Newswire Tone-Overlay Commodity Portfolios

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Abstract

This paper introduces the concept of newswire tone-overlay, which adjusts traditional commodity signals based on the level of optimism or pessimism in commodity newswires. By implementing the novel tone-overlay allocation strategy on 26 commodities using traditional allocation signals, we demonstrate that the resulting long-short portfolios yield substantial performance gains compared to the corresponding plain-vanilla traditional portfolios. Our findings indicate that newswire tone offers short-term predictive power for commodity futures returns beyond well-known commodity characteristics. The tone-overlay portfolios harness a temporary mispricing that reflects an overreaction of commodity futures prices to commodity-specific newswire tone. The outperformance of the tone overlay strengthens with the salience of the newswire tone, in line with theories of limited investor attention.

***Keywords*:** Newswire tone-overlay; Textual analysis; Sentiment; Commodity futures; Tactical allocation; Mispricing; Salience.

JEL classifications: Q02, G12, G14.

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1. Introduction

The contention that sentiment can cause prices to depart from fundamental values can be traced back to at least Keynes (1936). Several studies have tested the predictability of equity returns based on firm-specific news sentiment (or tone) extracted through textual analysis. Firm-level optimistic (pessimistic) news tone is followed by higher (lower) equity returns in the next few trading days, with a subsequent full reversal (see, e.g., Tetlock, 2007, 2011; Garcia, 2013; Ferguson et al., 2015; Fedyk and Hodson, 2023). The empirical insights from this firm-level news sentiment literature also echo Shiller's (2000) early argument that news media can induce irrational trading; investors often follow the printed word even when much of it is pure hype.

In this paper, we posit that the overall tone of commodity-specific newswires, including both recent and older news items, contains cross-sectional predictive ability for commodity futures returns beyond that of commodity futures fundamentals such as the basis or hedging pressure. To test this conjecture, we introduce the concept of newswire tone-overlay which is the upward (downward) adjustment of a fundamental signal according to the optimistic (pessimistic) tone of commodity newswires. Commodity futures markets are an interesting laboratory to study the role of commodity-level news sentiment (or tone) not only because research in this area is scarce, but also because the retail investors' participation in these markets remains very small.[1] Thus, our investigation can shed light on the widely-held assumption that irrational, unsophisticated retail investors are responsible for sentiment-induced mispricing.

We put forward a tactical allocation strategy that leverages commodity-specific newswire tone alongside the fundamental signals known to price commodity futures. For example, take the *basis* signal that is measured as the price difference between the front and second-nearest contracts. A new *tone-overlay basis* signal is derived by adjusting the original basis upward or

[1] In 2014, small non-reportable traders accounted for merely 13% of open interest in commodity futures markets (Bhardwaj et al., 2016).

downward to embed the level of optimism or pessimism in newswires. This adjustment can alter the attractiveness of each commodity for the long and short positions within the portfolio.

We operationalize the tone-overlay concept for a sample of 26 commodities by creating weekly-rebalanced long-short portfolios using various traditional allocation signals. The results demonstrate that embedding commodity-specific newswire tone into traditional investment strategies is fruitful. This is evidenced, for instance, by an average Sharpe ratio gain of 0.69 and an alpha of 7.78% per year compared to the "plain-vanilla" traditional portfolios. These findings suggest that the newswire tone signal exhibits additional predictive ability for the cross-section of commodity futures returns beyond that offered by well-known commodity futures characteristics.

Investigating the source of the added performance by the tone-overlay, we do not find support for the risk explanation. The results point towards a mispricing associated with investors' overreaction to newswire tone, followed by a full reversal within a week. Consistent with the temporary mispricing interpretation, we also find that the outperformance of the tone-overlay strategy is driven by more speculative commodities, which are subject to greater impediments to arbitrage, and that it deteriorates as the portfolio holding period extends beyond one week.

Through various additional tests, we show that the outperformance of the tone-overlay portfolios is not spurious, as evidenced by a placebo test, and is robust to different tone-overlay hyperparameter choices, transaction costs, and a broad universe of traditional signals. Moreover, we demonstrate that the outperformance of the tone-overlay strategy increases with the salience of the newswire tone. The tone-overlay strategy can be further improved through parameter cross validation and is found to be more effective than the resilient equal-weights style-integration approach as an alternative method to combine signals (Fernandez-Perez et al., 2019).

Our paper contributes to the literature that explores how sentiment extracted from financial or firm-specific news influences investor trading decisions, leading to temporary distortions of equity prices away from fundamentals (Tetlock, 2007, 2011; Garcia, 2013; Ferguson et al., 2015;

Fedyk and Hodson, 2023). A distinctive aspect of our study is providing evidence that commodity news tone induces short-term price overreactions in the commodity futures market. Furthermore, we introduce the tone-overlay concept to harness this predictability for trading strategies.

Our study connects findings from commodity futures markets with insights from behavioral finance and equity markets research. The evidence of a gradual price overreaction to newswire tone followed by a reversal is consistent with behavioral models suggesting that investors' overconfidence and self-attribution biases lead to short-term equity price momentum (Daniel et al., 1998) or that equity prices depart from fundamentals when the sentiment of noise traders increases (DeLong et al., 1990). Our commodity markets finding that the more salient the commodity-specific newswire tone the greater the outperformance accrued by the tone-overlay strategy aligns with extant research showing that, due to limited attention, equity investors tend to focus their decisions on the most salient attributes and information (Hirshleifer and Teoh, 2003; Bordalo et al., 2012, 2022; Cosemans and Frehen, 2021; Nekrasov et al., 2022).[2]

Our study bridges findings from commodity futures markets with insights from equity markets research and behavioral finance. The evidence of a gradual price overreaction to commodity newswire tone followed by a reversal aligns with behavioral finance models suggesting that equity investors' overconfidence and self-attribution biases contribute to short-term equity price momentum (Daniel et al., 1998), or that equity prices deviate from fundamentals as sentiment among noise traders intensifies (DeLong et al., 1990). Our finding that the more salient the commodity-specific newswire tone the greater the outperformance achieved by the tone-overlay resonates with existing research demonstrating that, due to limited attention, equity

[2] Bordalo et al. (2022) survey several models of salience and bottom-up attention in economic choice. The models share the intuition that "when decision-makers choose, the attributes of choice options act as stimuli […] The attention of decision makers is allocated bottom up to *salient* attributes, which are then overweighted, while non-salient attributes are underweighted."

investors tend to base their decisions on the most salient attributes and information (Hirshleifer and Teoh, 2003; Bordalo et al., 2012, 2022; Cosemans and Frehen, 2021; Nekrasov et al., 2022).

Given the predominance of institutional investors in commodity futures markets, our findings contribute to a literature illustrating that these investors often behave as noise traders, influenced by non-fundamental signals, trading on heuristics, and exhibiting behavioral biases. Examples include studies in equity markets (Rangvid et al., 2013; Edelen et al., 2016; Wang, 2018; De Vault et al., 2019; Coakley et al., 2021; Wang and Duxbury, 2021; Akepanidtaworn et al., 2023) and commodity futures markets (Fernandez-Perez et al., 2020; Fan et al., 2023).

Our paper also contributes to the literature documenting a significant premium capture from long-short allocations of commodity futures based on fundamental signals such as basis and hedging pressure inter alia (e.g., Miffre and Rallis, 2007; Basu and Miffre, 2013; Szymanowska et al., 2014; Fernandez-Perez et al., 2018; Boons and Prado, 2019; Fernandez-Perez et al., 2019; Sakkas and Tessaromatis, 2020). One practical outcome of our paper is providing a systematic approach for commodity investors to enhance the performance of these strategies by incorporating the predictive ability of newswire tone. Another significant finding is the validation of proprietary news analytics software that assigns sentiment scores to news directed at commodities.

The rest of the paper proceeds as follows. The tone-overlay method is presented in Section 2. Section 3 discusses the data, examines the performance of the tone-overlay portfolios relative to their traditional counterparts, and confronts two possible channels (risk versus mispricing) for the profitability gains. Section 4 provides robustness tests, and Section 5 concludes.

2. Methodology

2.1. Tone-overlay strategy

The essence of the newswire tone-overlay strategy that we propose is to adjust a traditional long-short commodity signal up or down based on the aggregate level of optimism or pessimism in recent commodity-specific newswires. These traditional signals include commodity futures characteristics that have been shown to predict cross-sectional variation in commodity futures returns, such as basis, momentum, hedging pressure, relative basis, convexity, skewness, basis-momentum, and liquidity. Formal definitions and key references are provided in Appendix A. For simplicity, all signals are measured so that higher values predict larger increases (smaller decreases) in futures prices, recruiting candidates for the long leg, while smaller values predict larger decreases (smaller increases) in futures prices, recruiting candidates for the short leg. If the newswire tone contains cross-sectional predictive ability beyond that of traditional commodity futures characteristics, then the tone-overlay strategy should be fruitful.

Let $x_{i,t}$ denote the cross-sectional standardized commodity futures characteristic for commodity i at portfolio formation time t. The commodity-specific newswire tone is an index, $0 \leq TONE_{i,t} \leq 100$, where values above 50 indicate optimistic sentiment (price expected to rise) and values below 50 indicate pessimistic sentiment (price expected to fall). The construction of the tone measure is discussed below in Section 2.2. The tone-overlay signal ($x_{i,t}^{TONE}$) represents the traditional commodity futures characteristic adjusted by the newswire tone.

To provide some intuition, suppose that at portfolio formation time t the ith commodity in the cross-section is characterized by a positive basis or downward term structure, $basis_{i,t} = ln\left(f_{i,t}^{T_1}\right) - ln\left(f_{i,t}^{T_2}\right) > 0$, with T_n denoting the nth nearest futures contract – this commodity is therefore a good candidate for the long leg of the basis portfolio. At the same time, if recent newswires on the commodity are overall optimistic (pessimistic), the basis signal is tilted upwards (downwards) to produce the tone-overlay basis (hereafter, $basis_{i,t}^{TONE}$). Thus, according to the new $basis_{i,t}^{TONE}$ signal, the commodity is a stronger (less strong) candidate for the long leg of the portfolio. Vice versa, if $basis_{i,t} < 0$, then the commodity is a good candidate for the short leg of the basis portfolio. The basis signal is tilted down (up) with pessimistic (optimistic) tone and hence, the commodity becomes a more (less) attractive candidate for the short portfolio with $basis_{i,t}^{TONE}$ than with the basis signal.

The tone-overlay signal is derived by adjusting the (cross-sectionally standardized) original signal, $x_{i,t}$, with the newswire tone signal, $TONE_{i,t}$, according to various parameters

$$x_{i,t}^{TONE} = f\big(x_{i,t}, TONE_{i,t}, \sigma_{i,t}, \boldsymbol{\theta}\big), \tag{1}$$

where t denotes each portfolio formation time, $\sigma_{i,t}$ is the volatility of $x_{i,t}$ and $\boldsymbol{\theta} = (\pi, \tau, (\delta^+, \delta^-))$ are hyperparameters, that is, user-specified parameters. In explicit form, the tone-overlay signal is obtained by tilting the original signal upwards or downwards as

$$x_{i,t}^{TONE} = x_{i,t} + \delta^+ I_{i,t,(1-\pi)}^{TONE+} \tau\sigma_{i,t} - \delta^- I_{i,t,\pi}^{TONE-} \tau\sigma_{i,t}, \tag{2}$$

The role of each of the hyperparameters $\boldsymbol{\theta} = (\pi, \tau, (\delta^+, \delta^-))$ is, intuitively explained, as follows:

Tone salience (π). The optimistic and pessimistic tone indicators, $I_{i,t,(1-\pi)}^{TONE+}$ and $I_{i,t,\pi}^{TONE-}$, respectively, are defined through the commodity-specific historical distribution of newswire tone – this allows commodity heterogeneity in the identification of news salience. Let $z_{i,t,\pi}$ and $z_{i,t,(1-\pi)}$ denote, respectively, the bottom πth and top (1-π)th percentiles of the historical distribution of newswire tone for commodity i over the prior L weeks, $\{TONE_{i,t-L+1}, \dots, TONE_{i,t-1}, TONE_{i,t}\}$. If the tone signal is salient optimistic for this commodity, i.e. $TONE_{i,t} > z_{i,t,(1-\pi)}$, we set $I_{i,t,(1-\pi)}^{TONE+} = 1$ and $I_{i,t,\pi}^{TONE-} = 0$, while if the tone is salient pessimistic, i.e. $TONE_{i,t} < z_{i,t,\pi}$, we set $I_{i,t,\pi}^{TONE-} = 1$ and $I_{i,t,(1-\pi)}^{TONE+} = 0$. Otherwise, $z_{i,t,\pi} < TONE_{i,t} < z_{i,t,(1-\pi)}$, and we set $I_{i,t,\pi}^{TONE-} = I_{i,t,(1-\pi)}^{TONE+} = 0$ which implies that the allocation relies solely on the traditional signal, $x_{i,t}^{TONE} = x_{i,t}$. Hence, the tone-overlay method is flexible, as the identification of salient news tone is both commodity-specific and dynamic. For instance, the salience parameter $\pi = 0.10$ implies that the overlay is triggered only for salient tone as dictated by the 10th and 90th percentiles of the tone distribution $\{TONE_{i,t-j}\}_{j=0}^{L-1}$.

Traditional-signal tilting (τ). The traditional signal for commodity i is adjusted up or down by $\tau\sigma_{i,t}$ where $0 < \tau < \infty$ is the *tilting* parameter and $\sigma_{i,t}$ is the volatility of the original signal estimated from his past L-week history, $\{x_{i,t-L+1}, \dots, x_{i,t-1}, x_{i,t}\}$. The closer τ is to zero, the weaker the tilting, $x_{i,t}^{TONE} \approx x_{i,t}$. Vice versa, setting the tilting parameter, say, at $\tau = 0.9$ implies that for each commodity *i* at any portfolio formation time *t* the signal $x_{i,t}$ is tilted by nearly a full standard deviation of its past distribution. A more flexible, commodity-heterogenous and dynamic, tilting can be achieved by setting this parameter at the (cross-sectionally standardized) tone, $\tau_{i,t} = |\widetilde{TONE}_{i,t}|$, or its weekly change, $|\Delta\widetilde{TONE}_{i,t}|$.

Optimism vs. pessimism (δ^+, δ^-) with each parameter bounded between 0 and 1. Investors might react similarly to optimistic and pessimistic news tone or asymmetrically, inducing different return predictability from both types of tone. The tone overlay accommodates these phenomena by allowing the traditional signal to be tilted symmetrically $\delta^+ = \delta^-$, more strongly when the tone is pessimistic than optimistic $\delta^+ < \delta^-$or vice versa.

