanges**	**YYYYMMDD**	**YYYYMMDD**	**Mean**	**StDev**	**AC1**	**LB4**		**Mean**	**StDev**	**AC1**	**LB4**	
I. Agricultural sector (N=16)														
Corn	Cereal grains	CBOT	20000103	20190731	-0.0741	0.2797	-0.0177	4.5813		0.2326	0.4527	0.2454	4.9792	
Oats	Cereal grains	CBOT	20000103	20190731	0.0205	0.3323	-0.0254	2.3688		0.4156	0.5420	0.7841	23.2152	***
Rough rice	Cereal grains	CBOT	20000103	20190731	-0.1099	0.2490	0.0567	2.8317		0.2195	0.6025	0.2325	5.8802	
Wheat CBT	Cereal grains	CBOT	20000103	20190731	-0.1062	0.2966	0.0040	1.7373		0.2073	0.4619	0.2340	1.2638	
Cotton no.2	Oilseeds	NYMEX/ICE	20000103	20190731	-0.0500	0.2802	0.0178	0.6269		0.2927	0.5188	0.2301	3.5791	
Soybeans	Oilseeds	CBOT	20000103	20190731	0.0517	0.2399	0.0233	3.2983		0.2861	0.4842	0.1641	4.4128	
Soybean meal	Oilseeds	CBOT	20000103	20190731	0.1281	0.2753	0.0305	1.4751		0.1548	0.6916	0.5162	10.8855	**
Soybean oil	Oilseeds	CBOT	20000103	20190731	-0.0240	0.2293	0.0371	1.1396		0.2458	0.5322	0.2081	5.7005	
Feeder cattle	Meats	CME	20000103	20190731	0.0227	0.1584	-0.0495	4.1557		0.4615	0.6762	0.6980	3.7644	
Lean hogs	Meats	CME	20000103	20150706	-0.0559	0.2603	0.0370	4.3728		0.4099	0.5748	0.3615	1.0540	
Live cattle	Meats	CME	20000103	20190731	0.0149	0.1587	-0.0568	24.4307	***	0.4015	0.6221	0.3797	2.0216	
Frozen pork bellies	Meats	CME	20000103	20110705	0.0501	0.2878	0.0073	6.8627		0.3330	0.7139	0.6701	9.1232	
Cocoa	Misc. other softs	NYMEX/ICE	20000103	20190731	0.0477	0.3066	0.0151	12.7692	**	0.3133	0.4916	0.2303	11.7705	**
Coffee C	Misc. other softs	NYMEX/ICE	20000103	20190731	-0.1239	0.3015	0.0138	10.0666	**	0.2561	0.4758	0.1370	3.5435	
Frozen Orange juice	Misc. other softs	ICE/NYMEX	20000103	20190731	-0.0285	0.3213	0.0206	6.7067		0.3002	0.6933	0.5984	5.6033	
Lumber	Misc. other softs	CME	20000103	20190731	-0.1405	0.3090	0.0254	6.6253		0.4071	0.6581	0.3839	8.2810	
II. Energy sector (N=5)														
Light crude oil	Energy	NYMEX	20000103	20190731	0.0015	0.3354	-0.0071	8.4339		0.0957	0.2943	0.0567	4.6837	
Gasoline RBOB	Energy	NYMEX	20051010	20190731	-0.0066	0.3208	-0.0153	13.2306	**	0.2599	0.4597	0.2902	0.6204	
Heating oil	Energy	NYMEX	20000103	20190731	0.0453	0.3137	0.0258	1.4690		0.2345	0.7103	0.2710	2.8640	
Natural gas	Energy	NYMEX	20000103	20190731	-0.2525	0.4518	0.0311	3.6754		0.0901	0.3145	0.1457	8.8259	
NY unleaded gas	Energy	NYMEX	20000103	20070102	0.2341	0.3583	-0.0168	1.6422		0.2599	0.4597	0.2902	0.6204	
III. Metals (N=5)														
Copper (High Grade)	Base metals	COMEX	20000103	20190731	0.0582	0.2628	-0.0295	7.2373		0.1651	0.3887	0.0492	2.6334	
Gold 100oz (CMX)	Precious metals	COMEX	20000103	20190731	0.0597	0.1728	-0.0212	1.0125		0.1173	0.3305	0.0888	2.4347	
Palladium	Precious metals	NYMEX	20000103	20190731	0.0466	0.3385	0.0492	3.2318		0.3002	0.6427	0.4248	0.8445	
Platinum	Precious metals	NYMEX	20000103	20190731	0.0464	0.2244	0.0418	1.3216		0.2599	0.6941	0.3690	17.8296	***
Silver 5000 oz	Precious metals	COMEX	20000103	20190731	0.0334	0.2998	0.0133	4.2484		0.0919	0.4855	0.1958	7.1475	

This table summary statistics for the commodity futures excess returns and media tone: mean, standard deviation, first-order autocorrelation (AC1), and Ljung-Box test statistic (LB4) for the null hypothesis that the first four autocorrelations are jointly zero.

3.2.4 Commodity Media Tone Index

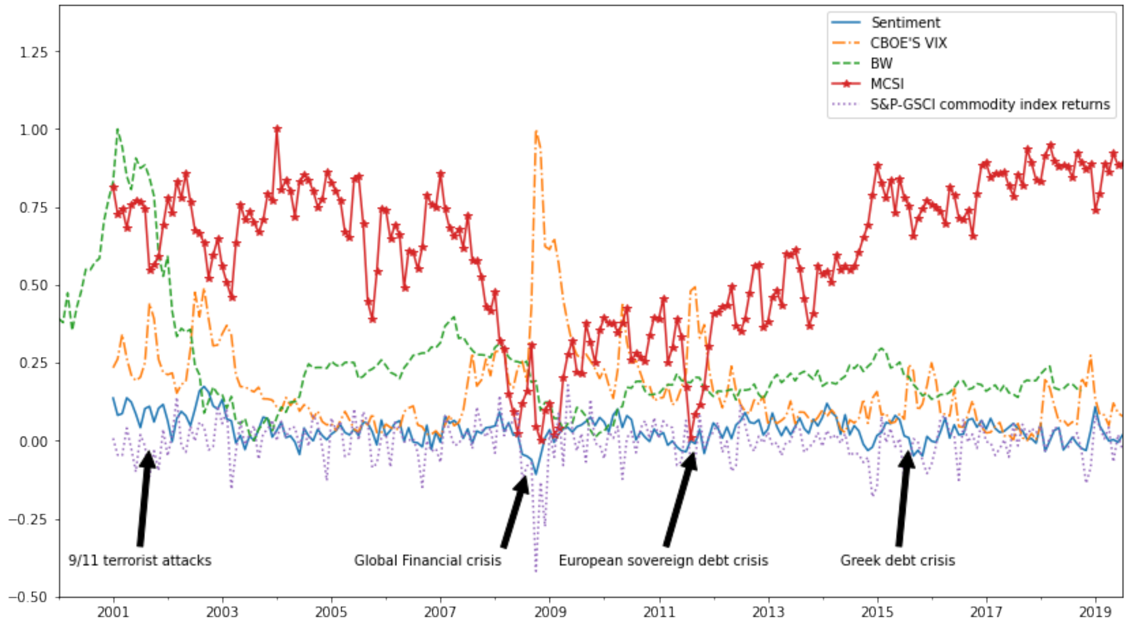
Next the commodity media tone scores are aggregated into an index that proxies commodity investor sentiment, $-1 \leq Sentiment_t \leq 1$, by weighing more heavily the sentiment scores of those commodities that have tended to receive greater media attention. Formally, the commodity investor sentiment index is obtained as follows

$$Sentiment_t = \frac{1/N \sum_{i=1}^{N} coverage_{i,t} * Med_{i,t} - 50}{50} \tag{3.2.2}$$

with the loading $coverage_{i,t}$ defined as the average number of news articles published on the ith commodity within the most recent 4-week window reflecting the commodity-specific trend in the intensity of news as a proxy for investor attention. Thus, the market Media-Tone Index for week t is defined as a weighted average of $Med_{i,t}$ using $coverage_{i,t}$ as weights. Figure 3.1 shows a comparison between the monthly market media tone index, Baker and Wurgler Sentiment Index (BW sentiment index hereafter) and the SP-GSCI commodity market index levels which is a proxy for the commodity futures market as a whole. Compare with the BW sentiment index, our constructed media tone index fits the fluctuations of the market index much better.

Reassuringly, the commodity media tone index thus constructed is positively correlated with widely-used sentiment measures in the empirical finance literature such as the VIX, Baker and Wurgler (2006) sentiment index, and Michigan Consumer Sentiment Index at -0.0062, 0.2171 and 0.3745, respectively. Table 3.3 reports the correlation coefficients.

Figure 3.1: A Plot of Media-Tone Index and Commodity Market Index Levels



This figure illustrates the Media Tone index, CBOE's VIX index, Baker and Wurgler Sentiment Index, Michigan Consumer Sentiment Index, and the S&P-GSCI Commodity Market Index over the sample period from January 2000 to July 2019. All indices are in monthly frequency and are re-scaled between -1 to 1.

3.3 Methodology

3.3.1 Predictive Ability of Media Tone Index for Commodity Market Movements

We begin by assessing the predictive ability of media tone for commodity futures returns through the following two-way fixed effects panel regression model:

$$r_{i,t+1} = \eta_i + \mu_t + \gamma MedTone_{i,t} + \theta Z_{i,t} + \epsilon_{i,t+1} \tag{3.3.1}$$

where $r_{i,t+1}$ denotes the excess return of the ith commodity futures contract on week $t+1$, the coefficients η_i (fixed effects) capture unobserved heterogeneity

Table 3.3: Correlations between Media Tone Index and Other Sentiment Indices

	MedTone	**ΔVIX**	**BW**	**MSCI**
MedTone	1.000	0.016	0.251	0.367
ΔVIX		1.000	0.054	0.052
BW			1.000	0.316
MSCI				1.000

among commodity futures contracts, μ_t accommodates also unobserved time effects that are common to all contracts, $MedTone_{i,t}$ is the commodity media tone or sentiment score for the ith commodity measured on week t (Monday), and the control vector $Z_{i,t}$ contains 9 commodity futures characteristics employed in the commodity futures markets literature as predictive signals for subsequent returns. Using the taxonomy in Fernandez-Perez et al. (2020), these characteristics are classified as related to fundamentals (roll yield, momentum, hedging pressure, convexity), tail risk (skewness, 1%VaR, and 99%VaR) and volatility/illiquidity (basis-momentum and illiquidity) as control variables; the sorting signals and background references are provided in Table 3.4. The null hypothesis that media tone has no predictive ability, $H_0 : \gamma = 0$, is tested with a t-statistic based on White Period standard errors that accommodate arbitrary heteroscedasticity and within cross-section serial correlation. Towards a more complete assessment of the predictive role of media tone, the following time-series regression is estimated for the commodity market as a whole:

$$r^{MKT}_{t+1} = \alpha + \gamma Sentiment_t + \theta S_t + \epsilon_{t+1} \tag{3.3.2}$$

where r^{MKT}_{t+1} is the cumulative excess return from the entire commodity market as proxied by the SP GSCI index. $Sentiment_t$ is the week t commodity investor sentiment index as defined in Equation (3.2.2), and the control vector S_t contains the VIX, the Baker and Wurgler (2006) investor sentiment index and the Michi-

Table 3.4: Sorting Signals and Background References

Panel A: Long-only portfolio					
Equally-weighted weekly rebalanced portfolio of all commodities		$AVG_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}$	All commodities	Observations at time t	Erb and Harvey (2006), Gorton and Rouwenhorst (2006), **Bakshi2019**
Panel B: Long-short portfolios					
Basis	Roll yield or basis defined as difference in log prices of the nearest and second-nearest futures contracts with maturity time $T1$ and $T2$, respectively	$ln(F_{i,t}^{T1}) - ln(F_{i,t}^{T2})$	Higher signal	Observations at time t	Gorton et al. (2013), Szymanowska et al. (2014), Bakshi et al. (2019), Koijen et al. (2018)
Momentum	Average weekly excess return of the commodity over the past year (W = number of weeks within the past year)	$\frac{1}{W}\sum_{w=0}^{W-1} r_{i,t-w}$	Higher signal	Observations in the 52 weeks preceeding t	Erb and Harvey (2006), Miffre and Rallis (2007), Bakshi et al. (2019)
Hedging pressure	Standardized weekly net open interest of hedgers (short positions minus long positions over total positions) on average over the past year	$\frac{1}{W}\sum_{w=0}^{W-1} \frac{H_{i,t-w}^{short} - H_{i,t-w}^{long}}{H_{i,t-w}^{short} + H_{i,t-w}^{long}}$	Higher signal	Observations in the 52 weeks preceeding t	Basu and Miffre (2013), Bianchi et al. (2015)
Convexity	Difference between front and further-into-the-curve basis scaled by the maturity time difference	$\frac{ln(F_{i,t}^{T1}) - ln(F_{i,t}^{T2})}{T2-T1} - \frac{ln(F_{i,t}^{T2}) - ln(F_{i,t}^{T3})}{T3-T2}$	Higher signal	Observations at time t	Gu et al. (2019)
Skewness	Cefficient of skewness for distribution of daily returns over past year (D = number of trading days within the previous year)	$\frac{\sum_{d=1}^{D}(r_{i,d}-\mu_i)^3}{D}$	Lower signal	D = Number of days in the year preceeding t	Fernandez-Perez et al. (2018)
VaR1	1st percentile of the distribution of daily returns within the past year ($d = 1, \ldots, D$)	$r_{i(1)} \| P(r_{i,d} > r_i(1) = 99\%)$	Lower signal	Daily observations in the year preceeding t	Atilgan et al. (2019)
VaR99	99th percentile of the distribution of daily returns within the past year ($d = 1, \ldots, D$)	$r_{i(99)} \| P(r_{i,d} > r_i(99) = 1\%)$	Lower signal	Daily observations in the year preceeding t	Atilgan et al. (2019)
Basis momentum	Difference in momentum of front contract and second nearest contract	$Mom_{i,t}^{T1} - Mom_{i,t}^{T2}$	Higher signal	Observations in the 52 weeks preceeding t	Boons and Prado (2019)
Liquidity	Daily price change per dollar volume on average over the past D2 days (D2 = number of trading days in the 2 months preceding t)	$\frac{1}{D}\sum_{j=0}^{D2-1} \frac{\|r_{i,t-j}\|}{\$Volume_{i,t-j}}$	Higher signal	D = Number of days in the 2 months preceeding t	Amihud (2002)

gan Consumer confidence index which are widely-used proxies of market sentiment in the literature. The null hypothesis is that sentiment has no predictive ability ($\gamma = 0$) for the dynamics of the commodity market, in which case Equation (3.3.2) reduces to the constant expected return model ($r_{t+1}^{MKT} = \alpha + \epsilon_{t+1}$). The first-order autocorrelation coefficient or correlation between the current week and the prior week's value of prediction (returns) is 0.01 and that of the predictor is 0.47. The no-predictive-ability hypothesis is assessed via t-tests with Newey-West h.a.c standard errors and, as in Huang et al. (2015) by means of the wild bootstrapped empirical p-value that accounts for general forms of the return distribution. Procedures of bootstrapped empirical p-value are shown in Appendix 3.8.2. Since the BW and Michigan Consumer Sentiment index observations available are month-end, Equation (3.3.2) is estimated at a monthly frequency. For this purpose, the weekly sentiment indices obtained as in Equation (3.2.2) for weeks one to four on each month-end are aggregated into an end-of-month sentiment index using an exponential-decay weighted average,

$$Sentiment_{t,month} = \frac{0.9^0 * Sentiment_t + ... + 0.9^3 * Sentiment_{t-3}}{0.9^0 + ... + 0.9^3}$$

3.3.2 Extensions of Predictability Analysis: General Forms of Asymmetry

The predictive regression tests based on Equations (3.3.1) and (3.3.2) are refined in two directions to study asymmetries in the impact of investor sentiment on commodity futures prices. First, the predictive ability of positive and negative media tone is gauged by generalizing Equations (3.3.1) and (3.3.2) as

$$r_{i,t+1} = \eta_i + \mu_t + \gamma^+ MedTone_{i,t} \times I_t^+ + \gamma^- MedTone_{i,t} \times (1 - I_t^+) + \gamma Z_{i,t} + \epsilon_{i,t+1} \tag{3.3.3a}$$

$$r_{t+1}^{MKT} = \alpha + \gamma^+ Sentiment_t \times I_t^+ + \gamma^- Sentiment_t \times (1 - I_t^+) + \theta S_t + \epsilon_{t+1} \tag{3.3.3b}$$

where I_t^+ is an indicator function equal to 1 if the sentiment index, Equation (3.2.2), is positive and 0 else. Second, as in Rapach et al. (2010), the Bai and Perron (1998) test for structural breaks is deployed in the context of Equations (3.3.1) and (3.3.2) to investigate whether there are changes over time in the predictive ability of sentiment.