2.2. Commodity sentiment measure

We proxy commodity-level sentiment by a news tone measure ($TONE_{i,t}$) that exploits metadata generated by *RavenPack News Analytics* (RPNA v.4) for all news stories released by Dow Jones Financial Wires, Wall Street Journal, Barron's and MarketWatch. Consequently, our investigation serves also as an indirect test on the effectiveness of RPNA sentiment metadata within the commodity investment domain. For each commodity (called entity) that is mentioned in a news story, RPNA generates a commodity-level record and assigns to it various fields or metadata.

a) Entity Name. A news story generates two records with an entity name each, for instance, copper and silver, if these two metals are mentioned in the story.

b) Relevance is a 0-100 score that indicates the role that the commodity plays in the news story. For instance, the relevance assigned to the news record for copper could be 95 if the news story centers on the growing demand for copper stemming from electric car production (and 100 if in addition copper features in the headline) while the relevance score of the record for silver could be 15 if this metal is only passively mentioned. To mitigate noise, RPNA recommends employing only records with entity relevance above 75; we conservatively adopt 90 as the cutoff.

c) Event Novelty Score (ENS) is a 0-100 index that indicates how "new" or novel the content of the entity-level news record is across all other (same entity) stories within a 24-hour window.

d) Event Sentiment Score (ESS) is a 0-100 index that conveys the likely short-term price movement of the commodity according to the news story – upward price movement or optimistic sentiment ($ESS > 50$) versus downward price movement or pessimistic sentiment ($ESS < 50$). A story with more emotionally charged language is assigned an ESS closer to either 0 or 100. Section A.1 of the online Annex provides further details on the RPNA metadata and construction.

On the first trading day per week (Monday-end denoted t) we obtain $TONE_{i,t}$ for commodity i as a weighted average of the *ESS* of the relevant news items in the prior 7-day (24-hour) period

$$TONE_{i,t} = \frac{\sum_{d=t}^{t-D+1} \gamma^{t-d} \left(\sum_{k=1}^{K_d} \phi_{k(d)} ESS_{d(k)} \right)}{\sum_{d=t}^{t-D+1} \gamma^{t-d}}, \quad 0 \leq TONE_{i,t} \leq 100, \tag{3}$$

where $ESS_{d(k)}$ is the event sentiment score of the kth news record on day d, with $d = t$ denoting the first 24-hour window preceding the Monday-end (which we conservatively set at 5:00 p.m. EST[3] for all commodities), $d = t - 1$ the second 24-hour window beforehand, and so on; $\phi_{k(d)}$ with $\sum_{k=1}^{K_d} \phi_{k(d)} = 1$ is the intra-day news weight that establishes the relative importance of each of the news items within the same 24-hour window, and $K_1, \ldots, K_7$ are the number of items in each of the 24-hour windows. Finally, the weight $0 < \gamma \leq 1$ represents the inter-daily news impact decay; $\gamma = 1$ implies no decay or that the news items in the immediately preceding 24-hour window are given the same role in the sentiment measurement as those released days ago; $\gamma < 1$ implies that the most recent news records are weighted more than the older ones, the smaller γ the faster the daily news decay. We weigh equally each of the K_d news items within the same

[3] The daily settlement times for futures contracts can vary depending on the exchange and commodity. Selecting 5 pm EST each Monday for portfolio formation is conservative, as by this time, all futures contracts in the cross-section of our study have settled.

24-hour window, $\phi_{k(d)} = \frac{1}{K_d}$, and allow for a very gradual daily decay, $\gamma = 0.9$. In a sensitivity analysis, we will examine the impact of considering alternative weighting schemes, $\phi_{k(d)}$ and γ.

2.3. Long-short portfolio construction

At each portfolio formation time *t*, the commodity-specific volatility $\sigma_{i,t}$ as input of the tone-overlay signal, Eq. (2), is estimated using the historical commodity-specific distribution of the traditional signal $\{x_{i,t-L+1}, \ldots., x_{i,t-1}, x_{i,t}\}$ over a L-week period. The salient tone indicators, $I_{i,t,(\pi)}^{TONE-}$ and $I_{i,t,(1-\pi)}^{TONE+}$ in Eq. (2), are extracted from the historical commodity-specific tone distribution $\{TONE_{i,t-L+1}, \ldots., TONE_{i,t-1}, TONE_{i,t}\}$. We use $L = 260$ weeks.

We set the hyperparameters in Eq. (2) at the values $\pi = 0.10$ (*salience*), $\tau = 0.9$ (*tilting*), and $\delta^{+} = \delta^{-} = 1$ (*optimism/pessimism*). The portfolio analysis using this baseline tone-overlay model will later be complemented with alternative hyperparameter specifications and a cross-validated tone-overlay approach that endogenously selects the hyperparameters.

The N commodities are sorted by the resulting tone-overlay signal $x_{i,t}^{TONE}$. We take long positions in the top-quintile commodities with the largest $x_{i,t}^{TONE}$ values that are expected to appreciate the most (or depreciate the least) and short positions in the bottom-quintile commodities with the smallest $x_{i,t}^{TONE}$ values that are expected to depreciate the most (or appreciate the least). The futures positions are equally weighted, fully collateralized and held for one week. The tone-overlay portfolios are formed each Monday-end (time *t*) using past data so there is no look-ahead bias and thus, the sequential approach enables a sequence of weekly out-of-sample (OOS) excess returns $r_{P,t+1}$. The traditional portfolios (adopted as benchmarks to appraise the tone-overlay portfolios) are constructed similarly using the original signals, $x_{i,t}$.

2.4. Portfolio performance evaluation

The superiority of the tone-overlay portfolios relative to their traditional counterparts is measured through the Sharpe ratio (SR) differential, $\Delta SR = SR_{overlay} - SR_{trad}$. To provide statistical significance to our findings we deploy the Ledoit and Wolf (2008) test for the hypotheses $H_0: \Delta SR \leq 0$ versus $H_A: \Delta SR > 0$. We also measure the alpha of the tone-overlay portfolio as the intercept of a spanning regression of its excess returns on the excess returns of the corresponding traditional portfolio. Finally, to incorporate utility in the portfolio evaluation, we calculate the gain in certainty equivalent return (CER) achieved by the tone overlay relative to the traditional portfolio, $\Delta CER = CER_{overlay} - CER_{trad}$ with $CER_P = \left(\frac{52}{T}\right)\sum_{t=0}^{T-1}\frac{(1+r_{P,t+1})^{1-\nu}-1}{1-\nu}$ where the relative risk aversion coefficient, ν, is set to 5 as in Brandt et al. (2009) inter alia and T is the number of OOS weeks. We also deploy the generalized method of moments (GMM) test of Anderson and Cheng (2016) for the hypotheses $H_0: \Delta CER = 0$ versus $H_A: \Delta CER \neq 0$.

3. Empirical Analysis

3.1. Commodities data

We collect daily commodity futures settlement prices and dollar trading volume from *Refinitiv Datastream*, and open interest from the CFTC's *Commitment of Traders Report*. The cross-section includes 26 commodities from different sectors: 5 energies, 4 grains, 4 livestock, 5 metals, 3 oilseeds and 5 softs. Excess returns are calculated as $r_{i,t} = \ln\left(f_{i,t}^{T_1}/f_{i,t-1}^{T_1}\right)$ using the front-maturity (T_1) contracts until the end of the month prior to the maturity month when we roll to the second-nearest contracts. This rolling technique avoids potential near-maturity erratic price behavior and addresses concerns regarding forced delivery after the first notice day (Bakshi et al., 2019). Open interest is the total number of outstanding contracts along the futures curve (all maturities) that have not been settled or closed. As dictated by the availability of commodity-level news sentiment metadata from RPNA, the sample period is January 3, 2000, to May 31, 2020.

Table 1 summarizes the commodity excess returns and newswire tone signal. The volume of news records available per commodity is extensive, averaging 369,231 over the sample period ranging from 15,097 for frozen pork bellies to 3,607,532 for crude oil. After filtering out the records with a *relevance* score below 90, our $TONE_{i,t}$ signal is based on 44 news records per week on average across commodities, ranging from 3 for livestock to 153 for energies.[4]

[Insert Table 1 around here]

Table 1 also shows that there is time variation in the $TONE_{i,t}$ signal for each commodity as suggested by the standard deviation and range over the sample period. The first-order autocorrelation in newswire tone (AC1) is uniformly positive at 0.52 on average across commodities – if the sentiment on commodity i on week *t* is upbeat, there is a good chance that the sentiment is also upbeat on the following week. By contrast, the AC1 of the weekly commodity excess returns hovers closely around zero (average absolute correlations at 0.03) confirming the stylized fact of scant time-series return predictability from own past returns.

The correlation structure of commodity newswire tone, $corr(TONE_{i,t}, TONE_{j,t})$, plausibly echoes the correlation structure in commodity excess returns, with the dependence being larger within sectors than across sectors. For instance, as shown in Table A.1 in the online Annex, the correlation in newswire tone for crude oil with other energies stands at 0.32 on average but it is negligible at 0.05 (with grains), -0.02 (livestock), 0.09 (metals), 0.04 (oilseeds) and 0.04 (softs). The newswire tone exhibits lower within-sector correlation than the excess return, for instance, at 0.36 versus 0.56 for energies, and 0.25 vs. 0.60 for metals which echoes the findings in Fan et al. (2023) for commodity-level sentiment proxied by Tweets. Indirectly, this evidence can be interpreted to suggest that the $TONE_{i,t}$ signal conveys moods and beliefs (sentiment), rather than commodity fundamentals with a sectoral element. For example, the agricultural sector is heavily influenced by weather conditions and crop yields, while the energy sector is influenced by geopolitical events and technological advancements in extraction methods.

[4] Each of the 26 commodities is covered by news items in all sample weeks before the $Relevance > 90$ filter is applied. After this filtering rule, if there are no news stories about commodity *i* on a week *t,* we set the news tone to default neutral ($TONE_{i,t} = 50$) and thus, the traditional signal is not tilted on that week.

Furthermore, the correlations between $TONE_{i,t}$ and each of the traditional signals, $x_{i,t}$ in Eq. (1), are mild, ranging from -0.28 to 0.32. The correlations between the returns of traditional long-short portfolios and the returns of a long-short portfolio sorted on $TONE_{i,t}$ are minimal, averaging 0.02 (see Table A.2 in the online Annex). This evidence supports the potential usefulness of overlaying newswire tone onto traditional commodity futures characteristics.

3.2. Commodity-level newswire tone and market-wide sentiment

A pertinent question is whether our newswire tone measure ($TONE_{i,t}$) simply reflects broad market sentiment (hereafter, denoted $Sentiment_t$). The correlations in newswire tone discussed above reveal large commodity heterogeneity which suggests that newswire tone may not just mimic market sentiment. To address the question more formally, we adopt various proxies of sentiment: (i) the CBOE's VIX "investors' fear" index, (ii) the Baker and Wurgler (2006; BW) sentiment index, (iii) the Federal Reserve Bank (FRB) of San Francisco sentiment index extracted from economic-related news articles in 24 major U.S. outlets including the *New York Times* and the *Washington Post* (Shapiro et al., 2020), (iv) the University of Michigan consumer confidence index which is a survey of how US consumers feel about the economy, business conditions, and personal finances, (v) the American Association of Individual Investors (AAII) sentiment index constructed from surveys of individual investors, and (vi) the photo news pessimism index of Obaid and Pukthuanthong (2022).[5] Figure 1 shows box-and-whisker plots of the commodity-by-commodity correlation between $TONE_{i,t}$, $i = 1,..,N$, and the broad market sentiment proxies.

[Insert Figure 1 around here]

The correlations between $TONE_{i,t}$ (for $i = 1, \dots, N$) and $Sentiment_t$ are low from -0.29 to 0.35, and commodity heterogeneous in line with a mild overlap in newswire tone across commodities,

[5] The data for the VIX, BW sentiment index, economic news sentiment index, consumer survey sentiment index, investors survey sentiment index and photo news pessimism index are from the websites of the FRB of St. Louis, Prof. J. Wurgler, the FRB of San Francisco, Michigan University, the AAII and Prof. K Pukthuanthong, respectively. The monthly BW and Michigan index data are linearly interpolated to weekly.

$corr(TONE_{i,t}, TONE_{j,t})$, especially across sectors, as discussed earlier. This evidence suggests that the $TONE_{i,t}$ measure captures moods and beliefs that are mostly commodity idiosyncratic.

To conduct formal tests, we estimate panel fixed effects regressions for the news tone

$$TONE_{i,t} = \alpha_i + \gamma Sentiment_t + \boldsymbol{\theta Z}_{i,t} + \varepsilon_{i,t}, i = 1, \ldots, N, t = 1, \ldots, T, \quad (4)$$

where the controls ($\boldsymbol{Z}_{i,t}$) are the basis, momentum, hedging pressure, convexity, skewness, basis-momentum, liquidity, and the excess return, and the α_i capture unobserved commodity effects.

[Insert Table 2 around here]

The largely insignificant coefficient γ and small explanatory power (Adjusted-R^2 with or without fixed effects) shown in Table 2 further document that the time variation in the $TONE_{i,t}$ signal (for $i = 1, .., N$) is generally not subsumed by the dynamics of market-wide sentiment.

3.3. Performance of tone-overlay portfolios

The out-of-sample performance of the traditional portfolios and corresponding tone-overlay portfolios is summarized in Table 3. The first OOS excess return is for week one of January 2005 as dictated by the estimation window ($L = 260$ weeks) used for the tone-overlay model, Eq. (2).

[Insert Table 3 around here]

The tone-overlay strategy, when deployed with the seven alternative traditional signals, generates Sharpe ratio gains, $\Delta SR = SR_{overlay} - SR_{trad}$, ranging from 0.53 (hedging pressure signal) to 0.80 (momentum signal), with an average of 0.69 across all seven tone-overlay portfolios. These risk-adjusted return improvements are not only economically attractive but also statistically significant, as evidenced by the very low p-values from the Ledoit and Wolf (2008) test.[6] Similar evidence is provided by the Sortino and Omega ratios. The outperformance of the

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[6] News sentiment metadata vendors occasionally calibrate or fine-tune their algorithms. RPNA version 4 was released on September 7, 2014 and so the then-backfilled news sentiment data hinges on future information. To alleviate any concerns of look-ahead bias, we evaluate the tone-overlay portfolios in the backfilled period (January 3, 2000 - September 1, 2014), and the live period (September 8, 2014 - May 25,

tone overlay reflects both its superior return capture and its more favorable risk profile (standard deviation, semi-deviation, skewness, excess kurtosis, 1% Value-at-Risk, and maximum drawdown) relative to the corresponding traditional strategies. Likewise, the certainty equivalent returns of the tone-overlay portfolios significantly surpass those of the underlying traditional portfolios by 5.61% p.a. on average. The alphas of the tone-overlay portfolios relative to the corresponding traditional benchmarks are sizeable at 7.78% p.a. on average and strongly significant at the 1% level as suggested by Newey-West robust *t*-statistics.

Figure 2 assesses the portfolios dynamically by plotting their cumulative Sharpe ratios vis-à-vis those of the corresponding traditional portfolios. The first Sharpe ratio is obtained from an initial window of 260 weeks, which is then expanded sequentially by one week. The plots confirm the effectiveness of the tone overlay and further reveal its ability to mitigate the performance decline observed in some traditional portfolios after the late 2000s Global Financial Crisis.

[Insert Figure 2 around here]

Next, we implement a placebo test on the efficacy of the tone overlay. It was documented earlier in Section 3.1 that the correlations between $TONE_{i,t}$ and $TONE_{j,t}$ for commodities *i* and *j* in different sectors are very low. For instance, the average correlation between the newswire tone of commodities in the energy and grain sectors is only 0.02. Accordingly, we implement a placebo test that is based on cross-sector randomization of the commodity news tone as follows. The commodity *i* is assigned the newswire tone of another commodity *j* randomly drawn from another sector, $TONE_{j,t}$. Since the randomized signal does not convey sentiment about commodity *i*, the tone overlay should not enhance the cross-sectional predictability of the corresponding traditional signal $x_{i,t}$ but rather contaminate it with noise. Table 4 confirms this conjecture.

[Insert Table 4 around here]

2020). The average improvement in Sharpe ratio afforded by the tone-overlay strategy in these two periods, at ΔSR=0.34 and ΔSR=1.29, respectively, suggests that our findings are not inflated by the backfilled data.

The randomized tone-overlay strategy incurs pervasive losses vis-à-vis the traditional allocations as borne out by Sharpe ratio differentials (ΔSR) ranging from -0.68 to -0.08 across portfolios. Thus, the placebo test suggests that the efficacy of the tone-overlay strategy documented earlier in Table 3 is not spurious (an artefact of data snooping or luck) but rather a reflection of the cross-sectional predictive ability of commodity-level newswire tone over and above that of traditional commodity characteristics. Given that commodity futures investors are primarily institutional, the significant benefits generated by incorporating newswire tone into traditional allocations through the tone-overlay strategy provide indirect evidence that sentiment-based trading is not exclusive to retail investors. Sentiment also influences institutional investors' decisions.

3.4. Risk premium channel of the tone-overlay outperformance

The above analysis of OOS returns has demonstrated that embedding the tone of commodity-specific newswires into traditional signals is beneficial for tactical allocation. A natural question is whether the outperformance of the tone-overlay strategy stems from additional risks.

To address this question, we first estimate factor spanning time-series regressions

$$r^{\perp}_{overlay_j,t} = \alpha + \sum_{\substack{k=1 \\ k\neq j}}^{K} \beta_k F_{k,t} + \varepsilon_t, \tag{5}$$

where $r^{\perp}_{overlay_j,t}$ is the time t excess return of the orthogonalized tone-overlay portfolio with respect to the underlying jth traditional signal[7] and $F_{k,t}, k = 1, \dots, K$ are a set of commodity risk factors (excess returns of basis, momentum, hedging pressure, convexity, skewness, basis-momentum, and liquidity long-short portfolios). The results are reported in Table 5.

[Insert Table 5 around here]

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[7] We regress the excess returns of the tone-overlay portfolio on the excess returns of the corresponding traditional portfolio and an intercept. The orthogonalized excess returns, $r^{\perp}_{overlay_j,t}$, which represent the abnormal performance of the tone overlay, are the residuals plus the intercept estimate.

The regression betas are mostly insignificant, and the commodity risk factors have no explanatory power for the tone-overlay outperformance (adjusted R^2 below 1%). By contrast, the alphas (intercepts) are positive, and both economically and statistically significant. These results suggest that the outperformance of the tone-overlay portfolios is not compensation for commodity risks.

The literature has shown that changes in the investment opportunity set can drive the performance of commodity risk factors (e.g., Bakshi et al., 2019). Thus, the outperformance of the tone overlay could be channeled through exposure to broad financial and macroeconomic risks. To test this alternative risk channel, we estimate the following time-series regression

$$r^{\perp}_{overlay_j,t} = c + \sum_{k=1}^{K} b_k I_{k,t} + \varepsilon_t, \tag{6}$$

where c is an intercept, and the regressors $I_{k,t}$ are a set of financial and macroeconomic risks proxied by the business conditions index of Aruoba et al. (2009; ADS), the 3-month LIBOR versus 3-month T-bill spread (TED), the 10-year T-bond minus 3-month T-bill yield (TERM), the change in the Federal funds effective rate (FED), the macroeconomic uncertainty index of Bekaert et al. (2022; UNC) as a percentage of annual volatility, the innovation in aggregate liquidity of Pastor and Stambaugh (2003; LIQUID), the year-on-year change in US industrial production (IP), and the year-on-year US CPI inflation (INFL).[8] Panel B of Table 5 shows that the outperformance of the tone-overlay portfolios is unrelated to broad financial and macroeconomic risks. With no support for a risk-based explanation, we next investigate the mispricing channel.

3.5. Mispricing channel of the tone-overlay benefits

We test the hypothesis that the additional performance of the tone-overlay portfolios arises from temporary commodity futures mispricing induced by the tone of commodity-specific news.[9]

[8] The data source is the FRB of St Louis for all variables except UNC and LIQUID, which are obtained from the websites of Prof. N. Wu and R. Stambaugh, respectively. Weekly IP and INFL observations are linearly interpolated from monthly data. The highest absolute correlation among the variables is 61%.

[9] One might conjecture that the outperformance of the tone overlay is due to mispricing related to how each commodity reflects market-wide sentiment. We test this conjecture by regressing the orthogonalized

Following Tetlock's (2007) methodology for testing the impact of firm-level news tone on equity returns, we estimate the following regression model using pooled data across commodities

$$r_{i,t} = \alpha_i + \tau_t + \sum_{j=1}^{4} \beta_j TONE_{i,t-j} + \boldsymbol{\theta Z}_{i,t-1} + \varepsilon_{i,t}, i = 1, \dots, N, t = 1, \dots, T, \quad (7)$$

where the regressand, $r_{i,t}$, is the weekly commodity excess return, and the regressors of interest are four lags of commodity-specific sentiment, $TONE_{i,t-j}$, $j = 1, \dots, 4$. The control variables, $\boldsymbol{Z}_{i,t-1}$, are lagged commodity futures characteristics (basis, momentum, hedging pressure, convexity, basis-momentum, skewness, liquidity and the excess return), with α_i and τ_t capturing unobserved commodity and year-week fixed effects. Table 6 presents the estimation results with test statistics calculated using two-way (by commodity and year-week) clustered standard errors.

[Insert Table 6 around here]

The results indicate a positive and significant β_1 and a negative and significant β_2. The null hypothesis $H_0: \beta_1 + \beta_2 = 0$ is not rejected at conventional significance levels. This evidence suggests a commodity futures mispricing that is fully corrected within a week, aligning with recent findings in the equity literature where media tone induces temporary price distortions (see e.g., Tetlock, 2007; Garcia, 2013; Ferguson et al., 2015, and Fedyk and Hodson, 2023). As shown also in Table 6, columns (5)-(6), the findings hold when controlling for market-wide sentiment, proxied by the FRB of San Francisco news sentiment index; other proxies such as the CBOE's VIX or the Baker and Wurgler (2006) index yield similar unreported results. The coefficient β_1 estimates indicate that a one-standard deviation change in the weekly tone of newswires affects next week's commodity excess returns by about 12.6 basis points. This indicates a substantial economic impact relative to the average weekly commodity excess returns (see Table 1).

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tone-overlay excess returns, $r^{\perp}_{overlay_j,t}$, on each of the broad market sentiment proxies mentioned in Section 3.2, either contemporaneously (pricing model) or with lags (predictive model). Consistent with our previous findings, the estimation results in online Annex Table A.3 do not support this hypothesis.

The evidence from this analysis suggests that the tone-overlay outperformance is channeled as a temporary tone-induced mispricing. Clearly, if media tone revealed fundamental information that is gradually impounded into prices, we would not observe a complete-return reversal; hence, the underreaction channel is not supported. The results are consistent with overreaction to the tone of commodity-specific news. Influenced by optimistic (pessimistic) newswire tone on a commodity, investors pile up long (short) positions in commodity futures which exerts temporary upward (downward) pressure on the price. These findings align with the overreaction model proposed by Daniel et al. (1998), where investors' overconfidence and self-attribution biases contribute to short-term price momentum. They also resonate with the model proposed by De Long et al. (1990), suggesting that irrational traders, following positive feedback strategies, temporarily push prices away from their fundamental value.

The evidence of reversal after the initial reaction could stem from the arrival of new information that makes investors aware of the mispricing and/or from arbitrageurs exploiting the mispricing. The complete return reversal implies that the commodity-specific newswire tone conveys moods and beliefs about the commodity rather than fundamentals. Given the small role of retail traders in commodity futures markets, these findings align with the equities literature attributing elements of irrationality and behavioral biases to institutional investors (see e.g., Rangvid et al., 2013; Edelen et al., 2016; De Vault et al., 2019; Wang and Duxbury, 2021).

For completeness, we test for asymmetry in the mispricing of commodity futures to optimistic versus pessimistic newswire tone by re-formulating Eq. (7) as follows

$$r_{i,t} = \alpha_i + \tau_t + \sum_{j=1}^{4} \beta_j TONE_{i,t-j} + \sum_{j=1}^{4} \delta_j TONE_{i,t-j} \times I_{i,t-j}^{TONE-} + \boldsymbol{\theta Z}_{i,t-1} + \varepsilon_{i,t}, \quad (8)$$

where $I_{i,t-j}^{TONE-} = 1$ if $0 < TONE_{i,t-j} < 50$ (pessimism), and 0 otherwise. The coefficients δ_j are small and statistically insignificant. Across all specifications, the Wald test p-values for the hypothesis $H_0\colon \delta_1 = \cdots = \delta_4 = 0$ are large, indicating no difference in the mispricing induced by optimistic versus pessimistic news tone (see Table A.4 in the online Annex). This contrasts with equity markets, where loss aversion of net-long investors triggers a stronger reaction to firm-level pessimistic news (e.g., Ferguson et al., 2015; Coakley et al., 2021). Since commodity futures are assets in zero-net supply, it is plausible that the fear of losses by long investors after pessimistic news induces a similar reaction to the fear of losses by short investors after optimistic news.

3.6. Commodity-specific arbitrage limits and speculativeness

The results thus far suggest that the portfolio performance improvement afforded by the newswire tone-overlay strategy stems from a temporary mispricing. Therefore, it is interesting to examine whether the tone premium is more prominent for commodity futures most prone to mispricing, as indicated by impediments to arbitrage or the speculative activity they attract.

Following Baker and Wurgler (2006), Birru (2018), and Liu and Han (2020) in equity markets, and Gao and Süss (2015) in commodity futures markets, we utilize commodity characteristics such as Amihud illiquidity, total open interest, and volatility to distinguish among commodities in the cross-section based on arbitrage impediments. Additionally, following Working (1960), Kumar (2009), and Birru (2018), we proxy commodity futures speculativeness using the Working T-Index, which measures speculation relative to hedging demand,[10] and two signals (skewness coefficient and maximum excess return in the past year) indicative of "lottery" features known to attract speculators. Appendix A provides definitions and key references.

Following Liu and Han (2020), we construct weekly rebalanced, long-short portfolios via a double-sort based on *arbitrage limits* and newswire *tone* characteristics of commodities. First, we sort the commodities into high-arbitrage-cost and low-arbitrage-cost portfolios using the median as the cutoff. Next, within the high-arbitrage-cost portfolio, we sort commodities based on their $TONE_{i,t}$ aspect using the median as the cutoff, and similarly for the low-arbitrage-cost

[10] Intuitively, the Working T-index reflects the extent by which the speculative positions exceed the minimum necessary to absorb any mismatch between long and short hedging positions.

portfolio. This double-sort process is repeated using commodity *speculativeness* in the first sort. Finally, we compute the Sharpe ratio using the resulting OOS weekly portfolio excess returns.

[Insert Table 7 around here]

Table 7 demonstrates that the tone premium is concentrated among commodity futures that are more susceptible to mispricing — those characterized by greater arbitrage impediments (higher illiquidity, lower total open interest, and higher volatility) and higher levels of speculation (higher Working T-index, more positive skew, and higher maximum return). This observation aligns closely with our behavioral interpretation of the tone-overlay portfolios' outperformance, suggesting it arises from short-term mispricing induced by commodity-specific newswire tone.

3.7. Tone-overlay strategy and portfolio holding period

The estimation results from Eq. (7) indicate that the cross-sectional predictability of the newswire tone signal is short-term, with the reversal occurring within a week. Therefore, it is likely to be best exploited with a short holding horizon for the portfolio. To test this implication, we evaluate the portfolios over increasing holding periods (h) ranging from one to eight weeks. Each portfolio formed at time t is held for h weeks to obtain an OOS return from t to $t + h$. The estimation window is rolled forward weekly to capture subsequent OOS return from $t + 1$ to $t + h + 1$, and so forth. Table 8 presents the profitability gain of each tone-overlay portfolio compared to the corresponding traditional portfolio ($\Delta SR = SR_{overlay} - SR_{trad}$) for $h = \{1, 2, 3, 4, 8\}$ weeks.

[Insert Table 8 around here]

The profitability gain afforded by the tone overlay declines monotonically from 0.69 (with $h = 1$ week, as adopted thus far) to 0.49 ($h = 2$ weeks; a 28% decrease in ΔSR) and further to 0.27 ($h = 3$ weeks; a 61% decrease), reaching a negligible 0.05 for the monthly holding period ($h = 4$) on average across portfolios. Consistently across tone-overlay portfolios, the Sharpe ratio gain is economically small and statistically insignificant for holding periods longer than two weeks as suggested by the Ledoit and Wolf test *p*-values. The rapid deterioration in the tone-overlay outperformance contrasts with the resilience of the traditional portfolios across holding periods, as evidenced by Sharpe ratios of 0.37 ($h = 1$), 0.32 ($h = 2$), 0.28 ($h = 3$) and 0.27 ($h = 4$) on average across signals. These findings align well with our interpretation of the tone premia as associated with a continued overreaction within a week that is subsequently reversed.