3.3.3 OOS Predictive Ability of Media Tone Index for Commodity Market Movements

In order to shield the preceding analyses from the potential criticism of look-ahead-bias or the problem that in-sample predictability does not necessarily translate into predictability in real time (e.g. Goyal and Welch (2008) the paper provides an out-of-sample predictive analysis. For this purpose, the panel fixed effect model, Equation (3.3.1), and time-series model, Equation (3.3.2), are estimated sequentially over rolling windows of fixed size T_0 weeks. This approach facilitates a sequence of one-step-ahead OOS forecasts, each of them is conditional on the sentiment prevailing on the last week of the rolling window; namely

$$\hat{r}_{i,t+1} = \hat{\eta}_i + \hat{\mu}_t + \hat{\gamma} MedTone_{i,t}, \;\; i = 1, ..., N \tag{3.3.4a}$$

$$\hat{r}^{MKT}_{t+1} = \hat{\alpha} + \hat{\gamma} Sentiment_t \tag{3.3.4b}$$

respectively for Equation (3.3.1) and (3.3.2). They also compute the historical average return over each rolling window $\bar{r}_{i,t+1}$ and $\bar{r}^{MKT}_{t+1}$ which represents the prediction from the constant expected return model. Thus they compute the OOS predictability measure of Campbell and Thompson (2008)

$$R^2_{OOS} = 1 - \frac{\sum_{i=1}^{N}\sum_{t=T_0}^{T}(r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{i=1}^{N}\sum_{t=T_0}^{T}(r_{i,t+1} - \bar{r}_{i,t+1})^2} \tag{3.3.5a}$$

$$R^2_{OOS} = 1 - \frac{\sum_{t=T_0}^{T}(r^{MKT}_{t+1} - \hat{r}^{MKT}_{t+1})^2}{\sum_{t=T_0}^{T}(r^{MKT}_{t+1} - \bar{r}^{MKT}_{t+1})^2} \tag{3.3.5b}$$

giving the proportional reduction in mean squared error that a predictive model attains versus the historical average benchmark. The initial estimation window contains 260 weeks (T_0) and thus R^2_{OOS} is based on 1022 forecasts ($T_1 = T - T_0$).

For completeness, the authors also provide a comparative analysis of the OOS predictive power of different commodity characteristics, $R^2_{OOS,j}$ where j denotes either the commodity-specific media tone scores, or either of the traditional commodity characteristics (roll-yield, momentum, hedging pressure, convexity, skewness, VaR1, VaR99, basis-momentum and illiquidity). A pooled regression for all $i = 1, .., N$ commodities with a predictive horizon of one week ($h = 1$) is estimated sequentially over rolling windows of fixed size T_0 weeks. This approach facilitates a sequence of one-step-ahead OOS forecasts, each of them obtained conditionally on the commodity characteristic measured on the last week of the rolling window, e.g. $\hat{r}_{i,t+1} = \hat{\mu} + \hat{\gamma} MedTone_{i,t}$ for the media tone scores and likewise for the other commodity characteristics. The size of the initial estimation window is as indicated above, 260 weeks (T_0) and thus $R^2_{OOS,j}$ summarizes a total of $T_1 \times N$ forecasts ($T_1 = T - T_0 = 1022$ and $N = 26$). A similar OOS forecasting exercise is computed for each of the alternative commodity characteristics.

3.3.4 Long-short Sentiment Portfolios

The paper further assesses whether it is possible to exploit media tone to generate economic value from a portfolio perspective. For this purpose, the paper begins by deploying a novel portfolio strategy using the media tone scores per commodity, Equation (3.2.1), as sorting signal $\theta_{i,t} \equiv Med_{i,t}$ on the Monday of each sample week t. Accordingly, the commodity futures contracts are grouped into quintiles and a long-short media tone portfolio is formed where long (short) positions are taking on the commodity futures contracts in the top (bottom) quintile Q1 (Q5) which are those with the most positive (negative) media-tone scores. The commodities in the long and short legs of the portfolios are equally weighted and the investor is fully invested; that is, the final allocation weights are $\widetilde{\theta}_{i,k,t} = \theta_{i,k,t} \sum_{i=1}^{\widetilde{N}} |\theta_{i,k,t}|$ such that $\sum_{i}^{\widetilde{N}} |\widetilde{\theta}_{i,k,t}| = 1$ with $\theta_{i,k,t} = 1$, and $\widetilde{N} = \frac{2}{5}N$ and $\sum_{i}^{L} \widetilde{\theta}_{i,k,t} = \sum_{i}^{S} |\widetilde{\theta}_{i,k,t}| = 0.5$. The long-short portfolios are held for one week on a fully-collateralized basis; thus the excess returns are given by half the longs returns minus half the shorts return (Q1/2-Q2/2).

The intuition is that the optimistic (pessimistic) news tone may have a short-term demand effect that will exert an upward (downward) pressure on prices so a short-term price increase is expected in the commodity futures contracts of Q1

(Q5). This intuition is aligned with the findings in Borovkova (2015) and Gao and Süss (2015) which suggest that adverse sentiment predicts lower commodity futures returns.

The performance of the sentiment portfolio is appraised in the context of a battery of benchmarks as in Fernandez-Perez et al. (2020). A long-only equally-weighted and weekly-rebalanced portfolio of all commodities (AVG) are considered as broad commodity market factors (Bakshi et al., 2019; Erb and Harvey, 2016; Gorton and Rouwenhorst, 2006). Additional risk factors are the excess returns of long-short portfolios inspired by the fundamentals of backwardation and contango; specifically, backwardated commodities with high roll-yield (Bakshi et al., 2019; Erb and Harvey, 2016; Gorton and Rouwenhorst, 2006), high past average returns (Bakshi et al., 2019; Erb and Harvey, 2016; Miffre and Rallis, 2007), high net-short hedging (Basu and Miffre, 2013; Bianchi et al., 2015; Kang et al., 2020) or a convex price curve (Gu et al., 2019) are expected to outperform contangoed commodities with opposite values of the aforementioned characteristics. It is also possible to motivate tail risk factors constructed as the returns of long-short portfolios sorted by skewness (Fernandez-Perez et al., 2018), 1% and 99% Value-at-Risk, hereafter denoted as VaR1 and VaR99 (Atilgan et al., 2019; Bali et al., 2009[2]) . Finally, the excess returns of the sentiment portfolio could relate to liquidity and volatility risks factors obtained as the returns of long-short portfolios where the sorting signal is the basis-momentum of Boons and Prado (2019) and the illiquidity measure suggested by Amihud (2002).

[2]As dictated by rational asset pricing theory, higher risk is associated with higher expected returns. Thus the skewness and VaR1 factors are constructed as the returns of portfolios with long positions in the futures contracts with the most negative skewness and VaR1 signals (see Table 3.4). Since investors have preferences for lottery type assets, the VaR99 factor is constructed as the returns of a portfolio with long (short) positions in futures contracts with the least (most) positive VaR99 signal.

3.3.5 Sentiment-adjusted Tactical Allocations

The next task is to embed the media tone information into extant tactical allocation strategies which rely on the commodity futures characteristics (sorting signals) listed in Table 3.4.

This paper's novel idea is to adjust the sorting signals to incorporate the information content of media tone. For example, if commodity i has a highly positive roll-yield (i.e., it is a good candidate for the long leg of the carry portfolio) the adjusted roll-yield signal is higher (lower) if the media tone score is extremely positive (negative), making it a more (less) attractive candidate for the long portfolio than otherwise it would have been. Vice versa, if commodity i has a relatively low (negative) roll-yield and is therefore a good candidate for the short leg of the carry portfolio, the adjusted roll-yield signal makes it a more (less) attractive candidate for the short portfolio if the media tone score is extremely negative (positive). The adjusted signals $x^*_{i,t}$ are derived from the original signals $x_{i,t}$ as follows

$$x^*_{i,t} = \frac{x_{i,t} + 1_{\{MedTone_{i,t} \in D_{10}\}} - 1_{\{MedTone_{i,t} \in D_1\}}}{\left| \sum_{i=1}^{N} x_{i,t-1} + 1_{\{MedTone_{i,t-1} \in D_{10}\}} - 1_{\{MedTone_{i,t} \in D_1\}} \right|} \tag{3.3.6}$$

where $1_{\{MedTone_{i,t} \in D_{10}\}}$ and $1_{\{MedTone_{i,t} \in D_1\}}$ are indicator functions equal to 1 if the ith commodity is in the 10th and 1st decile, respectively, of the commodities sorted by $MedTone_{i,t}$ in ascending order. The baseline long-short portfolio essentially uses $x_{i,t}/\sum_{i=1}^{N} x_{i,t-1}$ as sorting signals whereas the adjusted long-short term structure portfolio uses $x^*_{i,t}$ as sorting signal; the adjusted portfolios strategy proceeds otherwise (equal-weighting allocation scheme $\widetilde{\theta}_{i,k,t} = 1/\widetilde{N}$, full-collateralization and one-week holding period) as described earlier.

3.4 Empirical Results

3.4.1 Predictive Ability of Media Tone Index

The statistical tests based on the 2-way panel fixed effects regressions reported in Table 3.5 reveal that the coefficient of the one-week-lagged commodity-specific media tone score, γ in Equation (3.3.1), is significant and positive in the base model, and after controlling for fundamental (roll yield, momentum, hedging pressure, and convexity), tail-risk (skewness, VaR1, and Var99) and liquidity signals (basis-momentum, and Amihud measure). The positive coefficient suggests that an optimistic media tone exerts a short term upward effect on the commodity futures prices. This in-sample predictability of commodity-specific media tone is confirmed by the results in Table 3.6 which reveal that the news sentiment index, Equation (3.2.2), can significantly anticipate short term changes in the SP-GSCI index after controlling for other widely-used measures of broader market sentiment. Specifically, the in-sample predictive ability (Adj.-R^2) of the baseline model with the news sentiment index at 3.70% only increases slightly when the model also incorporates either the BW index (4.60%) or the Michigan Consumer Confidence Index (4.90%). The second row in Panel B shows that out-of-sample the predictive ability of the news sentiment index at 3.28% is greater than that of the BW index (1.54%) and Michigan index (1.31%).

As regards the out-of-sample predictive ability, as shown in Panel B of Table 3.5, the R^2_{OOS} in a model with media tone as a single predictor at 10.43% is in many cases similar to the R^2_{OOS} in the same model augmented with one other commodity characteristic ranging from 11.20% (base model augmented with skewness) to 15.35% (basis-momentum). The last row reports the R^2_{OOS} of the different single-predictor models. The last two columns reveal that the out-of-sample predictive ability of the full model can be increased by about 10.92% by adding the media

Table 3.5: In- and Out-of-sample Predictive Ability of Commodity-specific Media Tone Scores

	Base model	Base model augmented with													
		Fundamental signals					Tail risk signals				Iliquidity/volatility risk signals			All signals	
Panel A: In-sample predictive ability															
MedTone	0.1449	0.1480	0.1418	0.1347	0.1540	0.1431	0.1438	0.1430	0.1428	0.1436	0.1604	0.1391	0.1552		0.1473
	(2.95)	(2.99)	(2.89)	(2.71)	(3.15)	(2.88)	(2.93)	(2.92)	(2.91)	(2.93)	(3.12)	(2.80)	(2.98)		(2.77)
Basis		-0.7902				-0.2036								-0.5757	-0.7939
		(-1.18)				(-0.15)								(-0.40)	(-0.59)
Momentum			0.0335			0.0685								0.0216	-0.0585
			(0.40)			(0.78)								(0.21)	(-0.59)
Hedging pressure				0.1039		0.0278								0.1672	0.1878
				(0.87)		(0.23)								(1.24)	(1.43)
Convexity					-0.4109	-0.5336								-0.9737	-0.4230
					(-1.09)	(-0.69)								(-1.36)	(-0.53)
Skewness							0.0295			0.0285				0.0302	0.0149
							(0.94)			(0.92)				(0.82)	(0.46)
VaR1								-0.3983		-0.7765				-5.3907	-3.2664
								(-0.58)		(-0.59)				(-1.64)	(-2.15)
VaR99									-0.3758	-0.8125				-5.6667	-3.1443
									(-0.59)	(-0.65)				(-1.68)	(-1.98)
Basis-momentum											0.8863		0.8997	0.6978	1.1872
											(2.97)		(2.98)	(2.39)	(3.81)
Liquidity												-0.1316	-0.1629	-0.2485	-0.2054
												(-0.46)	(-0.56)	(-0.86)	(-0.68)
Adj.R^2 (%)	0.05	0.03	0.06	0.07	0.03	0.05	0.06	0.04	0.04	0.05	0.15	0.04	0.15	0.12	0.14
Panel B: Out-of-sample predictive analysis															
OOS R^2 (%)	10.43	11.50	11.38	11.94	14.76	17.85	11.20	11.53	11.55	12.87	15.35	12.68	17.39	13.00	23.92
OOS R^2 (%) single	10.43	-3.70	-3.24	-2.09	-2.05		-3.45	-2.90	-2.42		0.73	-2.39			

This table reports in Panel A the predictive-ability tests and diagnostics for regressions of the pooled excess returns of all commodity futures on their one-week-lagged media-tone, Equation (3.2.1), as single predictor without and with fundamental (roll-yield, momentum, hedging pressure, convexity), tail risk (skewness, VaR1, VaR99) and volatility/illiquidity (basis-momentum and Amihud illiquidity) signals as controls. The numbers in parenthesis are t-ratios based on the White Period covariance matrix that accommodates arbitrary heteroskedasticity and within cross-section serial correlation. Panel B reports the Campbell and Thompson (2008) OOS R2 for the one-week-ahead predictions obtained with the different models sequentially over rolling windows of size $T_0 = 260$ weeks. The sample period is January 2000 to July 2019.

Table 3.6: In- and Out-of-sample Predictive Ability of Commodity-specific Media Tone Index

	Dependent variable with									
	S&P GSCI index					**Bloomberg index**				
Panel A: In-sample predictive analysis										
MedTone index	3.3102	3.2946	2.881	4.1629	3.6139	1.8048	1.7937	1.5170	2.3910	2.0111
	(2.85)	(2.96)	(2.42)	(3.26)	(2.95)	(2.32)	(2.43)	(1.91)	(2.79)	(2.47)
VIX		-0.0427			-0.0424		-0.0306			-0.0309
		(-2.75)			(-2.83)		(-5.07)			(-5.12)
BW index			0.0072		0.1050			0.0048		0.0075
			(1.63)		(2.48)			(1.64)		(2.54)
MCCI				-0.1598	-0.1877				-0.1028	-0.1205
				(-1.90)	(-2.27)				(-1.82)	(-2.20)
Adj.-R^2 (%)	3.70	11.80	4.60	4.90	15.00	2.30	12.10	3.40	3.60	15.60
Panel B: Out-of-sample predictive analysis										
OOS R^2 (%)	3.28	8.33	3.43	3.73	9.96	1.75	9.37	2.51	2.20	7.60
OOS R^2 (%) single	3.28	5.67	1.54	1.31		1.75	4.62	1.63	0.55	

This table reports in Panel A the predictive-ability tests and diagnostics for regressions of the cumulative excess returns from the entire commodity market as proxied by the SP GSCI index and Bloomberg index on the one-week-lagged media-tone index, Equation (3.2.2), as single predictor without and with the VIX, the Baker and Wurgler (2006) investor sentiment index and the Michigan Consumer confidence index as controls. The numbers in parenthesis are HAC t-ratios that accommodates arbitrary heteroskedasticity and within cross-section serial correlation. Panel B reports the Campbell and Thompson (2008) OOS R2 for the one-week-ahead predictions obtained with the different models sequentially over rolling windows of size $T_0 = 260$ weeks. The sample period is January 2000 to July 2019.

tone predictor. Table 3.6 reports the R^2_{OOS} for the SP-GSCI index which indicates that the predictive ability of the commodity investor sentiment measure proposed in the paper is superior to that of widely-used sentiment measures which are more general as opposed to specific to the commodity market.

The analysis of asymmetries adduces more pervasive evidence (across different horizons) of predictability when the sentiment index reveals pessimism than when it reveals optimism. A structural break test applied to Equation (3.3.2) reveals two breaks and accordingly, three sub-periods of media-tone predictive ability: pre-crisis from January 1, 2000 to February 23, 2008, crisis from February 24, 2008 to November 18, 2012, and the post-crisis period from November 19, 2012 to July 31, 2019. The predictive ability of media tone in commodity markets is highest during the crisis period which aligns with the notion of wake-up calls namely, commodity futures investors pay more attention to the tone of news during crisis periods and loss aversion. The tests confirm the strongest predictive ability of media tone during the 2008 financial crisis. The evidence is interpreted as suggesting, in line with prospect theory, that institutional investors tend to behave as rational agents with Bayesian beliefs when they are within their comfort zone, namely, when news sentiment is optimistic, but reacts more strongly to adverse news (which acts as a wake-up call) due to loss aversion in potentially high-risk environments such as the 2008-2012 crisis period.

3.4.2 Long-short Sentiment Portfolios

A trading strategy that longs the top quintile of commodities with the most positive sentiment, defined as in Equation (3.2.1), and shorts the bottom quintile with the most negative sentiment generates attractive excess returns of 11.9% per annum (p.a.) and a high Sharpe ratio of 0.832 which compares with that of traditional long-short allocation strategies. The performance of the Q1 to Q5 quintiles

Table 3.7: Asymmetric Effects of Predictive Ability of Commodity-Specific Media Tone Scores

		Base predictive model augmented with														
		Fundamental signals					Tail risk signals				Illiquidity/volatility risk			All signals	
Panel A: In-sample predictive analysis															
γ^+	0.0840	0.0909	0.0831	0.0678	0.0829	0.0638	0.0836	0.0836	0.0851	0.0838	0.0899	0.0804	0.0850		0.0639
	(0.89)	(0.96)	(0.88)	(0.72)	(0.86)	(0.66)	(0.89)	(0.89)	(0.90)	(0.89)	(0.91)	(0.84)	(0.85)		(0.63)
γ^-	-0.2135	-0.2160	-0.2116	-0.2139	-0.2391	-0.2379	-0.2153	-0.2136	-0.2113	-0.2151	-0.2460	-0.2075	-0.2399		-0.2488
	(-2.01)	(-2.03)	(-1.98)	(-2.01)	(-2.19)	(-2.15)	(-2.03)	(-2.01)	(-1.97)	(-2.03)	(-2.18)	(-1.93)	(-2.10)		(-2.11)
Basis		-0.7928				-0.2025								-0.5758	-0.7919
		(-1.18)				(-0.15)								(-0.40)	(-0.59)
Momentum			0.0319			0.0660								0.0048	-0.0322
			(0.38)			(0.75)								(0.05)	(-0.34)
Hedging pressure				0.1092		0.0346								0.1709	0.1973
				(0.91)		(0.28)								(1.27)	(1.50)
Convexity					-0.4157	-0.5371								-0.9725	-0.4275
					(-1.10)	(-0.69)								(-1.36)	(-0.54)
Skewness							0.0299			0.0299				0.0302	0.0149
							(0.96)			(0.96)				(0.82)	(0.45)
VaR1								-0.3860		-0.7765				-5.3907	-3.2772
								(-0.56)		(-0.59)				(-1.64)	(-2.16)
VaR99									-0.3979	-0.8368				-5.6667	-3.1830
									(-0.62)	(-0.67)				(-1.68)	(-2.01)
Basis-momentum											0.8837		0.8969	0.6994	1.1895
											(2.96)		(2.97)	(2.39)	(3.82)
Liquidity												-0.1153	-0.1434	-0.2430	-0.1868
												(-0.40)	(-0.49)	(-0.84)	(-0.62)
Adj.-R² (%)	0.40	0.60	0.40	0.40	0.60	0.60	0.40	0.40	0.40	0.05	0.12	0.40	0.12	0.12	0.13

	Subperiod 1			Subperiod 2			Subperiod 3		
	Base model	Base model augmented with		Base model	Base model augmented with		Base model	Base model augmented with	
		All signals			All signals			All signals	
Panel B: In-sample predictive ability									
MedTone	0.0510		0.0593	0.6263		0.6232	0.2162		0.2354
	(0.73)		(0.77)	(2.23)		(2.18)	(2.75)		(2.80)
Basis		-0.2428	-1.1604		-3.9349	-6.1949		-0.2062	1.1127
		(-0.11)	(-0.56)		(-1.79)	(-2.32)		(-0.10)	(0.69)
Momentum		0.0016	0.3234		-0.5179	-0.7230		0.2116	-0.0600
		(0.01)	(2.03)		(-1.42)	(-1.91)		(0.67)	(-0.33)
Hedging pressure		0.2259	0.3285		0.5029	0.3674		-0.0086	-0.0163
		(0.88)	(1.31)		(0.69)	(0.50)		(-0.04)	(-0.08)
Convexity		-1.0520	-0.8895		0.5406	3.4727		-1.5592	-2.0761
		(-0.80)	(-0.72)		(0.39)	(2.13)		(-1.66)	(-2.24)
Skewness		-0.1695	-0.2196		-0.1185	0.0156		-0.3484	-0.0720
		(-1.58)	(-2.04)		(-0.38)	(0.05)		(-1.18)	(-0.57)
VaR1		-4.4891	-5.9461		3.8866	5.8041		-7.9087	-1.7094
		(-1.97)	(-2.56)		(0.74)	(1.08)		(-1.24)	(-0.72)
VaR99		-6.7949	-7.8065		1.9296	2.8889		-8.1885	-0.2137
		(-2.87)	(-3.37)		(0.39)	(0.54)		(-1.24)	(-0.08)
Basis-momentum		1.6459	2.0480		1.2697	0.7975		0.4949	0.3291
		(3.01)	(3.48)		(1.61)	(1.11)		(1.09)	(0.64)
Liquidity		-0.4622	-0.5966		3.3972	2.2558		2.0090	-0.0623
		(-1.15)	(-1.41)		(1.56)	(1.14)		(0.35)	(-0.01)
Adj.R²(%)	0.00	0.35	0.47	0.29	0.71	0.95	0.07	0.26	0.43

This table reports in Panel A the predictive ability of positive and negative media tone gauged by Equations (3.3.3a) and (3.3.3b). Panel B reports the changes over time in the predictive ability of sentiment. Subperiods 1-3 covers sub-samples ranging from January 1, 2000 to February 23, 2008, from February 24,2008 to November 18, 2012, and from November 19, 2012 toJuly 31, 2019 respectively.

and Q1-Q5 portfolio formed according to the sentiment measure are summarized in Table 3.8.

Table 3.8: Long-Short Sentiment Portfolios

	Long				Short	
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Mean	0.071	0.015	-0.031	-0.063	-0.048	0.119
	(2.27)	(0.44)	(-0.81)	(-2.63)	(-2.24)	(3.88)
Volatility	0.138	0.151	0.163	0.153	0.140	0.143
Downside risk	0.212	0.244	0.271	0.264	0.235	0.198
Skewness	-0.422	-0.569	-0.682	-0.857	-0.535	0.177
	(-5.33)	(-6.99)	(-8.17)	(-9.85)	(-6.61)	(2.30)
Excess Kurtosis	2.631	2.616	4.497	4.736	2.558	0.681
	(8.24)	(8.21)	(10.50)	(10.72)	(8.12)	(3.52)
JB normality test p-value	0.000	0.000	0.000	0.000	0.000	0.000
AC1	-0.011	0.047	0.020	-0.024	0.100	-0.044
1% VaR (Cornish Fisher)	-0.043	-0.048	-0.053	-0.051	-0.046	-0.044
Max drawdown	-0.421	-0.537	-0.820	-0.799	-0.703	-0.271
Sharpe ratio	0.512	0.103	-0.188	-0.410	-0.345	0.832
Sortino ratio	0.732	0.139	-0.249	-0.522	-0.452	1.324
Omega ratio	1.211	1.039	0.932	0.857	0.879	1.349
CER (power utility)	0.012	0.001	0.005	0.002	0.004	0.000

Firs five columns of this table report the performance of the Q1 to Q5 quintiles portfolios formed according to the sentiment measure $MedTone_{i,t}$. Column six reports the performance of a trading strategy that longs the top quintile of commodities with the most positive sentiment, defined as in Equation (3.2.1), and shorts the bottom quintile with the most negative sentiment. All measures are annualized.

The excess returns of the sentiment-sorted long-short portfolio are mildly correlated to those of traditional long-short portfolios formed according to an array of commodity characteristics such as hedging pressure, roll-yield, momentum and convexity. Details are shown in Table 3.9. For concreteness, the largest correlation in absolute value is 0.0699 for the sentiment portfolio and skewness portfolio and the smallest is 0.0044 for the sentiment portfolio and momentum portfolio.

Table 3.9: Correlation between the Sentiment-sorted Long-short Portfolio and Traditional Long-short Commodity Portfolios

	Sentiment	AVG	Agriculture	Metal	Energy	Carry	Momentum	Hedging Pressure	Convexity	Skewness	VaR1	VaR99	Basis_Mom	Liquidity
Sentiment	1.0000	-0.0093	0.0389	-0.0306	-0.0570	0.0445	0.0044	0.0155	0.0403	-0.0699	-0.0673	-0.0197	0.0637	-0.0140
AVG	-0.0093	1.0000	0.8494	0.6736	0.6842	0.1038	0.1472	0.1857	-0.2557	0.2041	0.4793	-0.4120	-0.0151	-0.1633
Agriculture	0.0389	0.8494	1.0000	0.4094	0.2942	-0.0574	0.0373	0.0294	0.1332	-0.0015	0.2256	-0.2680	0.0250	-0.2828
Metal	-0.0306	0.6736	0.4094	1.0000	0.3083	0.1363	0.2104	0.5258	-0.1504	0.3225	0.2424	-0.1315	0.0638	0.1558
Energy	-0.0570	0.6842	0.2942	0.3083	1.0000	0.2494	0.1671	0.0295	-0.7081	0.2827	0.6506	-0.4960	-0.1093	-0.1138
Carry	0.0445	0.1038	-0.0574	0.1363	0.2494	1.0000	0.5143	0.2262	-0.1627	0.1386	0.0740	-0.1924	0.3375	0.0535
Momentum	0.0044	0.1472	0.0373	0.2104	0.1671	0.5143	1.0000	0.3420	-0.1018	0.2009	-0.0436	-0.1868	0.4080	-0.1082
Hedging Pressure	0.0155	0.1857	0.0294	0.5258	0.0295	0.2262	0.3420	1.0000	0.0256	0.2699	0.0565	-0.0581	0.1547	0.1423
Convexity	0.0403	-0.2557	0.1332	-0.1504	-0.7081	-0.1627	-0.1018	0.0256	1.0000	-0.3125	-0.4621	0.2412	0.1616	0.0224
Skewness	-0.0699	0.2041	-0.0015	0.3225	0.2827	0.1386	0.2009	0.2699	-0.3125	1.0000	0.3616	0.1362	0.0150	-0.1903
VaR1	-0.0673	0.4793	0.2256	0.2424	0.6506	0.0740	-0.0436	0.0565	-0.4621	0.3616	1.0000	-0.6063	-0.1448	-0.0640
VaR99	-0.0197	-0.4120	-0.2680	-0.1315	-0.4960	-0.1924	-0.1868	-0.0581	0.2412	0.1362	-0.6063	1.0000	-0.0257	-0.0300
Basis_Mom	0.0637	-0.0151	0.0250	0.0638	-0.1093	0.3375	0.4080	0.1547	0.1616	0.0150	-0.1448	-0.0257	1.0000	0.0100
Liquidity	-0.0140	-0.1633	-0.2828	0.1558	-0.1138	0.0535	-0.1082	0.1423	0.0224	-0.1903	-0.0640	-0.0300	0.0100	1.0000

This table reports the correlation between the excess returns of the sentiment-sorted long-short portfolio and traditional long-short portfolios formed according to an array of commodity characteristics such as hedging pressure, roll-yield, momentum and convexity. AVG stands for the average return of all commodities. Agriculture, metal, and energy represent average returns of commodity future contracts within three sectors respectively.

3.4.3 Sentiment-Scaled Tactical Allocations

The sentiment-adjusted long-short portfolios are shown to accrue larger excess returns and/or lower volatility than the baseline (plain-vanilla) long-short portfolio counterparts which results in significantly larger Sharpe ratios. Results are shown in Table 3.10. For instance, the sentiment-adjusted momentum portfolio accrues a Sharpe ratio of 0.9294 which is significantly larger than the Sharpe ratio of the baseline momentum portfolio at 0.3830 according to the Ledoit and Wolf (2008) differential Sharpe ratio test ($H_0 : \Delta SR = 0$) p-value of 0.0057. Likewise for the carry portfolio (0.8903 vs 0.4945; p-value = 0.015), HP portfolio (0.9167 versus 0.6434; p-value = 0.045), BM portfolio (1.2154 vs 0.8882); p-value =0.016, and convexity portfolio (0.8130 versus 0.2685; p-value = 0.009). These results are not challenged in a battery of robustness checks. To give an intuitive view of the performance of sentiment-adjusted long-short portfolios, we plot in Figure 3.2 cumulative Sharpe ratios of the baseline (plain-vanilla) long-short portfolios against their sentiment adjusted counterparts.