4. Robustness Tests

In this section, we revisit various aspects of the tone-overlay strategy to re-examine its profitability relative to traditional strategies. We consider alternative hyperparameter choices for the tone-overlay model, redesigns of the commodity-specific newswire tone measure, trading costs, and other traditional signals. Finally, we compare the proposed tone-overlay strategy with the equally weighted style-integration approach advocated by Fernandez-Perez et al. (2019).

4.1. Sensitivity analysis for tone-overlay hyperparameters

Having established that the portfolios resulting from the tone-overlay model, Eq. (2) with baseline hyperparameters $\boldsymbol{\theta} = (\pi, \tau, (\delta^+, \delta^-)) = (0.1, 0.9, (1,1))$, significantly outperform the corresponding traditional portfolios, we now study alternative choices for the hyperparameters.

As explained in Section 2.1, the *salience* hyperparameter π is the threshold that defines the current newswire tone $TONE_{i,t}$ as salient (versus subdued) in the context of its own historical distribution $\{TONE_{i,t-L+1}, \dots, TONE_{i,t-1}, TONE_{i,t}\}$. We measure the Sharpe ratio gain of tone-overlay portfolios using $\pi = \{0.01, 0.05, 0.10. 0.15, 0.20, 0.25\}$ while maintaining the other hyperparameters $(\tau, (\delta^+, \delta^-))$ at their baseline values. Panel A of Table 9 shows the results.

[Insert Table 9 around here]

The tone-overlay portfolio with very strict *salience* hyperparameter $\pi = 0.01$ accrues the smallest gain (ΔSR of 0.34 on average). This is because the 1st and 99th percentiles are so strict that barely any news tone signals are classified as salient and hence, the tone overlay is not triggered ($x_{i,t}^{TONE} \approx x_{i,t}$). Leaving aside this very strict case, a clear pattern is noticeable: the more extreme the salience parameter, the greater the risk-adjusted return of the tone overlay strategy. On average across portfolios, the Sharpe ratio gain increases monotonically from $\Delta SR = 0.44$ with $\pi = 0.25$ to $\Delta SR = 0.76$ for $\pi = 0.05$. Thus, stronger outperformance is achieved by leveraging the tone-overlay strategy on more salient newswire tone. This finding may relate to limited-attention bias, a cognitive phenomenon where individuals, including investors in financial markets, have finite capacity to process information. Due to this limitation, they prioritize news stories with emotionally charged language (extreme optimism or pessimism). This bias can lead to overreactions, contributing to short-term price distortions (e.g., Bordalo et al., 2012, 2022).

Existing studies on the impact of limited attention in capital markets suggest that both retail and professional equity investors exhibit cognitive limitations, focusing selectively on news stories with the most salient tone (e.g., Nekrasov et al., 2022; Hirshleifer and Teoh, 2003). Our findings in commodity markets, dominated by institutional investors, align with this perspective and endorse the tone-overlay as a practical approach to systematically exploit this phenomenon.

Next, we study the *tilting* hyperparameter (τ) which dictates the extent of the traditional signal adjustment (proportionally to its volatility, $\sigma_{i,t}$)[11] according to the newswire tone. Now we construct tone-overlay portfolios using various fixed τ with $(\pi, (\delta^+, \delta^-))$ at their baseline values.

However, the fixed parameter τ setting can be seen as limited. Suppose that the news tone of commodities i and j is optimistic, $TONE_{i,t} = 90$ and $TONE_{j,t} = 70$, and categorized as salient according to their corresponding historical distributions, i.e., $I^{TONE+}_{i,t,(1-\pi)} = I^{TONE+}_{j,t,(1-\pi)} = 1$. If the traditional signal exhibits also similar historical volatility for the two commodities ($\sigma_{i,t} \approx \sigma_{j,t}$), its upward adjustment will be similar for both which overlooks the fact that $TONE_{i,t} > TONE_{j,t}$. The

[11] Ignoring the dispersion of the traditional signal by setting $\sigma_{i,t} = \sigma = 1$ in the tone-overlay model, Eq. (2), leads to a decrease in Sharpe ratios by 35% on average. The estimates $\widehat{\sigma}_{i,t}, i = 1, \dots, N$ from the historical distributions of the traditional signals, $\{x_{i,t-L+1}, \dots, x_{i,t-1}, x_{i,t}\}$, reveal commodity heterogeneity, e.g., at the first portfolio formation time the basis volatility $\hat{\sigma}^{basis}_{i,t=1}$ ranges from 0.0011 (copper) to 0.0743 (feeder cattle). The volatilities are persistent as revealed by autocorrelations above 0.95.

tone-overlay equation can exploit differences in newswire tone across commodities by adopting as tilting hyperparameter the cross-sectionally standardized tone signal, $\tau_{i,t} = |\widetilde{TONE}_{i,t}|$ with $\widetilde{TONE}_{i,t} = \frac{TONE_{i,t} - \overline{TONE}_t}{\sigma_{TONE,t}}$. Since the change in newswire tone from one week to the next may carry more cross-sectional predictive content than the tone level, we also consider the cross-sectionally standardized first-differenced tone signal, $\tau_{i,t} = |\Delta\widetilde{TONE}_{i,t}|$. Panel B of Table 9 evaluates the tone overlay with $\tau = \{0.4, 0.6, 0.8, 0.9, 1, 1.2, 1.5, |\widetilde{TONE}_{i,t}|, |\Delta\widetilde{TONE}_{i,t}|\}$.

Among the fixed *tilting* parameter cases, $\tau = 1$ is very effective. Adjusting the traditional signal up or down by one full standard deviation of its historical distribution generates Sharpe ratio gains (ΔSR) of 0.71 on average, very closely followed by the ΔSR from $\tau = 0.9$ and $\tau = 1.2$ at 0.69. Allowing for the tilting to be dictated by the tone change, $\tau_{i,t} = |\Delta\widetilde{TONE}_{i,t}|$, accrues the largest $\Delta SR = 0.80$ on average. This evidence is consistent with Fan et al. (2023), who find that Twitter-derived commodity sentiment, both in level and as change over time, predicts the performance across different commodities, with the change proving to be a stronger predictor.

We report in Panel C of Table 9 the Sharpe ratio gains of the portfolios based on the tone-overlay model (δ^+, δ^-) = $\{(0,1), (0.2,1), (0.8,1), (1,1), (1,0.8), (1,0.2), (1,0)\}$ where $(1,1)$ represents identical tilting of the traditional signal for pessimistic and optimistic tone, $(0,1)$ represents only-pessimism tilting and $(1,0)$ only-optimism tilting. It turns out that, alongside the $(\delta^+, \delta^-) = \{(0.2,1), (0.8,1)\}$ scenarios, the symmetric tone-overlay model with $(\delta^+, \delta^-) = (1,1)$ is very effective which dovetails nicely with our prior finding of a similar reaction of commodity futures prices to optimistic and pessimistic newswire tone.

4.2. Cross-validated tone-overlay

We now design a tone overlay with hyperparameter cross validation as in the machine learning literature. Let $\{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_H\}$ denote H plausible sets of candidate values for the hyperparameters $\boldsymbol{\theta} = \left(\pi, \tau, (\delta^+, \delta^-)\right)$ of the tone-overlay model, Eq. (2). In addition to the estimation window of L weeks required for the tone-overlay model, a window of S weeks is used for the cross-validation. Thus, the tone-overlay strategy is implemented H times and the hyperparameter vector that delivers the largest Sharpe ratio gain over the S window, $\boldsymbol{\theta}_t^*$, is adopted for the actual tone-overlay portfolio at time *t*. To save on computation costs, the cross validation is implemented every other week. Appendix B provides the detailed steps.

Our cross-validated tone-overlay exercise considers the $H = 1{,}620$ parameterizations associated with the salience hyperparameter $\pi = \{0.05, 0.10, 0.15, 0.20, 0.25\}$, tilting hyperparameter $\tau = \{0.4, 0.6, 0.8, 0.9, 1, 1.2, 1.5, |\widetilde{TONE}_{i,t}|, |\Delta\widetilde{TONE}_{i,t}|\}$, and the optimism versus pessimism hyperparameter vector (δ^+, δ^-) that results from $\delta^{+/-} = \{0, 0.2, 0.4, 0.6, 0.8, 1\}$. We adopt an estimation window of $L = 260$ weeks as hitherto, and a hyperparameter cross-validation window of $S = 52$ weeks; since the data starts on January 3, 2000, the first OOS return available is on January 3, 2006. As shown in Table A.5 of the online Annex, the cross-validated tone-overlay portfolios notably outperform the corresponding traditional portfolios, with an average Sharpe ratio gain of 0.79 and an average CER differential of 6.24%.

4.3. Daily news impact decay and intraday news novelty

Our analysis utilized the commodity-level news tone signal, $TONE_{i,t}$ from Eq. (3), computed with a daily news impact decay parameter $\gamma = 0.9$ (indicating very slow decay) and an intraday news weighting of $\phi_{k(d)} = \frac{1}{K_d}$, where K_d represents the total number of news items within each 24-hour period. Consequently, we assigned almost equal importance to news items within the 7×24-hour window before each portfolio formation time *t*. Figure 3, Panel A, shows the outperformance of the tone-overlay portfolios (Sharpe ratio gain versus the corresponding traditional portfolios), based on $TONE_{i,t}$ signals with γ values ranging from 0.1 to 1.0, where $\gamma = 1$ denotes no decay.

[Insert Figure 3 around here]

The graph reveals that the $TONE_{i,t}$ measure with $\gamma \geq 0.9$ (slow news impact-decay) delivers the best performing tone-overlay. This means that not only the news stories released within the 24-hour period immediately preceding the portfolio formation time play a role in the subsequent mispricing observed, but also the "stale" news items from prior days within the same 7-day period.

In Panel B of Figure 3, we plot the Sharpe ratio gains of tone-overlay portfolios using two $TONE_{i,t}$ measures that differ in their weighting of news items within each 24-hour window. The left panel shows results where all intraday news items are equally weighted, as in our earlier calculation. The right panel uses event novelty scores (ENS) metadata from RPNA to assign greater importance to news items with more novel content, $\phi_{d(k)} = \frac{ENS_{d(k)}}{\sum_{k=1}^{K_d} ENS_{d(k)}}$. Our findings indicate that incorporating within-day news novelty does not lead to improved performance.

In sum, the results suggest that a TONE signal assigning similar importance to news stories published over the previous seven days is highly effective in predicting out-of-sample cross-sectional commodity futures returns. This indicates that commodity futures prices react to the tone of outdated (redundant) news lacking fundamental information. Given the composition of commodity futures markets, this implies that institutional investors are influenced by news reflecting moods, beliefs, and opinions rather than fundamental changes. This novel evidence from commodity futures markets aligns with existing findings in equity markets, which also show substantial price overreactions to old news (Tetlock, 2011; Gilbert et al., 2012). Likewise, Fedyk and Hodson (2023) argue that sophisticated investors struggle to identify complex recombinations of "stale" information from various sources, leading to larger market reactions to recombined articles than to simple reprints, with these reactions reversing over the following week.

4.4. Tone-overlay performance after trading costs

To which extent do transaction costs erode the outperformance of the tone overlay (versus traditional) portfolios? To address this question, we start by measuring portfolio turnover as

$$TO = \frac{1}{T-1}\sum_{t=1}^{T-1}\sum_{i=1}^{N}\left|w_{i,t+1} - w_{i,t^+}\right|, \tag{9}$$

where $w_{i,t+1}$ denotes the target weight for the ith commodity at portfolio formation time $t+1$, and $w_{i,t^+} = w_{i,t} \times e^{r_{i,t+1}}$ is the actual portfolio weight immediately before the rebalancing at $t+1$ with $r_{i,t+1}$ the weekly return of the ith commodity from t to $t+1$.

[Insert Figure 4 around here]

Panel A of Figure 4 shows that the TO of each tone-overlay portfolio exceeds that of the corresponding traditional portfolio. This is consistent with the commodity news sentiment signal, $TONE_{i,t}$, exhibiting a lower weekly first-order autocorrelation (AC1) at 0.52 across commodities, than traditional commodity characteristics ($x_{i,t}$) with higher AC1 values – for instance, 0.89 for the basis signal and 0.98 for the momentum signal, on average across commodities. However, the higher turnover of tone-overlay strategies may not fully wipe out their outperformance relative to traditional portfolios. To investigate this, we calculate the net return of each portfolio as

$$r_{P,t+1} = \sum_{i=1}^{N} w_{i,t+1} r_{i,t+1} - TC \sum_{i=1}^{N} \left| w_{i,t+1} - w_{i,t^+} \right|, \tag{10}$$

where $TC = 8.6$bp is the average roundtrip transaction cost estimate of Marshall et al. (2012).

As shown in Panel B of Figure 4, the net Sharpe ratio gain of the tone-overlay strategy (with the baseline hyperparameter specification) remains attractive at 0.40 on average across portfolios.[12] Detailed performance metrics for net excess returns are in Table A.6 of the online Annex. This evidence is supported by breakeven transaction costs averaging 0.88% for tone-overlay portfolios, notably higher than the 0.22% for traditional portfolios (see online Annex Figure A.1). Therefore, the tone-overlay strategy remains attractive net of trading costs.

4.5. Tone-overlay with other "traditional" signals

Our earlier choice of the basis, momentum, basis-momentum, hedging pressure, skewness, basis-momentum, and liquidity investment strategies to exemplify the effectiveness of the tone-overlay

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[12] In an unreported analysis we also introduced trading costs in the cross-validated tone-overlay portfolios deployed in Section 4.2. The earlier average Sharpe ratio of 0.79 becomes 0.53 net of trading costs.

strategy was intentionally conservative. This approach sets a rigorous standard for evaluating the tone-overlay strategy, as we focus on traditional strategies already known to capture significant premia (see e.g., the combined-factor investing by Sakkas and Tessaromatis, 2020, and the style integration by Fernandez-Perez et al., 2019). We now consider the commodity futures value, speculative pressure, open interest change, inflation beta, USD beta, and volatility signals as the (cross-sectionally standardized) $x_{i,t}$ in Eq. (2). Formal definitions and key references are provided in Appendix A. All signals are consistently defined so that high (low) values predict an increase (decrease) in the commodity futures price and thus, dictate long (short) positions.