3.5 Pricing Role of Media Tone

3.5.1 Time-series Test

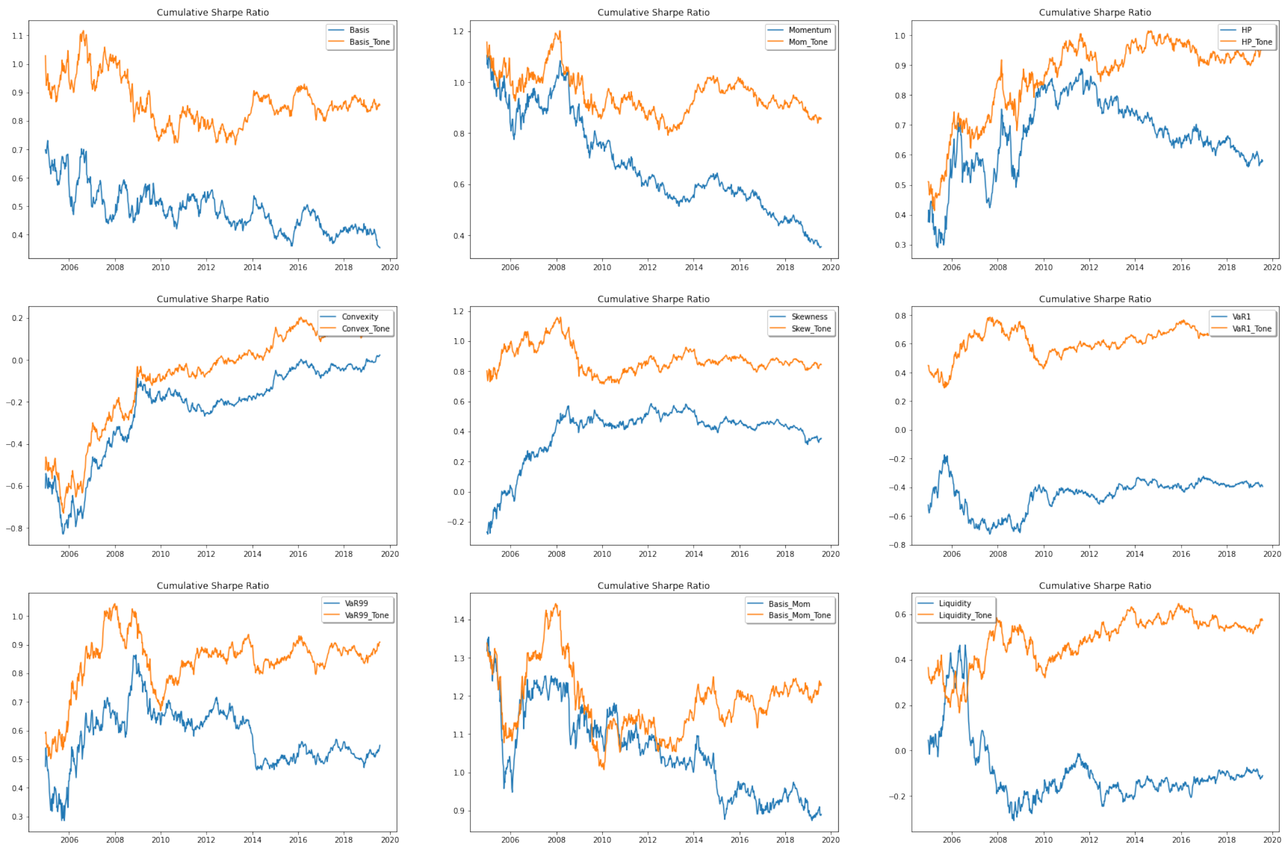
The analysis thus far has revealed that the media tone sentiment strategy is able to capture attractive mean excess returns in commodity futures markets. We now test whether the significant sentiment premium is merely compensation for exposure to risk factors. For this purpose, we start with the three-factor model of Bakshi et al. (2019) that includes the AVG, basis and momentum risk factors and estimate an OLS time-series spanning regression for the excess returns of the media tone sentiment portfolio. We then augment this baseline specification with various

Table 3.10: Sentiment-Scaled Tactical Allocations

	longs-short																	
	Basis	**Basis_Tone**	**Momentum**	**Mom_Tone**	**Hedging pres-sure**	**HP_Tone**	**Convexity**	**Convexity_Tone**	**Skewness**	**Skew_Tone**	**VaR1**	**VaR1_Tone**	**VaR99**	**VaR99_Tone**	**Basis-Momentum**	**BM_Tone**	**Liquidity**	**Liquidity_Tone**
Mean	0.0992	0.0849	0.0886	0.0920	0.1179	0.0809	0.0549	0.0754	0.0578	0.0740	-0.0243	0.0660	0.0130	0.0404	0.1838	0.0869	-0.0544	0.0592
	(2.18)	(3.85)	(1.83)	(4.16)	(2.83)	(4.14)	(1.22)	(3.28)	(1.32)	(3.42)	(-0.50)	(2.70)	(0.50)	(2.14)	(3.96)	(5.32)	(-1.45)	(3.02)
StDev	0.2006	0.0953	0.2314	0.0990	0.1833	0.0882	0.2043	0.0927	0.1987	0.0947	0.2174	0.1071	0.1059	0.0845	0.2069	0.0715	0.1696	0.0871
Downside risk	0.2993	0.1395	0.3541	0.1435	0.2722	0.1260	0.3126	0.1357	0.3051	0.1406	0.3493	0.1580	0.1702	0.1278	0.2822	0.0967	0.2719	0.1256
Skewness	-0.0310	-0.3835	-0.1793	-0.3005	-0.2043	-0.0865	-0.0278	-0.2963	-0.1709	-0.3531	-0.2075	-0.2050	-0.5955	-0.1959	0.2989	0.0499	0.0231	0.0532
	(-0.41)	(-4.88)	(-2.34)	(-3.87)	(-2.66)	(-1.14)	(-0.37)	(-3.82)	(-2.23)	(-4.51)	(-2.70)	(-2.67)	(-7.27)	(-2.55)	(3.85)	(0.66)	(0.30)	(0.70)
Excess Kurtosis	1.8422	2.1759	1.3162	1.4576	0.8129	0.4511	1.6950	2.2919	1.2900	2.8643	3.0446	2.0904	3.3464	1.4450	2.0526	0.5664	1.8575	3.4601
	(6.80)	(7.46)	(5.55)	(5.92)	(4.00)	(2.56)	(6.48)	(7.67)	(5.48)	(8.59)	(8.85)	(7.30)	(9.24)	(5.89)	(7.23)	(3.06)	(6.83)	(9.39)
JB normality test p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0069	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0009	0.0000	0.0000
AC1	0.0501	0.0069	-0.0331	-0.0395	0.0266	0.0134	0.0288	0.0331	-0.0278	-0.0147	-0.0341	-0.0195	0.0165	0.0017	-0.0158	0.0044	-0.0422	-0.0370
1% VaR (Cornish Fisher)	-0.0628	-0.0291	-0.0729	-0.0302	-0.0569	-0.0269	-0.0649	-0.0285	-0.0630	-0.0291	-0.0706	-0.0333	-0.0339	-0.0265	-0.0632	-0.0214	-0.0558	-0.0270
Max drawdown	-0.3929	-0.1693	-0.4897	-0.1708	-0.2837	-0.1598	-0.4830	-0.2209	-0.5456	-0.1570	-0.7903	-0.2552	-0.4998	-0.2706	-0.3626	-0.1428	-0.7801	-0.1581
Sharpe ratio	0.4945	0.8903	0.3830	0.9294	0.6434	0.9167	0.2685	0.8130	0.2911	0.7813	-0.1117	0.6168	0.1230	0.4774	0.8882	1.2154	-0.3209	0.6794
Sortino ratio	0.7294	1.3398	0.5509	1.4110	0.9540	1.4133	0.3863	1.2231	0.4173	1.1578	-0.1530	0.9202	0.1685	0.6953	1.4334	1.9778	-0.4407	1.0369
Omega ratio	1.1933	1.3837	1.1495	1.3944	1.2595	1.3858	1.1023	1.3454	1.1101	1.3348	0.9592	1.2521	1.0465	1.1892	1.3832	1.5411	0.8902	1.2864
CER (power utility)	0.0032	0.0032	0.0041	0.0025	0.0198	0.0035	0.0050	0.0024	0.0237	0.0052	0.0074	0.0058	0.0137	0.0007	0.0056	0.0004	0.0404	0.0102
LW SR test p-value	0.0150		0.0057		0.0450		0.0091		0.0417		0.0225		0.0136		0.0156		0.0141	

This table reports the performance of sentiment-adjusted long-short portfolios in comparison with its un-adjusted counterpart. Last row reports the Ledoit and Wolf (2008) Sharpe ratio test p-value with null hypothesis that sentiment adjusted portfolios have Sharpe ratio smaller or equal than their counterparts.

Figure 3.2: Cumulative Sharpe Ratios of Portfolios



This figure shows cumulative Sharpe ratios of portfolios constructed on 9 different characteristics and their media tone corrected counterparts using a 5-year rolling window.

factors, in turn, that emanate from the literature on the pricing of commodity futures (hedging pressure and convexity), tail-risk (skewness, VaR1 and VaR99) or the liquidity and volatility of commodities (basis- momentum and illiquidity). For each of the specifications, we look at the sign and significance of both the betas and alpha where the latter represents the average excess return of the sentiment portfolio that is not a compensation for the hypothesized risk factors.

Table 3.11 reports the results and shows that the excess returns of the media tone portfolio is insensitive to the risk factors considered. The last column of Table

3.11 reports the "kitchen-sink" model that includes all the risk factors. The only significant term is annualized alpha. Thus, compensation for risk factor exposures does not explain the media tone factor.

3.5.2 Cross-sectional Test

A cross-sectional pricing exercise a la Fama-MacBeth further uses $N = 54$ portfolios as tests assets (the quintiles obtained according to the 9 signals – media tone, roll-yield, HP, momentum, BM and convexity – and the equally-weighted weekly rebalanced portfolios of the commodities grouped into 3 (sub)sectors – agriculture, energy, and metals – suggests that the media tone factor is significantly priced, over and above traditional risk factors. We first estimate full-sample betas via OLS time-series regressions

$$r_{i,t} = \alpha_i + \beta_i * \mathbf{F}_t + \epsilon_{i,t}, \;\; t = 1, ..., T \tag{3.5.1}$$

where $r_{i,t}$ is the time t excess returns of the quintile portfolios sorted on (a) the media tone (b) the 9 characteristics we listed before, and (c) the equally weighted and weekly-rebalanced portfolios from the 4 commodity sub-sectors. Thus, we have $N = 54$ portfolios together. $\mathbf{F}_t$ includes the sentiment factor as well as the 9 characteristics. In step two, we estimate each week the following cross-sectional regression of average excess returns on the step-one estimated full-sample betas

$$\bar{r}_i = \lambda_0 + \boldsymbol{\lambda}\hat{\beta}_i + \epsilon_i, \;\; i = 1, ..., N \tag{3.5.2}$$

where $\boldsymbol{\lambda}$ is a vector containing the prices of risk associated with each of the factors. The baseline model entertains the three risk factors of Bakshi et al. (2019). We subsequently expand this model by cycling through each of the additional long-short risk premia considered in the time-series spanning tests, and then all together

Table 3.11: Time-series Spinning Tests

	Base model								**All risk factors**
		Fundamental risk factors		**Tail risk factors**			**Liquidity and volatility risk factors**		
Annualized alpha	0.0541	0.0542	0.0555	0.0517	0.0522	0.0507	0.0541	0.0542	0.0509
	(3.38)	(3.39)	(3.48)	(3.26)	(3.28)	(3.18)	(3.40)	(3.36)	(3.20)
AVG	-0.0064	-0.0060	-0.0015	0.0011	-0.0037	-0.0049	0.0021	-0.0064	0.0089
	(-0.56)	(-0.51)	(-0.13)	(0.09)	(-0.32)	(-0.42)	(0.17)	(-0.56)	(0.70)
Basis	0.0019	0.0067	0.0102	-0.0035	0.0015	0.0006	-0.0055	0.0009	0.0091
	(0.06)	(0.21)	(0.33)	(-0.11)	(0.05)	(0.02)	(-0.17)	(0.03)	(0.24)
Momentum	-0.0410	-0.0343	-0.0362	-0.0364	-0.0375	-0.0544	-0.0310	-0.0418	-0.0282
	(-1.51)	(-1.15)	(-1.34)	(-1.34)	(-1.37)	(-1.85)	(-1.10)	(-1.50)	(-0.88)
Hedging Pressure		-0.0161							-0.0326
		(-0.50)							(-0.93)
Convexity			-0.0635						-0.0533
			(-2.17)						(-1.34)
Skewness				-0.0650					-0.0324
				(-2.30)					(-0.72)
VaR1					0.0342				0.0153
					(1.21)				(0.34)
VaR99						0.0440			0.0386
						(1.62)			(1.36)
Basis-momentum							0.0571		0.0277
							(1.59)		(0.66)
Liquidity								0.0048	0.0104
								(0.14)	(0.27)
Adj.-R^2 (%)	0.34	0.38	0.91	1.06	0.52	0.66	0.75	0.34	1.84

This table reports estimation results from time-series regressions of the excess returns of the long-short media tone portfolio onto various systematic risk factors. The base model is the commodity pricing model of Bakshi et al. (2019) which we augment with one additional risk factor at a time, and with all risk factors. Alongside the annualized alpha, we report the betas (risk exposures) with Newey West h.a.c. t -statistics in parentheses and the adjusted- R2 of the regressions. The time period is January 2000 to July 2019.

("kitchen-sink" model). The second set of models adds to these pricing models the media tone factor. We assess the added value of the media factor through the adjusted- R2 (%) and mean absolute pricing error, $MAPE(\%) = \frac{100}{N}\sum_{i=1}^{N}|\hat{\epsilon}_i|$ of each model.

Table 3.12 reports the OLS estimates $\{\hat{\lambda}_0, \hat{\boldsymbol{\lambda}}\}$ and the significance of t-test based on the Shanken (1992) robust standard errors. Thus, consistent with the significantly improved performance of the media tone-adjusted tactical allocations, these cross-sectional pricing tests further reveal that the pricing ability of media tone is not subsumed by the pricing ability of systematic risk factors.

3.6 Robustness Check

3.6.1 Decay Parameter

When we calculate the media-tone scores, we assume that the impact of sentiment on commodity prices decays with the staleness of the news. Following Borovkova (2015), we model the staleness of media-tone in Equation (3.2.1) using a decay factor of 0.9. In this section, we explore the effects of different decay factors. We define the media-tone scores with different decay factors, *decay*, as follows:

$$MedTone_{i,t} = \frac{\sum_{j \in N_j} decay^{t_j} * ESS_{t_j}}{\sum_{j \in N_j} decay^{t_j}} \tag{3.6.1}$$

where i is the ith commodity future contract, t is the tth week, N_j denotes the total amount of news of ith contract in week t. We check decay factors $decay \in [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]$. When $decay = 1.0$, we define the media-tone score as an equally weighted average of the news articles.

Figure 3.3 plots the Sharpe ratios of long-short portfolios based on media-tone scores using different decay factors. We construct the portfolios using the same

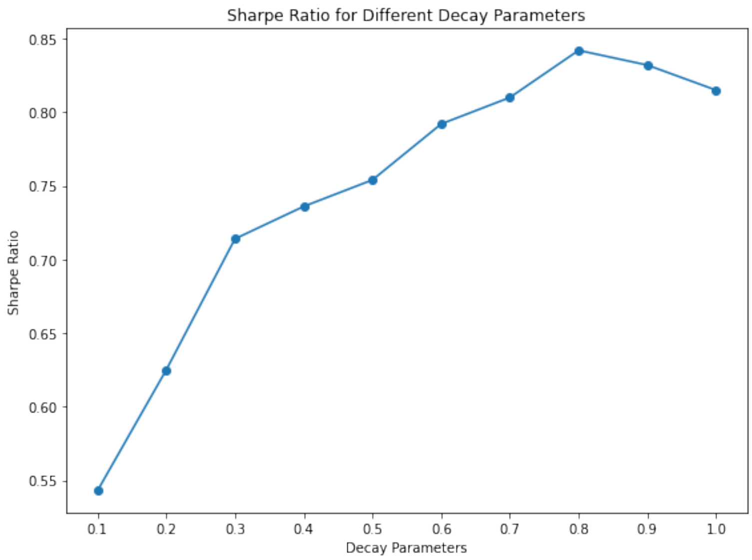
Table 3.12: Cross-sectional Pricing Tests

		Base model		l Base model augmented with														All risk factors	
				Fundamental risk factors				Tail risk factors						Liquidity and volatility risk factors					
Constant	-0.0003	-0.0002	-0.0003	-0.0002	-0.0003	0.0001	0.0000	-0.0004	-0.0005	-0.0001	-0.0002	-0.0005	-0.0006	-0.0005	-0.0006	-0.0003	-0.0004	-0.0004	-0.0003
	(-0.58)	(-0.32)	(-0.50)	(-0.34)	(-0.52)	(0.15)	(0.03)	(-0.80)	(-0.90)	(-0.23)	(-0.40)	(-1.01)	(-1.12)	(-0.94)	(-1.06)	(-0.51)	(-0.71)	(-0.67)	(-0.57)
MediaTonePortfolio	0.0346		0.0476		0.0472		0.0509		0.0441		0.0462		0.0439		0.0475		0.0477		0.0442
	(2.08)		(2.87)		(2.84)		(3.07)		(2.65)		(2.79)		(2.64)		(2.86)		(2.87)		(2.66)
AVG		-0.0922	-0.0627	-0.0829	-0.0540	-0.1466	-0.1233	0.0756	0.0845	0.0120	0.0371	0.0132	0.0311	0.0170	0.0364	-0.0801	-0.0499	0.0542	0.0271
		(-1.79)	(-1.22)	(-1.61)	(-1.05)	(-2.85)	(-2.40)	(1.47)	(1.64)	(0.23)	(0.72)	(0.26)	(0.61)	(0.33)	(0.71)	(-1.56)	(-0.97)	(1.06)	(0.53)
Basis		0.0659	0.0703	0.0627	0.0672	0.0595	0.0633	0.0599	0.0643	0.0571	0.0615	0.0620	0.0660	0.0629	0.0674	0.0688	0.0733	0.0616	0.0655
		(3.15)	(3.35)	(2.99)	(3.21)	(2.84)	(3.02)	(2.86)	(3.07)	(2.72)	(2.93)	(2.96)	(3.15)	(3.00)	(3.22)	(3.28)	(3.50)	(2.94)	(3.13)
Momentum		0.0507	0.0513	0.0437	0.0446	0.0531	0.0542	0.0494	0.0501	0.0557	0.0561	0.0297	0.0317	0.0552	0.0554	0.0545	0.0553	0.0419	0.0428
		(2.36)	(2.38)	(2.03)	(2.08)	(2.47)	(2.52)	(2.30)	(2.33)	(2.59)	(2.61)	(1.38)	(1.48)	(2.57)	(2.58)	(2.54)	(2.57)	(1.95)	(1.99)
Hedging pressure				0.0561	0.0563													0.0415	0.0431
				(2.23)	(2.24)													(1.65)	(1.72)
Convexity						0.0400	0.0445											0.0304	0.0355
						(1.95)	(2.17)											(1.48)	(1.73)
Skewness								-0.0511	-0.0493									-0.0281	-0.0268
								(-2.26)	(-2.18)									(-1.24)	(-1.18)
VaR1										0.0497	0.0486							0.0512	0.0499
										(2.33)	(2.28)							(2.40)	(2.34)
VaR99												0.0815	0.0796					0.0839	0.0814
												(3.63)	(3.55)					(3.74)	(3.63)
Basis-momentum														0.0264	0.0249			0.0040	0.0027
														(1.28)	(1.20)			(0.19)	(0.13)
Liquidity																0.0060	0.0067	0.0032	0.0033
																(0.30)	(0.33)	(0.16)	(0.17)
Adj R2	13.56	18.30	19.01	20.44	21.20	20.34	21.09	21.16	21.93	21.71	22.51	20.18	20.91	20.65	21.43	21.64	22.44	30.22	31.30
MAPE (%)	1.178	1.031	1.012	1.002	0.984	1.005	0.987	0.999	0.981	0.996	0.977	1.007	0.988	1.003	0.984	0.994	0.976	0.862	0.843
			0.71		0.76		0.75		0.77		0.80		0.73		0.78		0.80		1.08
Change in MAPE (%)			-0.019		-0.018		-0.018		-0.018		-0.019		-0.019		-0.019		-0.019		-0.019

The table reports the (annualized) prices of risk from cross-sectional regressions of average portfolio excess returns on full-sample betas with Shanken (1992) errors-in- variables corrected t-statistics in parentheses. The base model is the commodity pricing model of **Bakshi2019** which we augment with one additional risk factor at a time, and with all risk factors. The two last rows report the adjusted- R2 and MAPE (mean absolute pricing error) of each model. The time period is January 2000 to July 2019.

method as in Chapter 3.4.2. The Figure shows that the Sharpe ratio peaks when the decay factor equals 0.8. When it is higher than 0.8, the predictive power declines slightly. However, the equally weighted media-tone measure still has a strong predictive component. When the decay factor is smaller than 0.8, the Sharpe ratio decreases with the decline in the decay factors. But even when the decay factor equals 0.1, there is still significant predictability from the media-tone measure. Therefore, the choice of decay factor will not significantly influence our results.

Figure 3.3: A Plot of Sharpe Ratios with Different Decay Factors



This figure shows the Sharpe ratios of the long-short sentiment portfolios with different decay factors.

3.6.2 Turnover and Transaction Costs

In this section, we consider the influence of trading intensity on trading strategies. We measure the portfolio *turnover*(TO) defined as the time averaging of all the trading incurred

$$TO_j = \frac{1}{T-1}\sum_{t=1}^{T-1}\sum_{i=1}^{N}(|\tilde{\phi}_{j,i,t+1} - \tilde{\phi}_{j,i,t^+}|) \tag{3.6.2}$$

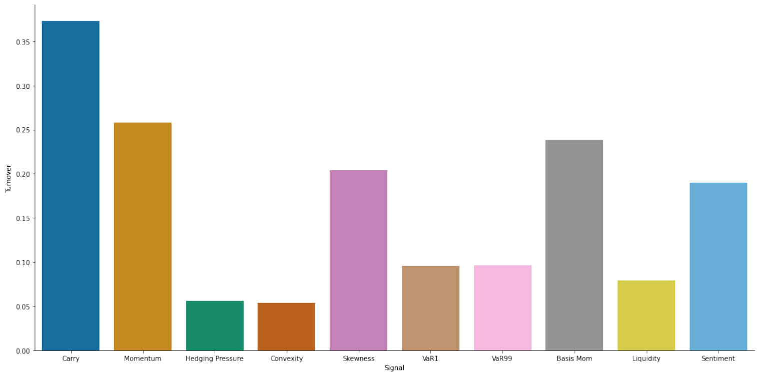
where $t = 1, \cdots, T$ denotes each of the portfolio formation period. $\tilde{\phi}_{j,i,t+1}$ is the ith commodity allocation weight at week t by the jth trading style while $\tilde{\phi}_{j,i,t^+} = \tilde{\phi}_{j,i,t}e^{r_{i,t+1}}$ is the actual portfolio weight right before the next rebalancing at $t+1$ with, the weekly return of the ith commodity from weekend t to weekend $t+1$. Thus the TO measure captures the mechanical evolution of the allocation weights due to within-week price dynamics. Figure 3.4 plots the turnovers of the long-short portfolios sorted on the media-tone score and other signals shown in Table 3.4. The figure suggests that the sentiment portfolio does not have a significant higher turnover rate. It has a higher turnover than hedging pressure, convexity, VaR1, VaR99, and liquidity portfolios but is lower than the others. Thus, transaction intensity will not significantly influence the economic benefit of utilizing media tone.

We also consider the influence of transaction cost. Using proportional trading costs of 3.3 bps (Locke & Venkatesh, 1997) and 8.6 bps (Marshall et al., 2012), we calculate the net return of each media tone gauged portfolio as:

$$\tilde{r}_{P,t+1} = \sum_{i=1}^{N}\tilde{\phi}_{i,t}r_{i,t+1} - TC\sum_{i=1}^{N}|\tilde{\phi}_{i,t} - \tilde{\phi}_{i,t-1^+}| \tag{3.6.3}$$

In Figure 3.5, we compare the Sharpe ratios for trading strategies with/without gauge by media tone under different transaction cost. The figure shows that incorporating media tone into other trading signals generates significant higher economic benefits. In addition, when transaction cost equals 3.3bp, the net Sharpe ratios of the gauged strategies are still significantly higher than the un-gauged

Figure 3.4: A Plot of Turnover for Different Trading Strategies



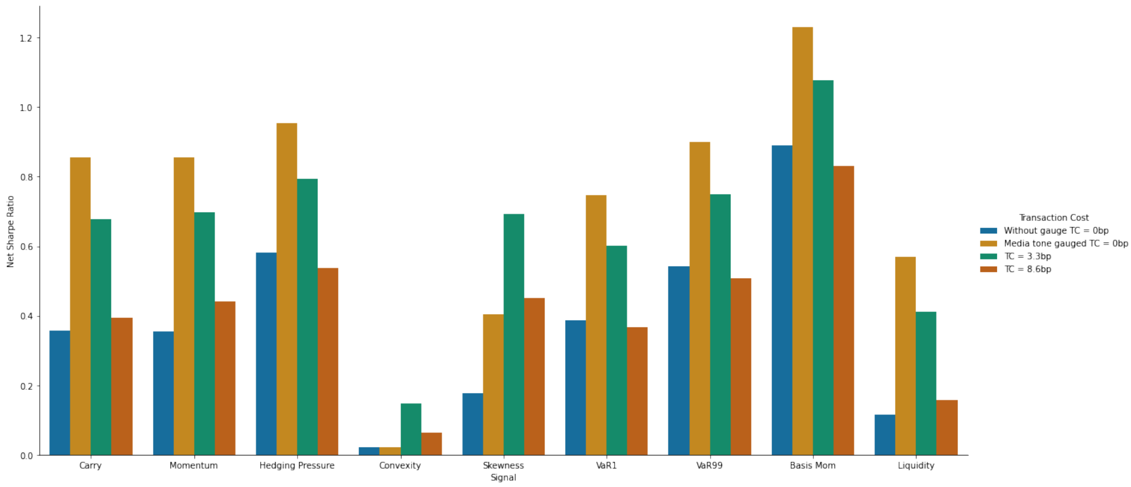
This figure shows the turnover of the long-short portfolios sorted on media-tone score and signals shown in Table 3.4.

ones. When transaction cost is 8.6bp, the economic benefits of carry, momentum, convexity, skewness, and liquidity are still significant after the gauge. Others are only slightly smaller than the original strategies. Thus, the economic benefit from the media tone is not influenced by including conventional proportional trading costs.

3.7 Conclusion

This paper explores the predictive and pricing role of news sentiment in commodity futures markets. Media tone scores based on the articles published over a week window are measured for each commodity and aggregated into an overall commodity sentiment measure. The predictability analysis suggests that the commodity-specific media tone scores are able to forecast the returns of commodity futures a week ahead after controlling for other well-known commodity characteristics such as roll-yield, hedging pressure or momentum. The sentiment index has greater predictive power for commodity market returns, in- and out-of-sample, than extant

Figure 3.5: A Plot of Net Sharpe Ratios for Different Trading Strategies



This figure shows the net Sharpe ratios of the long-short portfolios sorted on media-tone score and signals shown in Table 3.4. Blue pillars show the Sharpe ratios of trading strategies without gauging by media tone. Other pillars show the Sharpe ratios of trading strategies after gauging by media tone with different transaction costs.

measures of sentiment in the broad financial market such as the VIX, the Baker and Wurgler (2006) sentiment index, and the Michigan consumer confidence index. Positive (negative) sentiment anticipates higher (lower) returns but the forecast power is stronger for negative or pessimistic sentiment and, accordingly, it plays a stronger role as a driver of prices in periods of crises.

Long-short portfolios sorted on media tone accrue significant excess returns that are not compensation for exposure to known systematic risks. Thus motivated, the paper puts forward a simple strategy to enhance traditional long-short portfolio allocations by embedding the information content of media tone into traditional sorting signals. The paper provides an empirical cross-sectional asset pricing exercise suggesting that there is pricing ability in media tone over and above that of traditional risk factors. Overall, it is concluded that the presence of "animal spirits" (paraphrasing the British economist John Maynard Keynes) cannot be ruled out in commodity futures markets, namely, media tone can induce commodity futures mispricing and more so when the news is pessimistic or during overall market downturn periods. This specific asymmetric in the predictive role of sentiment for commodity futures prices is consistent with behavioural theories of investor risk aversion.

3.8 Appendix

3.8.1 Ravenpack Data Field Descriptions

RELEVANCE

A score between 0-100 that indicates how strongly related the entity is to the underlying news story, with higher values indicating greater relevance. For any news story that mentions an entity, RavenPack provides a relevance score. A score of 0 means the entity was passively mentioned while a score of 100 means the entity was prominent in the news story. Values above 75 are considered significantly relevant. Specifically, a value of 100 indicates that the entity identified plays a key role in the news story and is considered highly relevant. RavenPack's analysis is not limited to keywords or mentions when calculating relevance. Automated classifiers look for meaning by detecting the roles entities play in specific events like acquisitions or legal disputes or when announcing corporate actions, executive changes, product launches or recalls, among many other categories. An entity will be assigned a high mark of 100 if it plays a main role in these types of stories (context-aware).

If an entity is referenced in the headline or story body, it will receive a value between 0 and 99 (context-unaware). The score is assigned by a proprietary text positioning algorithm based on where the entity is first mentioned (i.e. headline, first paragraph, second paragraph, etc.), the number of references in the text, and the overall number of entities mentioned in the story. Usually, a relevance value of at least 90 indicates that the entity is referenced in the main title or headline of the news item, while lower values indicate references further in the story body. For example, a news story about IBM where the company is referenced in the headline of the story receives a minimum value of 90. If the headline read “IBM In Software Pact With Raytheon Unit For Navy Program” then IBM and Raytheon would receive a relevance score of 100 since they both play a key role in the story. If a headline reads “Bank of Spain: Data Points To 2Q GDP Contraction”, the system automatically infers this story is about the country “Spain”. Since this story would match the event category “gdp-guidance-down” designed to match a country, the entity “Spain” would receive a relevance score of 100 and the entity “Bank of Spain” a score of 90 or above.

If an entity is detected in a so-called “low-relevance” role, then it automatically gets a score of 20. For example, a brokerage or analyst firm making a recommendation on a company’s stock (i.e. upgrade or downgrade) plays a low-relevance role and therefore receives a default relevance score of 20.

If an entity is identified in a “source” role, then it’s given a lower score of 10. A source may be a publisher, data provider, or firm that authored, originated, or is referenced in the story. However, if an entity is identified in a source role but also detected as a non-source role within the story, then the source role is disregarded (for the purpose of computing relevance), and it’s treated the same as any other entity described above.

Entities not detected as explicitly mentioned in a story are not given a relevance score. While a story about Yahoo! might be considered in some other context to be relevant to Google, the company Google (US/GOOG) will not be given a relevance score unless that story explicitly mentions Google. The classifier detecting entities has access to information about each entity including short-names, long names, abbreviations, securities identifiers, subsidiaries information, and up-to-date corporate actions data. This allows for "point-in-time" detection of entities in the text. A news story relevant to multiple entities generates scores for each entity in separate "entity-level" records, each with their own relevance score.

ESS – EVENT SENTIMENT SCORE

A granular score between 0 and 100 that represents the news sentiment for a given entity by measuring various proxies sampled from the news. The score is determined by systematically matching stories typically categorized by financial experts as having short-term positive or negative financial or economic impact. The strength of the score is derived from a collection of surveys where financial experts rated entity-specific events as conveying positive or negative sentiment and to what degree. Their ratings are encapsulated in an algorithm that generates a score ranging from 0-100 where 50 indicates neutral sentiment, values above 50 indicate positive sentiment and values below 50 show negative sentiment.

ESS probes many different sentiment proxies typically reported in financial news and categorized by RavenPack. The algorithm produces a score for more than 2,000 types of business, economic, and geopolitical events ranging from earnings announcements to terrorist attacks. The score is determined by systematically detecting entities and the roles played by that those entities in a story using RavenPack's proprietary technology and extensive database of time sensitive information about entities. The algorithms then can dynamically assign an ESS score based on score ranges assigned by the experts and by performing analysis and computation when factors such as magnitudes, comparative values or ratings are disclosed in the story.

For example, the algorithm is capable of interpreting actual figures, estimates, ratings, revisions, magnitudes, and recommendations disclosed in news stories. It can compare actual vs. estimated figures about earnings, revenues or dividends and produce an ESS score based on the comparisons. It calculates percentage differences between financial figures and identifies and interprets stock and credit ratings disclosed by analysts. The ESS algorithms can factor information such as the Richter scale in the case of an earthquake or the number of casualties in a suicide bombing event. The use of emotionally charged language by authors is also factored when shaping the strength component of the ESS.

The ESS algorithm has embedded information on rating scales from all major brokerage firms, investment banks, and credit rating agencies. It uses this information to differentiate and assess the various actions taken by analysts. For example, the algorithm generates a lower (more negative) ESS score for stories about an analyst downgrade from a “Strong Buy to a Strong Sell” than from a “Buy to a Neutral”. In the case of stories about financial results or economic indicators, it computes the percentage change between the disclosed actual figures vs. the street consensus or any other benchmarks disclosed in the story. For example, a company beating earnings by 70% will receive a higher (more positive) ESS score than a company exceeding a benchmark by 1%.

ENS – EVENT NOVELTY SCORE

A score between 0 and 100 that represents how ”new” or novel a news story is within a 24-hour time window across all news stories in a particular package (Dow Jones, Web or PR Editions). Any two stories that match the same event for the same entities will be considered similar according to ENS. The first story reporting a categorized event about one or more entities is considered to be the most novel and receives a score of 100. Subsequent stories from the same package about the same event for the same entities receive scores following a decay function whose values are (100 75 56 42 32 24 18 13 10 8 6 4 3 2 2 1 1 1 1 0 ...) based on the number of stories in the past 24- hour window. If a news story is published more than 24 hours after any other similar story, it will again be considered novel and start a separate chain with a score of 100.