[Insert Figure 5 around here]

Figure 5 plots the Sharpe ratios of the tone-overlay portfolios alongside the corresponding traditional portfolios for a universe of thirteen traditional sorting signals. Regardless of the traditional portfolio's performance, leveraging newswire tone enhances it, as shown by consistently positive Sharpe ratio differentials averaging 0.60 across strategies. Therefore, the initial evidence supporting the merit of the tone-overlay strategy remains unchallenged.[13]

4.6. Tone-overlay strategy versus EWI

The style-integration strategy enables exposure to multiple risk factors by taking long (short) positions in assets for which an 'integrated' signal predicts the largest price increase (decrease). Various forms of style integration have been proposed, differing in how each asset characteristic is weighted (e.g., Brandt et al., 2009; Barroso and Santa-Clara, 2015). The equally-weighted style integration (EWI), which assigns equal role to all asset characteristics, has proven to be very competitive compared to sophisticated approaches that estimate weights based on historical data, such as those using volatility criteria (e.g., Fernandez-Perez et al., 2019).

We employ the equally-weighted integration (EWI) approach to construct portfolios that

[13] Augmenting the factor spanning regressions of Section 4.3 with value, speculative pressure, open interest change, inflation beta, USD beta, and volatility factors, we find that the outperformance of tone-overlay portfolios is not due to exposure to these commodity risks (see Table A.7 in the online Annex).

simultaneously harness the predictive power of two signals: a traditional commodity characteristic and newswire tone. Using the basis characteristic as an example, the sorting signal for the EWI portfolio is defined as $basis_{i,t}^{EWI} = 0.5 \times basis_{i,t} + 0.5 \times TONE_{i,t}$ where $basis_{i,t}$ and $TONE_{i,t}$ represent the cross-sectionally standardized values of the basis and tone signals of commodity i at time t. We compare the performance of this EWI portfolio with the tone-overlay portfolio constructed using Eq. (2) for the basis signal, and similarly for each of the other traditional characteristics. To ensure comparability with the tone-overlay strategy, the EWI strategy assigns equal weights to commodities in both the top quintile and bottom quintile.

A priori, the tone-overlay method is expected to be more effective than EWI. While both approaches combine a traditional commodity characteristic and newswire tone, the tone-overlay method leverages more information. First, it adjusts the traditional signal based solely on significant optimistic or pessimistic news content, potentially enhancing the signal-to-noise ratio. Second, it does so dynamically by considering the historical distribution of commodity-specific newswire tone at each portfolio formation time. Third, it dynamically accounts for the dispersion in traditional signals by considering their commodity-specific historical distributions.

The results in online Annex Table A.8 demonstrate that, for each characteristic, the tone-overlay approach is indeed more effective than EWI. For instance, the Sharpe ratios of tone-overlay strategies range from 0.86 to 1.39 with an average of 1.06 across portfolios in Table 3, whereas the corresponding figures for EWI are 0.38, 0.70, and 0.55, respectively.

Finally, to further challenge the tone-overlay strategy, we evaluate whether incorporating newswire tone enhances the performance of the style-integrated portfolio based on the seven traditional commodity characteristics used in the main analysis. We replace the baseline signal $x_{i,t}$ in Eq. (2) with the equal-weighted combination of the seven cross-sectionally standardized traditional signals. Unreported results confirm findings from Fernandez-Perez et al. (2019) that, with a Sharpe ratio of 0.76, the EWI(K=7) portfolio outperforms each standalone traditional portfolio (see Table 3). Importantly for this study, the EWI portfolio enhanced with news tone achieves a Sharpe ratio of 1.24, clearly surpassing the EWI(K=7) benchmark.

5. Conclusions

We devise an innovative tactical allocation strategy that leverages commodity-specific newswire sentiment alongside well-known allocation signals in commodity markets. Using a sample of 26 commodities, we demonstrate that adjusting a traditional signal up or down according to salient optimistic or pessimistic newswire sentiment, respectively, bears fruition by increasing the mean excess return capture, improving the risk profile, and more than doubling the risk-adjusted returns.

In line with theories of limited investor attention, the salience of newswires matters, as evidenced by greater profitability gains compared to traditional allocations when the tone overlay leverages the most salient newswire tone. Testing the risk versus mispricing channels for the tone-overlay outperformance, the evidence supports the mispricing explanation. Commodity futures prices overreact to newswire tone, with a full reversal observed within a week. Consistent with the behavioral explanation, the tone premium is best captured with a short one-week portfolio holding period and is concentrated among commodities that face greater impediments to arbitrage and attract more speculation, making them more prone to mispricing.

The outperformance afforded by the tone-overlay holds for a universe of thirteen traditional signals, is confirmed by a placebo test, and survives the consideration of trading costs and various choices of hyperparameters in the tone-overlay strategy. Furthermore, the outperformance is enhanced by incorporating cross validation, which allows for more informed and optimized hyperparameter selection. Given the broad applicability of the tone-overlay concept, we propose quantifying its benefits outside the commodity space as a direction for further research.

Appendix A. Commodity futures characteristics.

This appendix provides definitions, formulae, and key references for the commodity futures characteristics (or sorting signals) used in the analysis. The signals are organized alphabetically by name. The time t subscript denotes the time (Monday at 5 pm EST of each sample week) when the signals are measured.

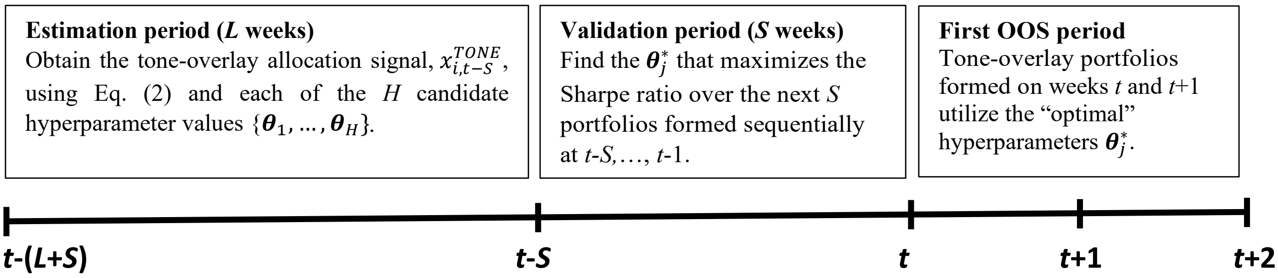
Name	Definition	Formula	Key references
Basis	Log price differencial between front- and second-nearest contracts with T_n denoting maturity.	$ln(f_t^{T_1}) - ln(f_t^{T_2})$	Szymanowska et al. (2014)
Basis momentum (Basis-Mom)	Difference in the average weekly log returns between front-end and second-nearest futures contracts over the prior year.	$\frac{1}{52}\sum_{w=0}^{51} r_{t-w}^{T_1} - r_{t-w}^{T_2}$	Boons and Prado (2019)
Convexity (or relative basis)	Difference between front and further-into-the-curve basis scaled by difference in times to maturity.	$\frac{ln(f_t^{T_1}) - ln(f_t^{T_2})}{t_2 - t_1} - \frac{ln(f_t^{T_2}) - ln(f_t^{T_3})}{t_3 - t_2}$	Gu et al. (2023)
Hedging pressure	Net short weekly positions of large commercial traders (hedgers, H) over their total positions averaged over the prior year.	$\frac{1}{52}\sum_{w=0}^{51} \frac{H_{t-w}^{short} - H_{t-w}^{long}}{H_{t-w}^{short} + H_{t-w}^{long}}$	Basu and Miffre (2013)
Illiquidity	Average absolute front-end daily return per dollar of daily trading volume over the past two	$\frac{1}{D}\sum_{d=0}^{D-1} \frac{\lvert r_{t-d}\rvert}{\$Volume_{t-d}}$	Szymanowska et al. (2014)
Inflation beta	Slope coefficient of a 52-week regression of front-end returns on unexpected inflation measured as the change in US CPI inflation.	$\underset{\beta_t}{\text{argmin}} \sum_{w=0}^{51} (r_{t-w} - \beta_t INFL_{t-w})^2$	Szymanowska et al. (2014)
Maximum return	Highest weekly front-end return in the last year.	$\max \{r_{t-w}\}_{w=0}^{51}$	Birru (2018)
Momentum (Mom)	Average of weekly front-end returns over the past year.	$\frac{1}{52}\sum_{w=0}^{51} r_{t-w}$	Miffre and Rallis (2007)
Open interest	Total number of outstanding contracts along the commodity futures curve (all maturities).	$N_t^{T_1} + N_t^{T_2} + \cdots + N_t^{T_n}$	Hong and Yogo (2012)
Skewness	Negative coefficient of skewness (third moment) of daily front-end returns over the past year.	$-\frac{\sum_{d=0}^{D-1}(r_{t-d} - \mu)^3/D}{\sigma^3}$	Fernandez-Perez et al. (2018)

Appendix A. Commodity futures characteristics (*Cont.*)

Name	Definition	Formula	Key references
Speculative pressure	Net long weekly positions of large non-commercial traders (or speculators, S) over their total positions averaged over the prior year.	$\frac{1}{52}\sum_{w=0}^{51}\frac{S_{t-w}^{long}-S_{t-w}^{short}}{S_{t-w}^{long}+S_{t-w}^{short}}$	Fan et al. (2020)
USD beta	Slope coefficient of a 52-week regression of front-end returns on the percentage change in the trade weighted US dollar index.	$\underset{\beta_t}{\operatorname{argmin}}\sum_{w=0}^{51}(r_{t-w}-\beta_t USD_{t-w})^2$	Szymanowska et al. (2014)
Value	Difference between the logarithm of the average front-end price from 5.5 to 4.5 years ago and the logarithm of the current front-end price.	$ln\left(\bar{f}_{t-5yr}^{T_1}\right)-ln\left(f_t^{T_1}\right)$	Asness et al. (2013)
Volatility	Standard deviation of weekly front-end returns in the past year.	$\sqrt{\frac{\sum_{w=0}^{51}(r_{t-w}-\mu)^2}{52-1}}$	Gorton et al. (2013)
Working T-Index	Excessive speculation (SS and SL : Short and long positions of all speculators; HS and HL : Short and long positions of all hedgers).	$\begin{cases}1+\frac{SS_t}{HS_t+HL_t} & \text{, if } HS_t \geq HL_t \\ 1+\frac{SL_t}{HS_t+HL_t} & \text{, if } HS_t < HL_t\end{cases}$	Working (1960), Sanders et al. (2010), Bohl et al. (2021)

Appendix B. Tone-overlay strategy with cross validation.

The graph below illustrates the cross validation of the hyperparameters $\boldsymbol{\theta} = \left(\pi, \tau, (\delta^{+}, \delta^{-})\right)$ in Eq. (2) where $(\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_H)$ denotes the set of H candidate values under consideration.



The cross-validated tone-overlay strategy proceeds in steps as follows:

Step 1: Using an estimation window of L weeks and the hyperparameters candidate $\boldsymbol{\theta}_1$, construct the tone-overlay signal, $x_{i,t-S}^{TONE}$, in Eq. (2). Then sort the commodities by $x_{i,t-S}^{TONE}$ in descending order. Buy the top quintile (expected to appreciate the most), sell the bottom quintile (expected to depreciate the most), and hold the position for a week on a fully-collateralized basis assigning an equal weight to each contract. This enables the first tone-overlay portfolio excess return from $t - S$ to $t - S + 1$.

Step 2: Using the same hyperparameters candidate $\boldsymbol{\theta}_1$, repeat the above step S times forward shifting each time the measurement window by one week. The resulting sequence of S weekly portfolio excess returns from week $t - S + 1$ to week t enables the first Sharpe ratio of the tone-overlay portfolio, $SR(\boldsymbol{\theta}_1)$.

Step 3: Repeat Steps 1 and 2 for all other hyperparameter candidates, $\boldsymbol{\theta}_2$, ...,$\boldsymbol{\theta}_H$. Choose at portfolio formation time t the hyperparameters that deliver the highest Sharpe ratio over the preceding S-week validation period, i.e., $\boldsymbol{\theta}_t^* = argmax\{SR(\boldsymbol{\theta}_1), \ldots, SR(\boldsymbol{\theta}_H)\}$. In our application, to save on computation costs, the hyperparameters, $\boldsymbol{\theta}_t^*$, are adopted for the sequential portfolios formed on week t and on week t+1. Then at t+1, the above Steps 1 to 3 are repeated, and so forth until the end of the sample period (bi-weekly cross validation).

References

Akepanidtaworn, K., Di Mascio, R., Imas, A., and Schmidt, L. D. W. (2023). Selling fast and buying slow: Heuristics and trading performance of institutional investors. *Journal of Finance* 78, 3055-3098.

Anderson, E. W., and Cheng, A. R. (2016). Robust Bayesian portfolio choices. *Review of Financial Studies* 29, 1330-1375.

Aruoba, S. B., Diebold, F. X., and Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business and Economic Statistics* 27, 417–427.

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

Baker, M., and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61, 1645-1680.

Bakshi, G., Gao, X., and Rossi, A. G. (2019). Understanding the sources of risk underlying the cross-section of commodity returns. *Management Science* 65, 619-641.

Barroso, P., and Santa-Clara, P. (2015). Beyond the carry trade: Optimal currency portfolios. *Journal of Financial and Quantitative Analysis* 50, 1037-1056.

Basu, D., and Miffre, J. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure. *Journal of Banking and Finance* 37, 2652-2664.

Bekaert, G., Engstrom, E. C., and Xu, N. R. (2022). The time variation in risk appetite and uncertainty. *Management Science* 68, 3975-4004.

Bhardwaj, G., Gorton, G. B., and Rouwenhorst, K. G. (2016). Investor interest and the returns to commodity investing. *Journal of Portfolio Management* 42, 44-45.

Birru, J. (2018). Day of the week and the cross-section of stock returns. *Journal of Financial Economics* 130, 182-214.

Bohl, M., Putz, A., and Sulewski, C. (2021). Speculation and the informational efficiency of commodity futures markets. *Journal of Commodity Markets* 23, 100159.

Boons, M., and Prado, M. P. (2019). Basis-momentum. *Journal of Finance* 74, 239-279.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience theory of choice under risk. *Quarterly Journal of Economics* 127, 1243-85.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2022). Salience. *Annual Review of Economics*, *14*, 521-544.

Brandt, M., Santa-Clara, P., and Valkanov, R. (2009). Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *Review of Financial Studies* 22, 3411-3447.

Coakley, J., Fuertes, A.-M., and Shen, Z. (2021). Media tone and investor demand for IPOs. SSRN Working Paper http://dx.doi.org/10.2139/ssrn.3971260.

Cosemans, M., and Frehen, R. (2021). Salience theory and stock prices. *Journal of Financial Economics* 140, 460-483.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market under- and overreaction. *Journal of Finance* 53, 1839-1885

De Long, J. B., Shleifer, A., Summers, H. L., and Waldmann, J. R. (1990). Noise trader risk in financial markets. *Journal of Political Economy* 98, 703–738.