Note that for any particular story, the ENS score is based on the number of similar stories in the most recent 24-hour window preceding that story. However, a chain of similar stories can span more than 24 hours, provided no two similar stories are more than 24 hours apart. Occasionally, the ENS score of a story which arrives more than 24 hours after the first story in the chain can be equal to or greater than the ENS score of some story earlier in the chain.

3.8.2 Bootstrap p-value Procedure

Assume there is no predictability for media tone index and the predictor follows an AR(p) process. The data are generated from the following model:

$$r_t^{MKT} = a_0 + \epsilon_{1,t} \tag{3.8.1}$$

$$Media\_Tone_t = b_0 + b_1 Media\_Tone_{t-1} + ... + b_p Media\_Tone_{t-p} + \epsilon_{2,t} \tag{3.8.2}$$

where the error term vector $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t})'$ is i.i.d. with covariance matrix Σ. Then estimate Eq. (3.8.1) and (3.8.2) by OLS. Identity lag p in Eq.(3.8.2) using AIC criteria. After estimation, we can obtain OLS estimates $\hat{a}_0, \hat{b}_0, ..., \hat{b}_p$ and residuals $\hat{\epsilon}_t = (\hat{\epsilon}_{1,t}, \hat{\epsilon}_{2,t})'$. Then we randomly draw (with replacement) $T + 100$ times from the residuals in tandem to preserve the correlation between the error terms of Eq. (3.8.1) and (3.8.2). This pseudo-series of residuals is denoted as $\{\hat{\epsilon}_t^*\}_{t=1}^{T+100}$. Using the pseudo-series of residuals, OLS estimates $\hat{a}_0, \hat{b}_0, ..., \hat{b}_p$, and Eq. (3.8.1) and (3.8.2), we can calculate a pseudo-sample of $T + 100$ observations for r_t and $Media\_Tone_t$. Set the initial observations for $(Media\_Tone_t, ..., Media\_Tone_{t-p})$ to be 0 and drop the first 100 pseudo observations, leaving us a pseudo-sample of T observations which is the same size as the original observations. Then we can calculate the $t-$ statistics corresponding to $\hat{\gamma}$ in the in-sample predictive regression model. Repeat this process for 1000 times. Then $p-$value of $\hat{\gamma}$ is the proportion of the bootstrap statistics that are greater than the statistics calculated using the original sample.

Chapter 4

Attention Spillovers between Equity and Commodity Futures Markets

4.1 Introduction

Limited attention is a widely documented behavioural bias in the psychological literature, and asset pricing theories have used it to explain a wide range of market phenomena. Traditional asset pricing theory requires investors to pay sufficient attention to the asset. But, attention is a scarce resource (Kahneman, 1973). Investors have limited attention, especially when faced with many assets. Few investors will check whether the attributes of each of the assets satisfy their preferences and beliefs. Odean (1999) and Barber and Odean (2008) suggest that investors will choose a small subset of assets that attract their attention. They argue that people tend to pay more attention to more salient choices which are those that differ most noticeably on observed attributes. However, when testing theories of attention, researchers face a substantial challenge: it is difficult to build a measure of investor attention that directly establishes the causal effect of limited attention. Variables that reflect investor attention in previous literature (e.g., trading volume, google search volume) are typically also associated with fundamental information.

During the past decade, a huge influx of institutional funds flew to commodity futures markets in the early 2000s, referred to as the financialization of commodities. Tang and Xiong (2012) find that after 2004 the behaviour of index commodities has become increasingly different from that of non-index commodities, with the former becoming more correlated with oil, and more correlated with the equity market. Cheng and Xiong (2014) also document that the correlation of commodity prices with prices in the equity market trended upward from 2004 to 2008 and has increased significantly since the collapse of Lehman Brothers in 2008. Since then, they have stayed at elevated levels compared with historical periods.

In this study, we exploit the financialization of commodity prices to study the limited attention effect in the commodity market. More specifically, we assume there is a spillover effect of investors' attention from the equity market to the commodity futures market. For example, when news of firms in the energy sector arrives, investors' attention about the firms will transfer from the equity market to the commodity futures market. Thus, the corresponding commodity futures will face more buying/selling pressure and should experience higher/lower returns in the subsequent weeks. Consequently, we arrive at the following key hypothesis: a commodity futures' return is associated with the amount of news of companies within the correlated sector.

To test the hypothesis, first, we construct a weekly attention spillover variable (*SpillAtt*) for each commodity futures contract, computed as the average amount of firm-specific news, which is news about firms' fundamentals. This measure helps to identify the causal effect of limited attention effect in the commodity futures market as firm-specific fundamental news are exogenous to fundamentals of commodity contracts and thus providing a cleaner identification. We then form quintile portfolios based on *SpillAtt* variable, and we find that the portfolio return increases as *SpillAtt* increases. Specifically, the equal-weighted long-short portfolio constructed by longing the quintile with the highest *SpillAtt* and shorting the quintile with the lowest *SpillAtt* earns an annualized return of 4.6% (t-stat = 2.46). Third, we show that these results remain significant after controlling for fundamental risk factors (roll yield, momentum, hedging pressure, and convexity); tail risk factors (skewness, 1% Cornish-Fisher VaR, and 99% Cornish-Fisher VaR); volatility and illiquidity risk factors (basis-momentum and illiquidity). In addition, we test whether the significant spillover attention premium is merely compensation for exposure to risk factors. For this purpose, we start with the three-factor model of Bakshi et al. (2019) that includes the AVG, basis and momentum risk factors and estimate an OLS time-series spanning regression for the excess returns of the media tone sentiment portfolio. We then augment this baseline specification with various factors we mentioned before. Results suggest that the predictive ability of the *SpillAtt* variable is not stemmed from the current known risk factors in the commodity market. Third, since the attention spillover effect should be transitory, we also test the long-term holding period return for portfolios sorted on *SpillAtt*. Evidence suggests the annualized alpha of the equal-weighted attention portfolio peaks at week 3 and is completely reversed thereafter which suggests the effect is indeed temporary. Lastly, as Stambaugh et al. (2012) argue, a mispricing driven anomaly should have a strong effect during the high-sentiment period. We test this assumption by applying a double sort portfolio analysis method. We first construct quintile portfolios of commodity futures contracts based on the corresponding media tone measures that we applied in Chapter 3. Then within each quintile, a long-short equally weighted portfolio is constructed by longing the top 50% contracts with the higher *SpillAtt* and shorting the 50% with the lower *SpillAtt*. Results confirm our assumption and suggest that the long-short portfolio return is the highest when sentiment is high.

The contribution of this paper is three folds. First, we contribute to the limited attention literature. In limited attention literature, researchers have developed many proxies to measure attention, such as abnormal trading volume and extreme return (e.g., Barber and Odean, 2008; Hou et al., 2009; Corwin and Coughenour, 2008); Google search volume index (e.g., Da et al., 2011); Bloomberg search volume and readership (e.g., Ben-Rephael et al., 2017); media coverage (e.g., Huberman and Regev, 2001; Fang and Peress, 2009; Kaniel and Parham, 2017). In the commodity futures market, Han et al. (2017a) study the effects of investor attention by utilizing the Google search volume as a proxy. In this study, we obtain a weekly commodity-specific attention measure by using firm-specific news articles coverage obtained by textual analysis algorithms. Second, this measure separates the asset pricing effect of attention from fundamental news. Firm-specific news is exogenous to the fundamentals of commodity contracts and thus provides a cleaner identification. Third, we contribute to the commodity financialization literature by providing a possible explanation for the co-movement of equity and commodity prices.

The remainder of the paper is organized as follows. Section 2 presents the data and the construction methods of the key variables. Section 3 presents the empirical evidence of the attention spillover effect on the commodity futures market. Section 4 contains the pricing ability test of our attention spillover factor. We also test the transitory effect and its relationship with sentiment measures. The final section concludes.

4.2 Data and Firm-specific News

4.2.1 Commodities Sample

This research employs data on a cross-section of 28 commodity futures contracts comprising 12 agricultural (4 cereal grains, 1 oilseeds, 3 meats, 4 miscellaneous other softs), 3 energy, and 3 metals (1 base, 2 precious). For each of the commodities, end-of-day futures settlement prices and daily dollar trading volume are obtained from *Refinitiv Datastream*, and open interest data from the *Commitment of Traders Report of the Commodity Futures Trading Commission*. The observations are sampled at the weekly frequency from January 1, 2000 to July 31, 2019. Excess returns are calculated as $ln(F_{i,t}^{T1}/F_{i,t-1}^{T1})$.

4.2.2 Firm-specific News

To construct the attention spillover measure, the first step involves identifying firms that are related to a certain futures contract. For computational reasons, we limit ourselves to S&P 500 subsection companies with at least 20 trading days during the period. We match a company with its related commodity futures contract by its Standard Industial Classification (SIC) code. For example, companies with SIC code 0111 are matched with wheat contracts, companies with code 0115 are matched with corns contracts, etc. Details of SIC codes and related contracts are shown in Table 4.1

Following Boudoukh et al. (2019), in this paper, we define firm-specific news as the firm-level public news which is relevant public information tied to specific firm events. For example, consider the news related to the employment of a company. Changes in the CEO, an executive of the firm or a board member; executive compensation; and employment issues including, strikes and changes in

Table 4.1: SIC codes and related commodity contracts

Commodity contracts	SIC	Description
Agriculture		
Wheat	0111	Wheat
Rice	0112	Rice
	2044	Rice Milling
Corn	0115	Corn
	2046	Wet Corn Milling
Soybeans	0116	Soybeans
Soybean oil	2075	Soybean Oil Mills
Cocoa	2066	Chocolate And Cocoa Products
Cotton	0131	Cotton
	0724	Cotton Ginning
Coffee	2095	Roasted Coffee
Feeder cattle	0211	Beef Cattle, Feedlots
Live cattle	0212	Beef Cattle, Except Feedlots
Lean hogs	0213	Hogs
Lumber	0811	Timber Tracts
	0831	Forest Nurseries And Gathering Of Forest Products
	0851	Forestry Services
Energy		
Light crude oil	1311	Crude Petroleum And Natural Gas
	1381	Drilling Oil And Gas Wells
	1382	Oil And Gas Field Exploration Services
	1389	Oil And Gas Field Services, Not Elsewhere Classified
	2911	Petroleum Refining
Natural gas	1311	Crude Petroleum And Natural Gas
	1321	Natural Gas Liquids
	1381	Drilling Oil And Gas Wells
	1382	Oil And Gas Field Exploration Services
	1389	Oil And Gas Field Services, Not Elsewhere Classified
	4922	Natural Gas Transmission
	4923	Natural Gas Transmission And Distribution
	4924	Natural Gas Distribution
Unleaded gas	2911	Petroleum Refining
	5541	Gasoline Service Stations
Metals		
Copper	1021	Copper Ores
	3331	Primary Smelting And Refining Of Copper
	3351	Rolling, Drawing, And Extruding Of Copper
	3366	Copper Foundries
Gold	1041	Gold Ores
Silver	1044	Silver Ores

This table shows the commodity futures contracts and their related Standard Industrial Classification (SIC) codes. Description column shows a short description of the industry a code stands for.

the workforce are classified as firm-specific news. These pieces of news are largely uncorrelated with the fundamentals of the commodity market. To identify the firm-specific news, we apply measures from the *Wharton Research Data Services (WRDS) Ravenpack* section. *Ravenpack* uses machine learning algorithms to process text from not only the Dow Jones Newswire but also the Wall Street Journal, direct regulatory feeds, and thousands of social media websites, into machine-readable content to identify a company's news in terms of "relevance". Relevance score from 0 to 100. While this score is a black box, a relevance score of 100 generally coincides with the company playing a main role in the story and the article type being identified. Therefore, we select pieces of news that have relevance scores of 100 as firm-specific news. The observations are sampled at the millisecond frequency. At each weekend t, we aggregate news for each firm j into a weekly frequency measure, $count_{j,t}$, by taking the count of the news of firm j within a week. Then we construct the spillover limited attention measure (limited attention measure thereafter) for a commodity futures contract as the average of firm-specific news of its related firms. Specifically, for commodity futures contract i, its spillover attention measure at week t is defined as,

$$SpillAtt_{i,t} = \frac{1}{N_i} \sum_{j=1}^{N_i} count_{j,t} \tag{4.2.1}$$

where N_i is the number of related firms for commodity futures contract i.

4.2.3 Control Variables

To tease out the effects of attention spillover, we control for different categories of variables that are known to affect commodity futures returns.

The performance of the attention portfolio is appraised in the context of a battery of benchmarks as in Fernandez-Perez et al. (2020). A long-only equally-weighted and weekly-rebalanced portfolio of all commodities (AVG) is considered as a broad commodity market factor (Bakshi et al., 2019; Erb and Harvey, 2016; Gorton and Rouwenhorst, 2006). Additional risk factors are the excess returns of long-short portfolios inspired by the fundamentals of backwardation and contango; specifically, backwardated commodities with high roll-yield, *roll* (Bakshi et al., 2019; Erb and Harvey, 2016; Gorton and Rouwenhorst, 2006), high past average returns, momentum (Bakshi et al., 2019; Erb and Harvey, 2016; Miffre and Rallis, 2007), high net-short hedging pressure, HP (Basu and Miffre, 2013; Bianchi et al., 2015; Kang et al., 2020) or a convex price curve, convexity (Gu et al., 2019) are expected to outperform contangoed commodities with opposite values of the aforementioned characteristics. It is also possible to motivate tail risk factors constructed as the returns of long-short portfolios sorted by skewness (Fernandez-Perez et al., 2018), 1% and 99% Value-at-Risk, hereafter denoted as VaR1 and VaR99 (Atilgan et al., 2019; Bali et al., 2009[1]). Finally, the excess returns of the attention portfolio could relate to liquidity and volatility risks factors obtained as the returns of long-short portfolios where the sorting signal is the basis-momentum of Boons and Prado (2019) and the illiquidity measure suggested by Amihud (2002). In addition, we include a commodity market media tone measure to compare the investors' sentiment and limited attention effect. Following Chapter 3, the media tone measure, $MedTone_{i,t}$ is calculated as a weighted average of sentiment per piece of news extracted using textual analysis. Details of control variables and background references are provided in Table 3.4.

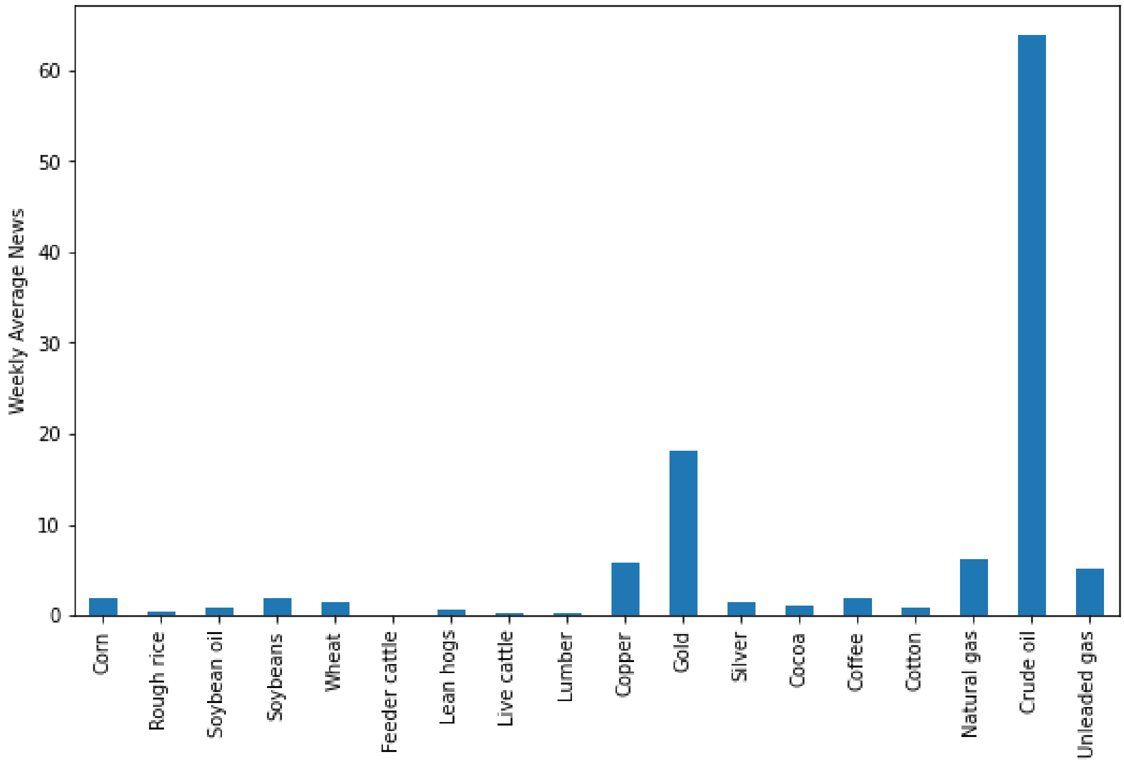
[1]As dictated by rational asset pricing theory, higher risk is associated with higher expected returns. Thus the skewness and VaR1 factors are constructed as the returns of portfolios with long positions in the futures contracts with the most negative skewness and VaR1 signals. Since investors have preferences for lottery type assets, the VaR99 factor is constructed as the returns of a portfolio with long (short) positions in futures contracts with the least (most) positive VaR99 signal.

4.2.4 Summary Statistics

Figure 4.1 shows the average of the limited attention measure, $SpillAtt_{i,t}$, across time. The crude oil futures contract has received far more firm-specific news than others, which is consistent with our expectations. Gold received the second-highest attention from investors, followed by natural gas, copper, and 1unleaded gasoline. Agriculture futures contracts, on average, received fewer media coverage.

Table 4.2 reports the correlation between the limited attention measure and other

Figure 4.1: Average Limited Attention Measure for Commodity Futures over Time



This figure illustrates the average of the limited attention measure, $SpillAtt_{i,t}$, over the sample period from January 2000 to July 2019 for 18 commodity futures contracts.

control variables. Generally, the correlations between them are low. The largest positive correlation is between $SpillAtt_{i,t}$ and convexity which is 0.350. The most negative one is with *1% VaR* which is -0.357. The lowest correlation in absolute value is 0.033. This suggests the limited attention measure may capture different predictive elements from the media tone measure.

4.3 Methodology and Empirical Results

This section explores the ability of *SpillAtt* variable to explain future returns of the commodity futures contract. We start with a one-way portfolio analysis. To rule out potentially confounding effects, we also conduct a series of characteristic adjusted two-way portfolios sorts.

4.3.1 One-Way Sort Portfolio Analysis

We assess whether it is possible to exploit the limited attention measure to generate economic value from a portfolio perspective. For this purpose, the paper begins by deploying a portfolio strategy using the limited attention measure per commodity, as sorting signal $\theta_{i,t} \equiv SpillAtt_{i,t}$ at the end of each sample week t. Accordingly, the commodity futures contracts are grouped into quintiles and a long-short limited attention portfolio is formed where long (short) positions are taking on the commodity futures contracts in the top (bottom) quintile Q1 (Q5) which are those with the most positive (negative) media-tone scores. The commodities in the long and short legs of the portfolios are equally weighted and the investor is fully invested. The long-short portfolios are held for one week on a fully-collateralized basis; thus the excess returns are given by half the longs returns minus half the shorts returns.

Table 4.3 reports the results for the one-way sort portfolio results. All returns are annualized and the t-statistics are computed based on standard errors with

Table 4.2: Correlation between Limited Attention Measure and Other Control Variables

	SpillAtt	MedTone	AVG	Roll	Momentum	Hedging Pressure	Convexity	Skewness	VaR1	VaR99	Basis_Mom	Liquidity
SpillAtt	1											
MedTone	0.033	1										
AVG	-0.248	-0.087	1									
Roll	-0.079	-0.045	0.057	1								
Momentum	0.172	-0.017	-0.027	0.391	1							
Hedging Pressure	-0.043	-0.046	0.137	0.349	0.351	1						
Convexity	0.350	0.025	-0.276	-0.052	0.223	0.092	1					
Skewness	-0.135	-0.062	0.127	0.092	0.030	0.245	-0.112	1				
VaR1	-0.357	-0.085	0.434	0.028	-0.217	-0.004	-0.389	0.240	1			
VaR99	0.218	0.058	-0.417	-0.099	-0.090	-0.039	0.221	0.254	-0.647	1		
Basis_Mom	0.218	0.053	-0.061	0.274	0.411	0.113	0.204	-0.044	-0.178	0.018	1	
Liquidity	-0.125	0.042	-0.050	0.241	0.029	0.312	-0.190	-0.031	-0.062	0.072	0.111	1

This table summarizes the correlation between the limited attention measure and other control variables which include: 1. fundamentals (roll yield, momentum, hedging pressure, convexity); 2. tail risk (skewness, 1%VaR, and 99%VaR); 3. volatility/illiquidity (basis-momentum and illiquidity); 4. media tone measure; and 5. AVG which is the equally weighted weekly rebalanced portfolio for all commodities.

Newey-West adjustments of 12 lags. The results suggest a clear monotonic relation between *SpillAtt* and future returns. The difference between Q1 and Q5 is around 4.6% per year, and the t-statistics is 2.46. The intuition is that an increase in investors' attention results in temporary positive price pressure. As Barber and Odean (2008) argue, when investors are buying, they have to choose from a large set of available alternatives. However, when they are selling, they can only sell what they own. This means that shocks to attention should lead, on average, to net buying from these uninformed traders. Therefore, higher attention leads to a short-term demand effect that will exert an upward (downward) pressure on prices so a short-term price increase is expected in the commodity futures contracts of Q1 (Q5).

4.4 Pricing Role of Media Tone

4.4.1 Time-series Test

The analysis thus far has revealed that the limited attention strategy is able to capture attractive mean excess returns in commodity futures markets. We now test whether the significant premium is merely compensation for exposure to risk factors by simultaneously controlling for various confounding factors. For this purpose, we start with the three-factor model of Bakshi et al. (2019) that includes the AVG, basis and momentum risk factors and estimate an OLS time-series spanning regression for the excess returns of the limited attention portfolio. We then augment this baseline specification with various factors, in turn, that emanate from the literature on the pricing of commodity futures (hedging pressure and convexity), tail-risk (skewness, VaR1 and VaR99) or the liquidity and volatility of commodities (basis- momentum and illiquidity). Specifically, we are testing the

Table 4.3: Long-Short Limited Attention Portfolios

	Long Q1	**Q2**	**Q3**	**Q4**	**Short Q5**	**Q1-Q5**
Mean	0.037	-0.003	-0.069	-0.049	-0.056	0.046
	(2.94)	(-1.45)	(-1.33)	(-1.99)	(-2.24)	(2.46)
Volatility	0.139	0.157	0.176	0.167	0.148	0.073
Downside risk	0.216	0.269	0.305	0.272	0.248	0.103
Skewness	-0.214	-0.467	-0.751	-0.251	-0.438	0.253
	(-2.24)	(-4.71)	(-7.14)	(-2.62)	(-4.45)	(2.64)
Excess Kurtosis	1.753	1.210	2.642	1.650	2.552	0.366
	(5.40)	(4.31)	(6.74)	(5.22)	(6.63)	(1.80)
JB normality test p-value	0.000	0.000	0.000	0.000	0.000	0.005
AC1	0.034	0.082	0.079	0.020	0.092	-0.025
1% VaR (Cornish Fisher)	-0.044	-0.052	-0.058	-0.055	-0.049	-0.023
Max drawdown	-0.479	-0.768	-0.820	-0.676	-0.602	-0.126
Sharpe ratio	0.268	-0.462	-0.394	-0.293	-0.378	0.638
Sortino ratio	0.379	-0.595	-0.501	-0.395	-0.495	0.997
Omega ratio	1.105	0.844	0.862	0.898	0.868	1.251
CER (power utility)	0.010	0.015	0.010	0.005	0.023	0.008

Note: in the top (bottom) quintile Q1 (Q5) are those with the highest(lowest). First five columns of this table report the performance of the Q1 to Q5 quintiles portfolios formed according to the limited attention measure $SpillAtt_{i,t}$. Column six reports the performance of a trading strategy that longs the top quintile of commodities with the highest attention, and shorts the bottom quintile with the lowest attention. All measures are annualized.

following model:

$$SpillAtt_{t+1} = \alpha + \beta_1 AVG_t + \beta_2 Roll_t + \beta_3 Momentum_t + \theta Z_t + \epsilon_{t+1} \tag{4.4.1}$$

where Z_t includes other augmented risk factors. For each of the specifications, we look at the sign and significance of both the betas and alpha where the latter represents the average excess return of the limited attention portfolio that is not a compensation for the hypothesized risk factors.

Table 4.4 reports the results of the two-way sort portfolio analysis. The adjusted return spread is around 4.10%–5.13% per year after adjusting for different characteristics. The last column of Table 4.4 reports the "kitchen-sink" model that includes all the risk factors. The annualized alpha is still significant. Thus, compensation for risk factor exposures does not fully explain the limited attention factor.

4.4.2 Cross-sectional Test

A cross-sectional pricing exercise a la Fama-MacBeth further uses $N = 54$ portfolios as tests assets (the quintiles obtained according to the 9 signals – limited attention, roll-yield, HP, momentum, BM and convexity – and the equally-weighted weekly rebalanced portfolios of the commodities grouped into 3 (sub)sectors – agriculture, energy, and metals – suggests that the limited attention factor is significantly priced, over and above traditional risk factors. We first estimate full-sample betas via OLS time-series regressions

$$r_{i,t} = \alpha_i + \beta_i * \mathbf{F}_t + \epsilon_{i,t},\ \ t = 1, ..., T \tag{4.4.2}$$

where $r_{i,t}$ is the time t excess returns of the quintile portfolios sorted on (a) the limited attention (b) the 9 characteristics we listed before, and (c) the equally weighted and weekly-rebalanced portfolios from the 4 commodity sub-sectors. Thus, we have $N = 54$ portfolios together. $\mathbf{F}_t$ includes the limited attention factor as well as the 9 characteristics. In step two, we estimate each week the following cross- sectional regression of average excess returns on the step-one estimated full-sample betas

$$\bar{r}_i = \lambda_0 + \boldsymbol{\lambda}\hat{\beta}_i + \epsilon_i,\ \ i = 1, ..., N \tag{4.4.3}$$

where $\boldsymbol{\lambda}$ is a vector containing the prices of risk associated with each of the factors. The baseline model entertains the three risk factors of Bakshi et al. (2019). We

Table 4.4: Time-series Spinning Tests

	Base model	Fundamental risk factors		Tail risk factors			Liquidity/vol risk factors		All risk factors
Annualized alpha	0.0468	0.0489	0.0513	0.0504	0.0447	0.0426	0.0410	0.0447	0.0410
	(2.31)	(2.42)	(2.69)	(2.55)	(2.26)	(2.12)	(2.08)	(2.20)	(2.26)
AVG	-0.1387	-0.1352	-0.0619	-0.1315	-0.0724	-0.1005	-0.1320	-0.1433	-0.0223
	(-5.49)	(-5.37)	(-2.78)	(-5.24)	(-2.53)	(-3.42)	(-5.25)	(-5.65)	(-0.89)
Basis	-0.1309	-0.1218	-0.0704	-0.1237	-0.1085	-0.1255	-0.1532	-0.1041	-0.0555
	(-3.06)	(-2.73)	(-2.04)	(-2.98)	(-2.82)	(-2.98)	(-3.72)	(-2.27)	(-1.63)
Momentum	0.1739	0.1829	0.0697	0.1739	0.1240	0.1839	0.1224	0.1668	0.0506
	(4.84)	(4.85)	(2.09)	(4.93)	(3.63)	(5.17)	(3.08)	(4.49)	(1.27)
Hedging Pressure		-0.0373							-0.0562
		(-1.00)							(-1.52)
Convexity			0.5064						0.4584
			(12.05)						(10.63)
Skewness				-0.0897					-0.0459
				(-2.01)					(-0.92)
VaR1					-0.2169				-0.0658
					(-5.15)				(-1.08)
VaR99						0.1309			0.0518
						(2.93)			(0.78)
Basis-momentum							0.1543		0.0888
							(3.44)		(2.47)
Liquidity								-0.0973	-0.0254
								(-2.72)	(-0.71)
Adj.-R^2 (%)	10.50	10.53	31.70	11.34	15.75	12.32	13.28	11.58	34.22

This table reports estimation results from time-series regressions of the excess returns of the long-short limited attention portfolio onto various systematic risk factors. The base model is the commodity pricing model of Bakshi et al. (2019) which we augment with one additional risk factor at a time, and with all risk factors. Alongside the annualized alpha, we report the betas (risk exposures) with Newey West h.a.c. t -statistics in parentheses and the adjusted- R^2 of the regressions. The time period is from January 2000 to July 2019.

subsequently expand this model by cycling through each of the additional long-short risk premia considered in the time-series spanning tests, and then all together ("kitchen-sink" model). The second set of models adds to these pricing models the media tone factor. We assess the added value of the media factor through the adjusted- R2 (%) and mean absolute pricing error, $MAPE(\%) = \frac{100}{N}\sum_{i=1}^{N}|\hat{\epsilon}_i|$ of each model.

Table 4.5 reports the OLS estimates $\{\hat{\lambda}_0, \hat{\boldsymbol{\lambda}}\}$ and significance of t-test based on the Shanken (1992) robust standard errors. Thus, consistent with the performance of the one-way and two-way sort portfolio allocations, these cross-sectional pricing tests further reveal that the pricing ability of limited attention is not subsumed by the pricing ability of systematic risk factors.

4.5 Additional Results

4.5.1 Long-run Return of the Limited Attention Portfolio

If the higher return in the next week predicted by a higher *SpillAtt* variable is indeed coming from attention spillover, the price impact should be temporary and revert in the long run.

Figure 4.2 plots the equally weighted annualized cumulative alphas of the long-short portfolio Q1-Q5 based on *SpillAtt* from week t to week $t+12$ after including all controlling variables in Eq. 4.4.1. We see that the alpha of the equally weighted portfolio peaks from the beginning and is completely reversed by the 4th week. This outcome suggests that the price impact is indeed temporary and unlikely to be explained by related firms' fundamentals.