De Vault, L., Sias, R., and Starks, L. (2019). Sentiment metrics and investor demand. *Journal of Finance* 74, 985–1024.

Edelen, R. M., Ince, O. S., and Kadlec, G. B. (2016). Institutional investors and stock return anomalies. *Journal of Financial Economic*s 119, 472-488.

Fan, J. H., Binnewies, S., and De Silva, S. (2023). Wisdom of crowds and commodity pricing. *Journal of Futures Markets* 43, 1040–1068.

Fan, J. H., Fernandez-Perez., A., Fuertes, A.-M., and Miffre, J. (2020). Speculative pressure. *Journal of Futures Markets* 40, 575-597.

Fedyk, A., and Hodson, J. (2023) When can the market identify old news?, *Journal of Financial Economics* 149, 92-113.

Ferguson, N.J., Philip, D., Lam, H. Y., and Guo, J. M. (2015) Media content and stock returns: The predictive power of press. *Multinational Finance Journal* 19, 1-31.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., and Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking and Finance* 86, 143-158.

Fernandez-Perez., A., Fuertes, A.-M., and Miffre, J. (2019). A comprehensive appraisal of style-integration methods. *Journal of Banking and Finance* 105, 134-150.

Fernandez-Perez, A., Fuertes, A.-M., Gonzalez-Fernandez, M., and Miffre, J. (2020). Fear of hazards in commodity futures markets. *Journal of Banking and Finance* 119, 105902.

Gao, L., and Süss, S. (2015). Market sentiment in commodity futures returns. *Journal of Empirical Finance* 33, 84-103.

Garcia, D. (2013). Sentiment during recessions. *Journal of Finance* 68, 1267-1300.

Gilbert, T., Kogan, S., Lochstoer, L., and Ozildirim, A. (2012). Investor inattention and the market impact of summary statistics. *Management Science* 58, 336-250.

Gorton, G., Hayashi, F., and Rouwenhorst, G. (2013). The fundamentals of commodity futures returns. *Review of Finance* 17, 35-105.

Gu, M., Kang, W., Lou, D., and Tang, K. (2023). Relative basis: A better measure of the convenience yield. SSRN Working Paper http://dx.doi.org/10.2139/ssrn.3404561.

Hirshleifer, D., and Teoh, S. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36, 337-386.

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

Keynes, J. M. (1936). *The general Theory of Unemployment, Interest and Money*. London, Macmillan.

Kumar, A. (2009). Hard-to-value stocks, behavioral biases, and informed trading. *Journal of Financial and Quantitative Analysis* 44, 1375-1401.

Ledoit, O., and Wolf, M. (2008). Robust performance hypothesis testing with the Sharpe ratio. *Journal of Empirical Finance* 15, 850–859.

Liu, S., and Han, J. (2020). Media tone and expected stock returns. *International Review of Financial Analysis* 70, 101522.

Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N. (2012). Commodity liquidity measurement and transaction costs. *Review of Financial Studies* 25, 599-638.

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

Nekrasov, A., Teoh, S. H., and Wu, S. (2022). Limited attention and financial decision-making. In *The Handbook of Financial Decision Theory* by G. Hilary and D. McLean (eds.).

Obaid, K., and Pukthuanthong, K. (2022). A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. *Journal of Financial Economics* 144, 273-297.

Pastor, L., and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642-685.

Rangvid, J., Schmeling, M., and Schrimpf, A. (2013). What do professional forecasters' stock market expectations tell us about herding, information extraction and beauty contests? *Journal of Empirical Finance* 20, 109–129.

Sakkas, A., and Tessaromatis, N. (2020). Factor based commodity investing. *Journal of Banking and Finance* 115, 105807.

Sanders, D. R., Irwin, S. H., and Merrin, R. P. (2010). The adequacy of speculation in agricultural futures markets: Too much of a good thing?. *Applied Economic Perspectives and Policy* 32, 77-94.

Shapiro, A., Sudhof, M., and Wilson, D. (2020). Measuring news sentiment. *Journal of Econometrics* 228, 221-243.

Shiller, R. J. (2000). *Irrational exuberance*. Princeton University Press. Princeton.

Szymanowska, M., De Roon, F., Nijman, T., and Van Den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *Journal of Finance* 69, 453-482.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance* 62, 1139-1168.

Tetlock, P. C. (2011). All the news that's fit to reprint: Do investors react to stale information? *Review of Financial Studies* 24, 1481-1512.

Wang, W. (2018). The mean-variance relation and the role of institutional investor sentiment. *Economic Letters* 168, 61-64.

Wang, W., and Duxbury, D. (2021). Institutional investor sentiment and the mean-variance relationship: Global evidence. *Journal of Economic Behavior and Organization* 191, 415-441.

Working, H. (1960). Speculation on hedging markets. *Food Research Institute Studies* 1, 185-220.

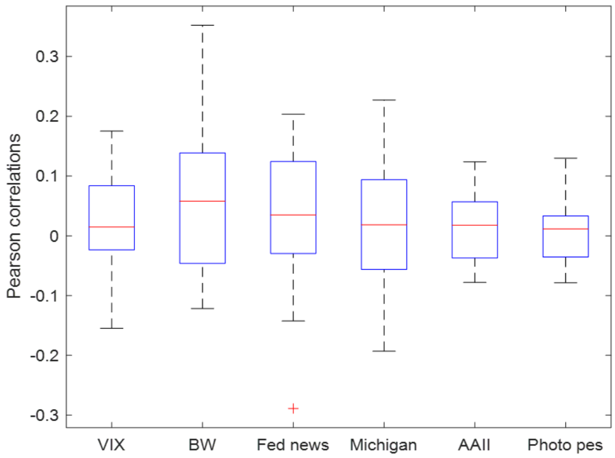


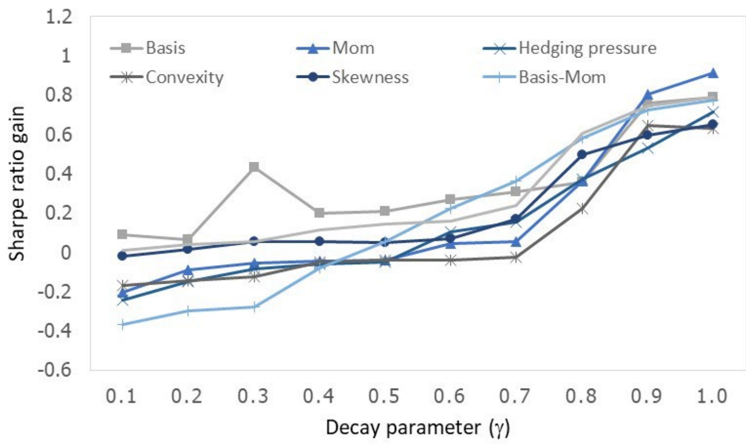
Figure 1. Commodity-specific newswire tone and market-wide sentiment.

The figure shows box-and-whisker plots of the correlation between the news tone signal per commodity, $TONE_{i,t}, i = 1, \dots, N,$ and market-wide sentiment proxies – CBOE's VIX "investors' fear" index, Baker and Wurgler (2007) sentiment index, FRB of San Francisco news sentiment index, Michigan University consumer confidence index, AAII investors' survey sentiment index, and Obaid and Pukthuanthong (2022) photo news pessimism index. The sample period is January 3, 2000 to May 31, 2020.

Figure 2. Dynamic appraisal of tone-overlay portfolios and corresponding traditional portfolios.

The figure plots the cumulative Sharpe ratio of traditional portfolios (dotted line) and corresponding tone-overlay portfolios (full line) based on the tone-overlay model, Eq. (2), with hyperparameters $\pi = 0.1$ (salience), $\tau = 0.9$ (tilting), and $\delta_t^+ = \delta_t^- = 1$ (optimism/pessimism weighting). The estimation window length for the remaining parameters of the tone-overlay model is $L = 260$ weeks. The first Sharpe ratio plotted is based on an initial five-year window of out-of-sample excess returns which is recursively expanded forward by one week. The analysis is based on data from January 3, 2000 to May 31, 2020.

Panel A. Daily news-impact decay parameter



Panel B. Intraday-news weights

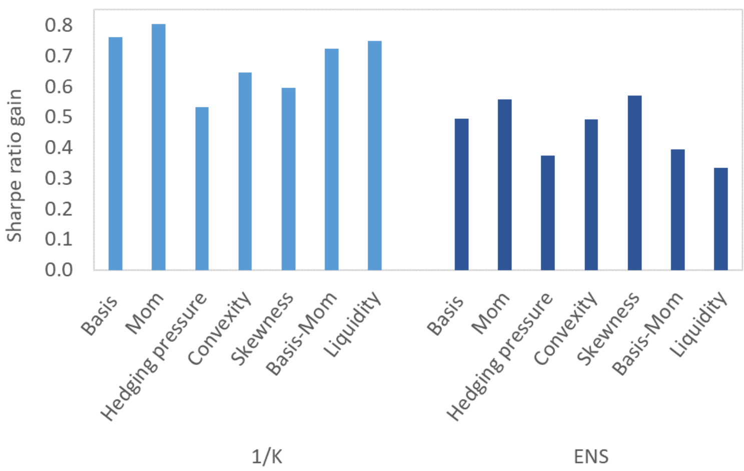
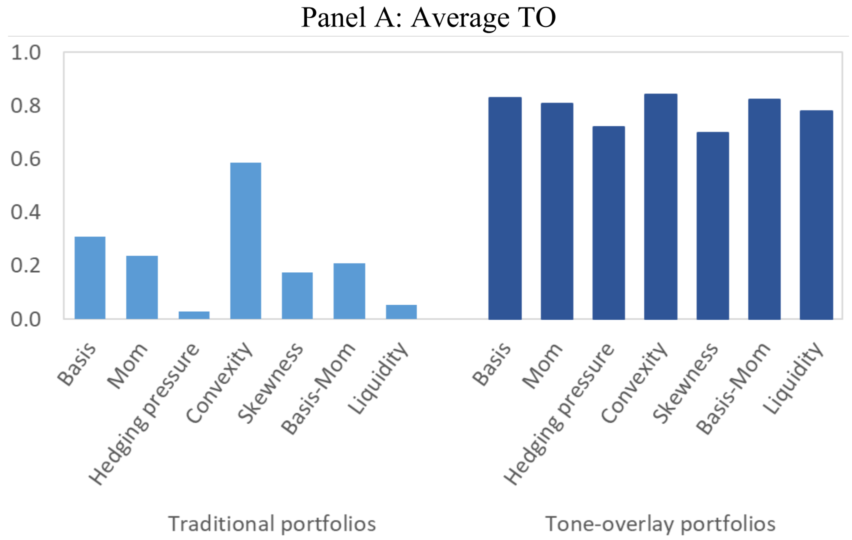


Figure 3. Performance of tone-overlay strategy with alternative TONE measures.

The figure shows the Sharpe ratio gain of tone-overlay portfolios ($\Delta SR = SR_{overlay} - SR_{trad}$) implemented with alternative designs of the commodity-level news sentiment measure, $TONE_{i,t}$ from Eq. (3). In Panel A, the horizontal axis represents the inter-daily news impact decay parameter γ, ranging from 0.1 to 1, with $\gamma = 1$ indicating no decay. In Panel B, intraday news items are either equally weighted (left side) or weighted by normalized event novelty scores from RPNA (right side). The tone-overlay model, Eq. (2), employs the baseline specification of the hyperparameters $(\pi, \tau, (\delta^+, \delta^-)) = (0.1, 0.9, (1,1))$. The analysis is based on data from January 3, 2000, to May 31, 2020.



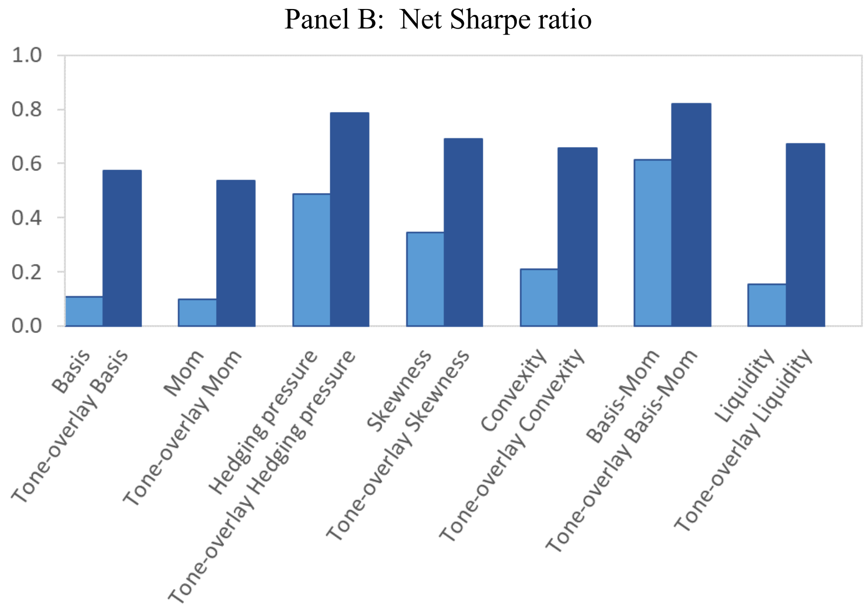


Figure 4. Portfolio turnover and net Sharpe ratio.

In Panel A, the figure plots the turnover (TO) of traditional portfolios alongside tone-overlay portfolios using the baseline specification of the hyperparameters $(\pi, \tau, (\delta^+, \delta^-)) = (0.1, 0.9, (1,1))$ in Eq. (2). In Panel B, the figure plots net Sharpe ratios incorporating an average roundtrip transaction cost estimate (8.6bp) from Marshall et al. (2012). The analysis covers data from January 3, 2000, to May 31, 2020.