Table 4.5: Cross-sectional Pricing Tests

			Base model	Base model augmented with															All risk factors	
				Fundamental risk factors				Tail risk factors						Liquidity and volatility risk factors					
Constant	-0.0003	0.0000	-0.0012	-0.0002	-0.0011	-0.0008	-0.0010	0.0004	-0.0010	-0.0008	-0.0020	-0.0013	-0.0028	-0.0003	-0.0013	0.0000	-0.0016	-0.0004	-0.0011
	(-0.58)	(-0.01)	(-1.16)	(-0.34)	(-1.10)	(-0.85)	(-1.01)	(0.44)	(-0.92)	(-0.69)	(-1.76)	(-1.16)	(-2.36)	(-0.35)	(-1.22)	(0.01)	(-1.62)	(-0.38)	(-0.93)
Attention	0.0009		0.0010		0.0012		0.0009		0.0011		0.0010		0.0011		0.0010		0.0012		0.0009
	(2.08)		(2.35)		(2.67)		(2.21)		(2.60)		(2.35)		(2.51)		(2.22)		(2.71)		(2.07)
AVG		-0.0009	0.0003	-0.0829	0.0003	-0.0001	0.0002	-0.0013	0.0001	-0.0001	0.0012	0.0004	0.0019	-0.0006	0.0004	-0.0009	0.0008	-0.0004	0.0002
		(-1.18)	(0.47)	(-1.61)	(0.38)	(-0.10)	(0.26)	(-1.75)	(0.14)	(-0.14)	(1.59)	(0.52)	(2.61)	(-0.75)	(0.55)	(-1.20)	(1.04)	(-0.61)	(0.29)
Basis		0.0006	0.0009	0.0627	0.0006	0.0009	0.0010	0.0005	0.0009	0.0006	0.0010	0.0005	0.0010	0.0005	0.0009	0.0006	0.0008	0.0005	0.0006
		(1.14)	(1.86)	(2.99)	(1.20)	(1.78)	(1.90)	(0.95)	(1.79)	(1.20)	(1.94)	(1.08)	(1.91)	(1.05)	(1.73)	(1.21)	(1.54)	(1.07)	(1.20)
Momentum		0.0011	0.0008	0.0437	0.0003	0.0006	0.0006	0.0011	0.0006	0.0009	0.0006	0.0009	0.0005	0.0010	0.0007	0.0011	0.0007	0.0002	0.0002
		(1.98)	(1.35)	(2.03)	(0.50)	(1.15)	(1.12)	(1.89)	(1.13)	(1.68)	(1.03)	(1.58)	(0.81)	(1.70)	(1.25)	(1.98)	(1.21)	(0.42)	(0.30)
Hedging pressure				0.0561	0.0014													0.0013	0.0014
				(2.23)	(2.62)													(2.52)	(2.63)
Convexity						0.0010	0.0445											0.0007	0.0005
						(2.26)	(2.17)											(1.74)	(1.29)
Skewness								0.0010	0.0012									0.0007	0.0007
								(2.19)	(2.47)									(1.48)	(1.53)
VaR1										-0.0008	-0.0006							-0.0002	-0.0001
										(-1.46)	(-1.13)							(-0.29)	(-0.22)
VaR99												0.0010	0.0009					0.0009	0.0009
												(1.90)	(1.69)					(1.78)	(1.68)
Basis-momentum														0.0011	0.0010			0.0012	0.0012
														(2.10)	(1.82)			(2.36)	(2.19)
Liquidity																0.0001	0.0004	-0.0002	-0.0001
																(0.13)	(0.74)	(-0.34)	(-0.13)
Adj R2	13.56	15.10	18.44	20.52	23.78	18.17	21.37	18.68	22.04	18.28	21.70	19.97	23.31	16.81	20.04	19.22	21.76	32.51	34.26
MAPE (%)	1.178	1.015	0.978	0.966	0.926	0.981	0.948	0.981	0.943	0.985	0.945	0.973	0.936	0.995	0.958	0.973	0.942	0.812	0.788
Change in Adj R2 (%)			3.34		3.26		3.20		3.36		3.42		3.34		3.23		2.54		1.75
Change in MAPE (%)			-0.037		-0.040		-0.033		-0.038		-0.040		-0.037		-0.037		-0.031		-0.024

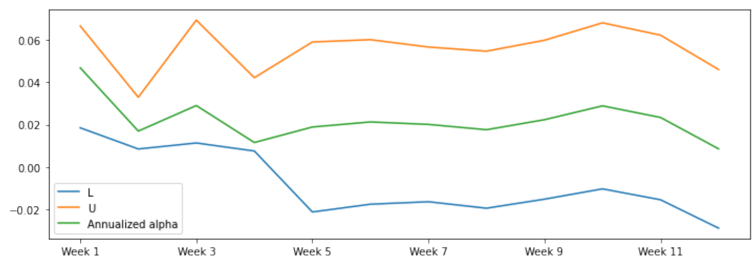
The table reports the (annualized) prices of risk from cross-sectional regressions of average portfolio excess returns on full-sample betas with Shanken (1992) errors-in- variables corrected t-statistics in parentheses. The base model is the commodity pricing model of Bakshi et al. (2019) which we augment with one additional risk factor at a time, and with all risk factors. The two last rows report the adjusted- R2 and MAPE (mean absolute pricing error) of each model. The time period is January 2000 to July 2019.

4.5.2 Moderating Effect of Investor Sentiment

We then examine how the return pattern we document varies with the investor sentiment. When investor sentiment is higher, we expect the return pattern to be stronger as correction of such mispricing becomes more difficult. Following Chapter 3, we employ their media tone measure as a proxy for investors' sentiment. At the end of each week t, we first sort the commodity futures contracts into five groups by their *SpillAtt* measure. Then within each group, we sort the contracts into the "High" category if their media tones are positive. Otherwise, we sort them into the "Low" category. Finally, we calculate the return spread (High-Low).

Table 4.6 reports the return of *SpillAtt* strategy in high versus low sentiment periods. For each quantile, the return pattern is significantly stronger in high-sentiment periods. Meanwhile, when attention is the highest (Q1), the spread is 4.69% which is the highest. Therefore, consistent with our conjecture, the return pattern is indeed stronger in high-sentiment periods.

Figure 4.2: Long-run Annualized Alphas of the Limited Attention Portfolios



This figure shows the long-run annualized alphas of equally-weighted limited attention portfolios over 11 weeks horizon.

Table 4.6: Limited Attention and Investors' Sentiment

		Q1	Q2	Q3	Q4	Q5
Media Tone	High	0.203	0.031	0.018	0.046	0.058
	Low	-0.266	-0.104	-0.019	-0.042	-0.023
	High-Low	0.469	0.135	0.036	0.087	0.082
	t-statistic	11.084	2.914	2.070	2.187	2.434

This table shows the return of *SpillAtt* strategy in high versus low sentiment periods.

4.6 Robustness Checks

4.6.1 Turnover and Transaction Cost

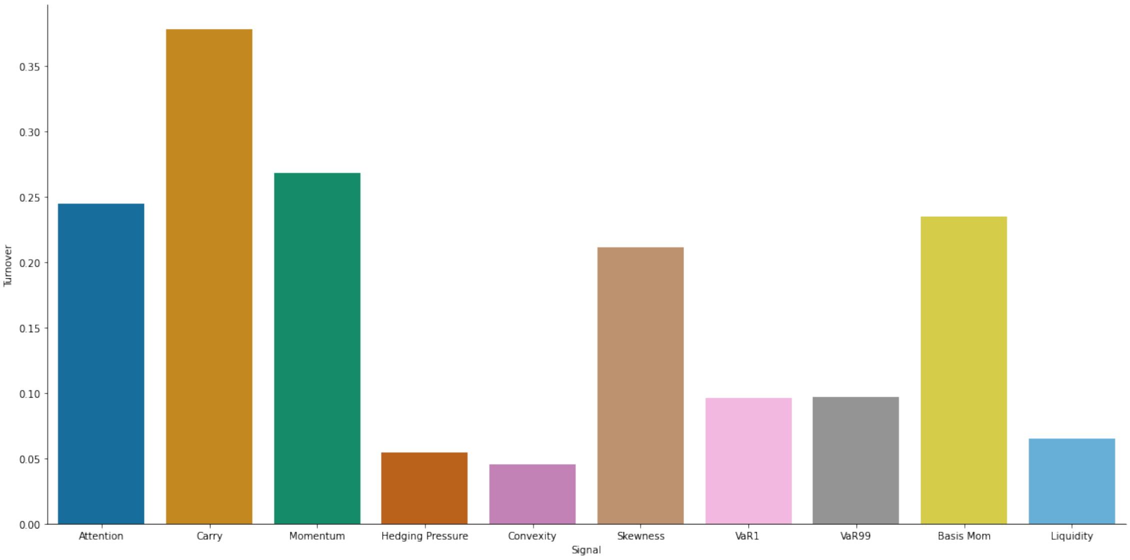
In this section, we consider the influence of trading intensity on trading strategies. We measure the portfolio $turnover(TO)$ defined as the time averaging of all the trading incurred

$$TO_j = \frac{1}{T-1} \sum_{t=1}^{T-1} \sum_{i=1}^{N} (|\tilde{\phi}_{j,i,t+1} - \tilde{\phi}_{j,i,t^+}|) \tag{4.6.1}$$

where $t = 1, \cdots, T$ denotes each of the portfolio formation period. $\tilde{\phi}_{j,i,t+1}$ is the ith commodity allocation weight at week t by the jth trading style while $\tilde{\phi}_{j,i,t^+} = \tilde{\phi}_{j,i,t} e^{r_{i,t+1}}$ is the actual portfolio weight right before the next rebalancing at $t+1$ with, the weekly return of the ith commodity from weekend t to weekend $t+1$. Thus the TO measure captures the mechanical evolution of the allocation weights due to within-week price dynamics. Figure 4.3 plots the turnovers of the long-short portfolios sorted on the limited attention and other signals shown in Table 3.4.

The figure shows that the turnover of the attention portfolio does not significantly higher than other strategies. It is higher than hedging pressure, convexity,

Figure 4.3: A Plot of Turnover for Different Trading Strategies



This figure shows the turnover of the long-short portfolios sorted on limited attention and signals shown in Table 3.4.

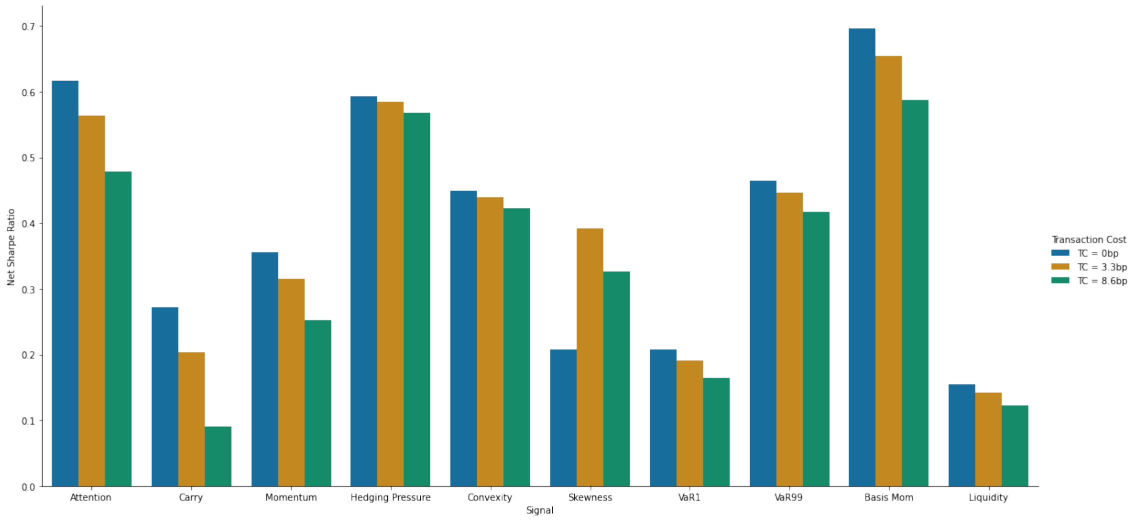
skewness, VaR1, VaR99 and liquidity strategies but is lower than carry, momentum, and basis momentum strategies. Thus, the trading intensity does not have a significant influence on attention trading strategy.

We then consider the influence of transaction cost. Using proportional trading costs of 3.3 bps (Locke & Venkatesh, 1997) and 8.6 bps (Marshall et al., 2012), we calculate the net returns of the long-short limited attention portfolio and portfolios sorted on other signals as:

$$\tilde{r}_{P,t+1} = \sum_{i=1}^{N} \tilde{\phi}_{i,t} r_{i,t+1} - TC \sum_{i=1}^{N} |\tilde{\phi}_{i,t} - \tilde{\phi}_{i,t-1^{+}}| \tag{4.6.2}$$

Figure 4.4 shows the net Sharpe ratios of different trading strategies. After deducting a proportional 3.3bp or 8.6bp as the trading cost, the limited attention portfolio still has a higher net Sharpe ratio than other trading strategies except for the hedging pressure and basis momentum. Thus, the economic benefit of the limited attention measure is not significantly influenced by transaction cost.

Figure 4.4: A Plot of Net Sharpe Ratios for Different Trading Strategies



This figure shows the net Sharpe ratios of the long-short portfolios sorted on limited attention and signals shown in Table 3.4.

4.7 Conclusion

This paper explores the limited attention effect in commodity futures markets. Specifically, we verify there is an attention spillover effect between the equity market and the commodity futures market. Investors' attention to firm-specific news will spill to their related commodity futures market which results in buying behaviours. Therefore, we create limited attention scores for each commodity futures contract by coverage of their related firm-specific news. The portfolio analysis suggests that the commodity-specific limited attention scores are able to forecast the returns of commodity futures a week ahead after controlling for other well-known commodity characteristics such as roll-yield, hedging pressure or momentum.

Long-short portfolios sorted on limited attention accrue significant excess returns that are not compensation for exposure to known systematic risks. The paper provides an empirical cross-sectional asset pricing exercise suggesting that there is pricing ability in limited attention over and above that of traditional risk factors. To further verify the limited attention effect, we test the long-run return of the equally weighted limited attention portfolio. The alphas of the portfolios reverse after 4 weeks which suggests that the impact of limited attention is indeed temporary. We also show that when investors' sentiment is high, the effect of limited attention is stronger as correction of such mispricing becomes more difficult.

Overall, it is concluded that the presence of the limited attention effect cannot be ruled out in commodity futures markets, namely, limited attention of investors can induce commodity futures mispricing and more so when an investor's sentiment is high.

Chapter 5

Conclusions

This thesis contributes to the empirical literature on the commodity futures market. As the commodity futures are used more widely for portfolio diversification, it is important to figure out the sources of commodity futures premium. In this thesis, we extend the current understanding by answering the following questions:

- Is it possible to exploit multiple commodity risk premia using style integration?
- What is the role of sentiment in the commodity futures market?
- How to identify the causal effect of the limited attention effect in the commodity futures market?

We answer the first question in the second chapter. We confirm the benefit of style integration in the commodity market and find out the best sophisticated integration approach that incorporates model and parameter uncertainties. Specifically, we start by calculating five standalone style portfolios which are term structure, hedgers' hedging pressure, momentum, skewness, and basis momentum. After that, we combine the five standalone styles with several integration methods. An equally weighted approach (EWI) is first calculated as a benchmark in order to confirm the benefit of style integration. Alternative integration portfolios based on sophisticated strategies are calculated after that and compared with the benchmarks. To conquer the parameter uncertainty problem, we solve the style weights via a Bayesian portfolio optimization method which incorporates investors' objective view of the portfolio.

Our key finding is that style integration is confirmed to be more efficient in capturing the risk premia of commodity futures. Incorporating parameter uncertainty into the sophisticated approach will bring significantly better performance in terms of both reward-to-risk and crash risk measures. This result is robust to turnover, trading cost, sub-period analysis, using alternative score schemes, and different estimation windows. Thus, we conclude that parameter uncertainty plays an important role in style integration. By considering this, investors will have a better way of constructing portfolios and could be more efficient in assets diversification.

In the third chapter, we study the role of sentiment in the commodity futures market. We construct media tone measures, which serve as proxies for investors' sentiment, from news articles published over a week window for each commodity contract. The predictability analysis suggests that the commodity-specific media tone scores are able to forecast the returns of commodity futures a week ahead after controlling for well-known commodity characteristics such as roll-yield, hedging pressure or momentum, etc. We then aggregate media tone scores into a market-wide sentiment index. The sentiment index has greater predictive power for commodity market returns, in- and out-of-sample, than extant measures of sentiment in the broad financial market. We also confirm the asymmetric effect of sentiment on the market i.e. negative or pessimistic sentiment has stronger forecast power and it plays a stronger role as a driver of prices in periods of crises.

Long-short portfolios sorted on media tone accrue significant excess returns that are not compensation for exposure to known systematic risks. Thus motivated, the paper puts forward a simple strategy to enhance traditional long-short portfolio allocations by embedding the information content of media tone into traditional sorting signals. The paper provides an empirical cross-sectional asset pricing exercise suggesting that there is pricing ability in media tone over and above that of traditional risk factors.

We identify the causal effect of limited attention in the fourth chapter. To create a clear measure for investors' attention, we utilize the attention spillover effect between the equity market and commodity futures market. We argue that investors' attention to firm-specific news will spill to their related commodity futures market which results in buying behaviours of investors. Therefore, we create limited attention scores for each commodity futures contract by coverage of their related firm-specific news. The portfolio analysis suggests that the commodity-specific limited attention scores are able to forecast the returns of commodity futures a week ahead after controlling for other well-known commodity characteristics.

Long-short portfolios sorted on limited attention accrue significant excess returns that are not compensation for exposure to known systematic risks. The paper provides an empirical cross-sectional asset pricing exercise suggesting that there is pricing ability in limited attention over and above that of traditional risk factors.

To further verify the limited attention effect, we test the long-run return of the equally weighted limited attention portfolio. The alphas of the portfolios reverse after 4 weeks which suggests that the impact of limited attention is indeed temporary. We also show that when investors' sentiment is high, the effect of limited attention is stronger as correction of such mispricing becomes more difficult.

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