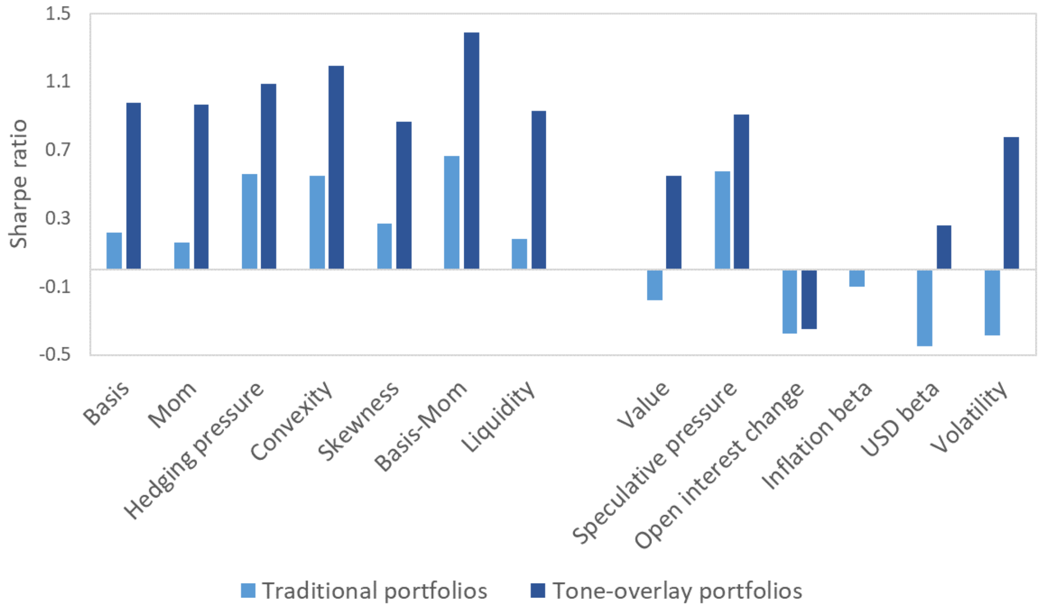


Figure 5. Outperformance of tone-overlay portfolios for a universe of traditional signals.

The figure plots the Sharpe ratios of traditional and tone-overlay portfolios based on a universe of thirteen commodity futures characteristics: those used in the main analysis – basis, momentum (Mom), hedging pressure, convexity, skewness, basis-momentum (Basis-Mom), and liquidity – and those considered in the robustness test of Section 4.5 – value, speculative pressure, open interest change, inflation beta, USD beta, and volatility. The tone-overlay model, Eq. (2), uses the baseline hyperparameter specification $(\pi, \tau, (\delta^{+}, \delta^{-})) = (0.1, 0.9, (1,1))$. The analysis is based on data from January 3, 2000 to May 31, 2020.

Table 1. Summary statistics for commodity futures excess returns and news tone.

The table reports summary statistics per commodity for the weekly excess returns, news coverage (*Dow Jones Financial Wires*, *Wall Street Journal*, *Barron's* and *MarketWatch*) and commodity-specific newswire sentiment measured as $TONE_{i,t}$ in Eq. (3) using daily news impact decay $\gamma = 0.9$ and intraday news weights $\phi_{k(d)} = \frac{1}{K_d}$. Mean and standard deviation (StDev) of excess returns have been annualized. AC1 is the first-order autocorrelation coefficient. The sample period is January 3, 2000 to May 31, 2020.

Sector	Commodity	Excess return		News coverage			TONE					#Obs
		Mean	AC1	#News	#News (*Relevance* score > 90)	#News/week (*Relevance* score > 90)	Mean	StDev	Min	Max	AC1	
Energy	Heating oil	-0.021	0.043	60,059	2,917	2.74	50.632	14.176	28	76	0.582	1065
	Natural gas	-0.353	0.009	1,104,993	65,150	61.17	49.550	7.938	12	76	0.225	1065
	RBOB gasoline	-0.048	0.098	413,420	55,426	52.04	52.640	11.338	13	100	0.593	765
	Unleaded gasoline	0.193	-0.040	342,414	8,510	7.99	56.188	16.053	12	100	0.558	360
	WTI crude oil	-0.060	0.063	3,607,532	681,766	640.16	50.592	5.329	28	66	0.204	1065
Grains	Corn	-0.086	-0.021	266,862	20,581	19.32	53.103	9.029	29	93	0.380	1065
	Oats	0.049	-0.024	23,260	242	0.23	56.273	12.088	35	91	0.919	1065
	Rough rice	-0.075	0.060	93,685	5,856	5.50	51.157	13.141	4	88	0.496	1065
	Wheat	-0.097	0.004	341,922	16,371	15.37	52.689	8.969	31	94	0.463	1065
Livestock	Feeder cattle	0.016	-0.077	75,570	527	0.49	57.994	11.900	30	68	0.875	1065
	Lean hogs	-0.086	-0.010	125,672	5,948	5.58	54.363	9.127	33	70	0.365	1065
	Live cattle	0.010	-0.050	50,137	3,549	3.33	51.601	12.372	19	93	0.563	1065
	Frozen pork bellies	0.048	0.032	15,097	924	0.87	48.311	13.159	22	68	0.677	599
Metals	Copper	0.056	-0.030	440,461	61,988	58.20	51.742	8.507	13	86	0.212	1065
	Gold	0.075	-0.040	1,226,862	194,225	182.37	50.367	7.308	25	79	0.092	1065
	Palladium	0.020	0.029	77,566	3,878	3.64	50.948	18.138	7	92	0.668	1065
	Platinum	0.019	0.039	83,455	4,004	3.76	51.636	16.693	8	93	0.624	1065
	Silver	0.049	0.005	195,706	16,483	15.48	46.179	13.560	6	91	0.559	1065
Oilseeds	Soybeans	0.048	0.024	231,815	20,413	19.17	53.546	12.874	18	95	0.531	1065
	Soybean meal	0.102	0.030	65,147	2,476	2.32	52.769	11.470	16	94	0.451	1065
	Soybean oil	-0.017	0.048	131,914	8,734	8.20	48.712	15.399	7	93	0.691	1065
Softs	Cocoa	0.067	0.021	148,220	11,164	10.48	53.351	12.498	10	99	0.446	1065
	Coffee	-0.089	0.025	250,937	21,134	19.84	53.875	9.772	26	96	0.411	1065
	Cotton	-0.060	0.011	173,669	9,747	9.15	52.303	10.731	19	94	0.495	1065
	Frozen orange juice	-0.009	0.027	15,282	2,222	2.09	52.297	13.685	13	77	0.796	1065
	Lumber	-0.105	0.017	38,341	1,862	1.75	56.036	11.643	33	91	0.597	1065

Table 2. Commodity-specific newswire tone and broad market sentiment.

The table reports estimation results for panel fixed effects (FE) regressions of weekly commodity-specific newswire sentiment ($TONE_{i,t}$) on market-wide sentiment proxied by CBOE's VIX, Baker-Wurgler sentiment index (Baker and Wurgler, 2006), FRB of St Louis news sentiment index (Shapiro et al., 2020), University of Michigan consumer sentiment index, American Association of Individual Investors (AAII) sentiment index, and photo news pessimism index (Obaid, and Pukthuanthong, 2022). The controls are commodity futures characteristics – basis, momentum, hedging pressure, convexity, skewness, basis-momentum, liquidity, and excess return. All regressors are standardized to have zero mean and one standard deviation at the pooled level. The *t*-statistics in parentheses use two-way clustered (by commodity and time) standard errors. The analysis is based on data from January 3, 2000 to May 31, 2020.

	Commodity-specific newswire sentiment (TONE)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VIX	0.214	0.202										
	(1.191)	(1.131)										
BW			0.627	0.647								
			(2.307)	(2.419)								
Fed news					0.427	0.413						
					(2.221)	(2.151)						
Michigan							0.319	0.313				
							(1.478)	(1.530)				
AAII									0.122	0.090		
									(0.954)	(0.719)		
Photo pes											0.094	0.089
											(0.731)	(0.671)
Controls $\boldsymbol{Z}_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	25,476	25,476	25,476	25,476	25,476	25,476	25,476	25,476	25,476	25,476	14,669	14,669
Adjusted R^2	0.012	0.037	0.014	0.039	0.013	0.037	0.012	0.037	0.011	0.036	0.004	0.045

Table 3. Performance of tone-overlay portfolios and corresponding traditional portfolios.

The table summarizes in Panel A the traditional portfolios and in Panel B the tone-overlay portfolios based on Eq. (2) with the hyperparameters set at $\pi = 0.10$ (salience), $\tau = 0.9$ (tilting), and $\delta^{+} = \delta^{-} = 1$ (optimism/pessimism). Mean excess return, standard deviation (StDev) and semi deviation are annualized. $\Delta SR = SR_{overlay} - SR_{trad}$ is the Sharpe ratio gain of the tone-overlay (vs. traditional) portfolios and $\Delta CER = CER_{overlay} - CER_{trad}$ is the certainty equivalent return gain based on power utility and relative risk aversion $\nu = 5$. The Ledoit and Wolf (2008) test p-value in italics is for $H_0: \Delta SR \leq 0$ versus $H_A: \Delta SR > 0$. The p-value of the GMM test of Anderson and Cheng (2016) in italics is for $H_0: \Delta CER = 0$ vs $H_A: \Delta CER \neq 0$. α and β are coefficient estimates from factor spanning regressions of the excess returns of the tone-overlay portfolio on the excess returns of the underlying traditional portfolio. The t-statistics, shown in parentheses, are based on Newey-West standard errors. The portfolios are rebalanced weekly and implemented on data from January 2, 2000 to May 31, 2020. The OOS return sequence commences on January 3, 2005 as dictated by the estimation window length ($L = 260$ weeks) of the tone-overlay strategy.

	Panel A. Traditional portfolios							Panel B. Tone-overlay portfolios						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
Mean	0.0222	0.0188	0.0606	0.0507	0.0291	0.0637	0.0189	0.0868	0.0861	0.0914	0.1046	0.0804	0.1195	0.0800
	(0.84)	(0.68)	(2.27)	(2.04)	(1.09)	(2.79)	(0.64)	(4.17)	(4.23)	(4.58)	(5.05)	(3.66)	(6.34)	(3.78)
StDev	0.1041	0.1171	0.1087	0.0925	0.1090	0.0962	0.1051	0.0890	0.0893	0.0839	0.0877	0.0932	0.0862	0.0862
Skewness	-0.5762	-0.0774	-0.3743	-0.1749	-0.7727	-0.0851	-0.1901	-0.0046	-0.1866	-0.1536	0.2475	-0.4678	-0.0332	0.1437
	(-6.28)	(-0.90)	(-4.24)	(-2.03)	(-8.06)	(-0.99)	(-2.20)	(-0.05)	(-2.16)	(-1.78)	(2.85)	(-5.21)	(-0.39)	(1.67)
Excess kurtosis	4.2476	2.0188	2.2040	3.4436	7.1331	2.8387	0.5944	0.3921	0.5874	1.3604	2.1643	2.8219	0.2424	2.0447
	(9.18)	(6.41)	(6.72)	(8.38)	(11.13)	(7.65)	(2.85)	(2.07)	(2.83)	(5.08)	(6.66)	(7.63)	(1.40)	(6.46)
Semi deviation	0.0716	0.0798	0.0773	0.0628	0.0803	0.0648	0.0705	0.0561	0.0596	0.0556	0.0531	0.0652	0.0530	0.0534
1% VaR	-0.0331	-0.0374	-0.0339	-0.0289	-0.0346	-0.0298	-0.0335	-0.0271	-0.0272	-0.0253	-0.0263	-0.0285	-0.0255	-0.0263
Max drawdown	-0.2819	-0.3881	-0.1803	-0.2479	-0.3453	-0.1821	-0.3743	-0.1156	-0.1710	-0.0869	-0.1008	-0.1756	-0.1077	-0.2351
Sharpe ratio	0.2134	0.1604	0.5580	0.5479	0.2670	0.6626	0.1802	0.9752	0.9634	1.0889	1.1922	0.8631	1.3860	0.9277
ΔSR								0.7618	0.8030	0.5309	0.6443	0.5961	0.7235	0.7474
Ledoit-Wolf test p-value								*0.0029*	*0.0010*	*0.0258*	*0.0103*	*0.0018*	*0.0038*	*0.0039*
Sortino ratio	0.2977	0.2255	0.8048	0.8050	0.3725	0.9936	0.2535	1.5299	1.4659	1.6990	1.9772	1.2846	2.2992	1.4711
Omega ratio	1.0795	1.0603	1.2279	1.2217	1.1062	1.2764	1.0669	1.4132	1.4083	1.4794	1.5379	1.3676	1.6318	1.3968
CER	0.0185	0.0140	0.0566	0.0477	0.0250	0.0605	0.0151	0.0841	0.0833	0.0890	0.1019	0.0774	0.1169	0.0774
ΔCER								0.0656	0.0693	0.0324	0.0542	0.0524	0.0564	0.0623
GMM test p-value								*0.0075*	*0.0034*	*0.0213*	*0.0134*	*0.0044*	*0.0043*	*0.0079*
α (alpha)								0.0787	0.0794	0.0715	0.0840	0.0633	0.0942	0.0739
								(4.06)	(4.24)	(3.83)	(4.38)	(3.71)	(5.04)	(3.96)
β (traditional risk factor beta)								0.3662	0.3557	0.3284	0.4063	0.5889	0.3971	0.3200
								(9.90)	(10.80)	(8.83)	(9.67)	(23.20)	(12.64)	(10.36)

Table 4. Placebo test for tone-overlay efficacy.

The table summarizes the performance of randomized-tone-overlay portfolios. At portfolio formation time *t*, commodity i is assigned the newswire tone of a randomly-drawn commodity j from a different sector, $TONE_{j,t(j\neq i)}$. Mean excess return, standard deviation (StDev) and semi deviation are annualized. The t-statistics, shown in parentheses, are based on Newey-West standard errors. $\Delta SR = SR_{overlay} - SR_{trad}$ is the Sharpe ratio gain of the tone-overlay portfolios and $\Delta CER = CER_{overlay} - CER_{trad}$ is the certainty equivalent return gain based on power utility with coefficient of relative risk aversion $\nu = 5$. The tone-overlay portfolios are based on Eq. (2) with hyperparameters $(\pi, \tau, (\delta^+, \delta^-)) = (0.1, 0.9, (1,1))$. The Ledoit and Wolf (2008) test p-value in italics is for $H_0\colon \Delta SR \leq 0$ versus $H_A\colon \Delta SR > 0$. The p-value of the GMM test of Anderson and Cheng (2016) in italics is for $H_0\colon \Delta CER = 0$ vs $H_A\colon \Delta CER \neq 0$. The analysis is based on data from January 3, 2000 to May 31, 2020.

	Tone-overlay portfolios with commodity-randomized TONE signal						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
Mean	0.0073	0.0012	0.0165	0.0051	-0.0070	0.0307	-0.0318
	(0.41)	(0.22)	(0.84)	(0.34)	(-0.08)	(1.26)	(-1.00)
StDev	0.0930	0.1010	0.0873	0.0951	0.0967	0.0997	0.0959
Skewness	-0.0918	0.0259	-0.1367	-0.0411	-0.2712	0.0146	-0.1991
	(-1.04)	(0.29)	(-1.54)	(-0.46)	(-3.01)	(0.17)	(-2.23)
Excess kurtosis	0.5183	1.8671	0.7270	2.4455	1.5753	0.6770	1.2953
	(2.50)	(5.95)	(3.22)	(6.89)	(5.39)	(3.05)	(4.78)
Semi deviation	0.0609	0.0671	0.0573	0.0630	0.0664	0.0615	0.0663
1% VaR	-0.0298	-0.0325	-0.0278	-0.0305	-0.0312	-0.0315	-0.0315
Max drawdown	-0.3421	-0.3554	-0.2699	-0.2989	-0.2950	-0.3450	-0.4306
Sharpe ratio	0.0781	0.0121	0.1889	0.0536	-0.0726	0.3083	-0.3322
ΔSR	-0.0843	-0.0903	-0.3345	-0.4593	-0.6779	-0.3240	-0.4607
Ledoit-Wolf test p-value	*0.4565*	*0.6092*	*0.8843*	*0.9062*	*0.9602*	*0.8396*	*0.9230*
Sortino ratio	0.1192	0.0182	0.2881	0.0809	-0.1058	0.4996	-0.4802
Omega ratio	1.0459	1.0231	1.0870	1.0382	0.9911	1.1331	0.8987
CER	0.0250	0.0166	0.0630	0.0520	0.0176	0.0922	-0.0175
ΔCER	0.0086	0.0028	0.0175	0.0065	-0.0056	0.0318	-0.0309
GMM test p-value	*0.1932*	*0.3749*	*0.1665*	*0.2464*	*0.8004*	*0.1173*	*0.9099*

Table 5. Tone-overlay outperformance and risk factors.

The table shows in Panel A the estimation results of factor spanning time-series regressions for the tone-overlay portfolio excess returns, orthogonalized with respect to the corresponding traditional portfolio excess returns. The reported alphas are annualized. Panel B presents estimation results for regressions of the orthogonalized tone-overlay excess returns on proxies for broad financial and macroeconomic risks (as described in Section 3.4), with an unreported intercept. The *t*-statistics in parentheses use Newey-West standard errors. The analysis is based on data from January 3, 2000, to May 25, 2020.

	Orthogonalized tone-overlay portfolio returns						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
Panel A. Commodity risk factors							
α	0.0751	0.0783	0.0632	0.0836	0.0600	0.0947	0.0653
	(3.79)	(4.12)	(3.39)	(4.23)	(3.58)	(5.09)	(3.39)
β_{Basis}	-	0.0652	-0.0041	0.0053	0.0633	0.0321	-0.0097
		(1.70)	(-0.10)	(0.16)	(2.15)	(0.80)	(-0.23)
β_{Mom}	-0.0030	-	-0.0016	-0.0016	-0.0150	0.0032	0.0155
	(-0.08)		(-0.05)	(-0.04)	(-0.49)	(0.09)	(0.41)
$\beta_{Hedging\ pressure}$	-0.0546	-0.0442	-	-0.0545	-0.0163	-0.0432	-0.0480
	(-1.15)	(-1.07)		(-1.36)	(-0.47)	(-1.09)	(-1.27)
$\beta_{Convexity}$	0.0215	-0.0228	0.0716	-	-0.0190	0.0187	0.0684
	(0.57)	(-0.65)	(1.37)		(-0.49)	(0.43)	(1.05)
$\beta_{Skewness}$	-0.0231	-0.0233	0.0113	-0.0140	-	-0.0006	0.0101
	(-0.62)	(-0.76)	(0.39)	(-0.44)		(-0.02)	(0.24)
$\beta_{Basis\text{-}Mom}$	0.0916	0.0582	0.0599	0.0586	0.0576	-	0.1200
	(2.47)	(1.71)	(1.62)	(1.61)	(1.67)		(2.67)
$\beta_{Liquidity}$	0.0363	0.0243	0.0353	0.0160	0.0215	0.0236	-
	(1.04)	(0.68)	(1.12)	(0.45)	(0.74)	(0.62)	
Adjusted R^2	0.0096	0.0071	0.0107	0.0012	0.0089	-0.0030	0.0242
Panel B. Broad financial and macroeconomic risks							
Intercept	0.0022	0.0030	0.0018	0.0016	-0.0004	0.0021	0.0034
	(0.76)	(1.14)	(0.74)	(0.49)	(-0.17)	(0.69)	(1.14)
ADS	-0.0003	-0.0002	-0.0002	-0.0004	-0.0002	-0.0002	-0.0003
	(-1.27)	(-1.19)	(-0.49)	(-2.64)	(-0.87)	(-0.90)	(-0.80)
TED	0.0000	0.0012	0.0002	-0.0011	0.0001	0.0008	0.0005
	(0.00)	(1.12)	(0.15)	(-1.01)	(0.07)	(0.78)	(0.34)
TERM	0.0108	-0.0044	-0.0112	-0.0207	0.0027	-0.0076	-0.0232
	(0.31)	(-0.13)	(-0.30)	(-0.58)	(0.09)	(-0.23)	(-0.70)
FED	0.5223	0.6265	0.5138	0.7407	0.5743	0.4816	0.1691
	(0.97)	(1.59)	(1.66)	(2.16)	(1.84)	(1.60)	(0.43)
UNC	-0.0007	-0.0008	-0.0001	0.0002	0.0004	-0.0005	-0.0005
	(-0.55)	(-0.67)	(-0.10)	(0.13)	(0.39)	(-0.39)	(-0.35)
LIQUID	0.0009	0.0037	-0.0047	0.0047	0.0008	-0.0003	0.0008
	(0.10)	(0.41)	(-0.52)	(0.46)	(0.10)	(-0.04)	(0.08)
IP	-0.0169	-0.0084	-0.0014	-0.0081	0.0038	-0.0072	0.0056
	(-1.06)	(-0.59)	(-0.10)	(-0.50)	(0.31)	(-0.51)	(0.35)
INFL	0.0387	-0.0112	-0.0055	0.0151	0.0236	0.0306	-0.0494
	(0.81)	(-0.27)	(-0.13)	(0.32)	(0.65)	(0.74)	(-1.07)
Adjusted R^2	-0.0026	-0.0026	-0.0049	0.0062	-0.0001	-0.0033	-0.0045

Table 6. Predicting commodity futures returns with commodity newswire tone.

The table shows estimation results for panel fixed effects (FE) predictive regressions of weekly commodity futures returns on lagged commodity-specific newswire tone, lagged broad-market sentiment, and lagged commodity controls (basis, momentum, hedging pressure, convexity, basis-momentum, skewness, liquidity and futures return). Broad market sentiment is proxied by the FRB of San Francisco news index (Shapiro et al., 2020). All regressors are standardized at the panel level. The coefficients of $TONE_{i,t-j}$ are scaled by 100. Significance t-statistics are reported in parentheses. The Wald test p-value is for the null hypothesis $H_0: \beta_1 + \beta_2 = 0$ versus $H_A: \beta_1 + \beta_2 \neq 0$ where β_1 and β_2 are the coefficients of $TONE_{i,t-j}, j = 1, 2$. The inferences are based on two-way (commodity and year-week) clustered standard errors. The sample period is January 3, 2000 to May 25, 2020.

	Commodity excess returns				
	(1)	(2)	(3)	(5)	(6)
$TONE_{i,t\text{-}1}$	0.126	0.126	0.115	0.125	0.126
	(3.767)	(3.728)	(3.614)	(3.803)	(3.766)
$TONE_{i,t\text{-}2}$	-0.084	-0.083	-0.07	-0.084	-0.084
	(-2.530)	(-2.529)	(-2.357)	(-2.550)	(-2.546)
$TONE_{i,t\text{-}3}$	-0.020	-0.020	-0.027	-0.021	-0.021
	(-0.667)	(-0.634)	(-0.865)	(-0.689)	(-0.654)
$TONE_{i,t\text{-}4}$	0.048	0.049	0.053	0.048	0.048
	(1.263)	(1.311)	(1.664)	(1.248)	(1.298)
$Sentiment_{t\text{-}1}$				0.004	0.004
				(1.530)	(1.525)
$Sentiment_{t\text{-}2}$				0.002	0.002
				(0.457)	(0.456)
$Sentiment_{t\text{-}3}$				-0.003	-0.003
				(-0.714)	(-0.710)
$Sentiment_{t\text{-}4}$				-0.002	-0.002
				(-0.861)	(-0.870)
Controls $\boldsymbol{Z}_{i,t\text{-}1}$	Yes	Yes	Yes	Yes	Yes
Commodity FE	No	Yes	Yes	No	Yes
Year-week FE	No	No	Yes	No	No
Observations	25,428	25,428	25,428	25,428	25,428
Adjusted R^2	0.002	0.002	0.163	0.004	0.004
Wald test p-value (β_1+β_2=0)	0.238	0.228	0.133	0.239	0.227

Table 7. **Impact of arbitrage limits and speculativeness.**

The table presents the annualized Sharpe ratios of weekly-rebalanced double-sort commodity portfolios. Commodities are initially categorized into high-arbitrage-cost and low-arbitrage-cost portfolios in Panel A (high-speculativeness and low-speculativeness portfolios in Panel B). Commodities within each of these portfolios are further categorized by their $TONE_{i,t}$ characteristic into high-TONE versus low-TONE portfolios. The proxies for arbitrage limits are Amihud illiquidity, total open interest, and volatility (Panel A), while the proxies for speculativeness are the Working T-index, and "lottery" aspect measured with the skewness coefficient (third moment) and maximum of prior year weekly return distribution (Panel B). Appendix A provides details on these variables. The cutoff point for the high vs low categorization is the median. The analysis is based on data from January 3, 2000, to May 25, 2020.

	Panel A. Limits to arbitrage		Panel B. Speculativeness	
	High	Low	High	Low
	Illiquidity		Working T-index	
High TONE	0.2564	0.0518	0.1455	0.0084
Low TONE	-0.3098	-0.2195	-0.1671	-0.1734
H-L	0.5996	0.2790	0.3003	0.2127
	Open interest		Skewness	
High TONE	0.2452	-0.0220	0.4391	-0.1728
Low TONE	0.0185	-0.4037	-0.1064	-0.3617
H-L	0.2285	0.4005	0.6147	0.1908
	Volatility		Maximum return	
High TONE	0.3641	0.0130	0.2273	-0.0338
Low TONE	-0.4114	-0.1262	-0.1973	-0.2773
H-L	0.8172	0.1480	0.4469	0.2794

Table 8. Tone-overlay portfolio performance for different holding periods.

The table reports the annualized mean excess return, standard deviation (StDev), Sharpe ratio and Sharpe ratio gain of each tone-overlay portfolio versus the underlying traditional portfolio ($\Delta SR = SR_{overlay} - SR_{trad}$) for holding periods $h = \{1,2,3,4,8\}$ weeks. The tone-overlay model, Eq. (2), is deployed with hyperparameters $(\pi, \tau, (\delta^{+}, \delta^{-})) = (0.1, 0.9, (1,1))$. The Ledoit and Wolf (2008) test p-value is for $H_0: \Delta SR \leq 0$ versus $H_A: \Delta SR > 0$. The analysis is based on data from January 3, 2000 to May 25, 2020.

Holding period (weeks)		Tone-overlay portfolios							
		Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	*Average*
h = 1	Mean	0.0868	0.0861	0.0914	0.1046	0.0804	0.1195	0.0800	0.0927
	StDev	0.0890	0.0893	0.0839	0.0877	0.0932	0.0862	0.0862	0.0879
	Sharpe ratio	0.9752	0.9634	1.0889	1.1922	0.8631	1.3860	0.9277	1.0566
	ΔSR	0.7618	0.8030	0.5309	0.6443	0.5961	0.7235	0.7474	0.6867
	Ledoit-Wolf test p-value	*0.0029*	*0.0010*	*0.0258*	*0.0103*	*0.0018*	*0.0038*	*0.0039*	
h = 2	Mean	0.0598	0.0537	0.0813	0.0850	0.0668	0.0814	0.0668	0.0707
	StDev	0.0849	0.0849	0.0810	0.0875	0.0934	0.0882	0.0870	0.0867
	Sharpe ratio	0.7046	0.6329	1.0036	0.9712	0.7155	0.9230	0.7671	0.8168
	ΔSR	0.5630	0.5608	0.5505	0.4459	0.4436	0.3243	0.5749	0.4947
	Ledoit-Wolf test p-value	*0.0127*	*0.0046*	*0.0138*	*0.0330*	*0.0072*	*0.0248*	*0.0238*	
h = 3	Mean	0.0322	0.0392	0.0598	0.0565	0.0515	0.0568	0.0435	0.0485
	StDev	0.0872	0.0877	0.0837	0.0875	0.0951	0.0898	0.0873	0.0883
	Sharpe ratio	0.3695	0.4467	0.7148	0.6453	0.5410	0.6323	0.4982	0.5497
	ΔSR	0.2791	0.3975	0.2631	0.3154	0.2022	0.0933	0.3291	0.2685
	Ledoit-Wolf test p-value	*0.1165*	*0.0665*	*0.1255*	*0.0782*	*0.1131*	*0.3418*	*0.1080*	
h = 4	Mean	0.0112	0.0196	0.0402	0.0302	0.0373	0.0339	0.0272	0.0285
	StDev	0.0913	0.0909	0.0858	0.0879	0.0941	0.0896	0.0877	0.0896
	Sharpe ratio	0.1231	0.2160	0.4681	0.3431	0.3959	0.3780	0.3100	0.3192
	ΔSR	0.0072	0.1951	0.0080	0.0586	-0.0008	-0.0963	0.1540	0.0465
	Ledoit-Wolf test p-value	*0.4867*	*0.1731*	*0.4857*	*0.3851*	*0.5017*	*0.6701*	*0.2578*	
h = 8	Mean	0.0153	0.0120	0.0311	0.0273	0.0335	0.0332	0.0236	0.0251
	StDev	0.0861	0.0901	0.0835	0.0881	0.0921	0.0863	0.0849	0.0873
	Sharpe ratio	0.1774	0.1328	0.3731	0.3100	0.3641	0.3841	0.2784	0.2886
	ΔSR	-0.0292	0.1018	-0.1042	0.0427	-0.0704	-0.1034	0.0982	-0.0092
	Ledoit-Wolf test p-value	*0.5589*	*0.2901*	*0.6891*	*0.3927*	*0.6744*	*0.6716*	*0.3411*	

Table 9. Alternative hyperparameter specifications in the tone-overlay model.

The table reports the Sharpe ratio gains of the tone-overlay portfolios versus the corresponding traditional portfolios for various hyperparameter specifications in the tone-overlay model, Eq. (2). The baseline specification (π, τ, (δ^{+}, δ^{-}) =(0.1, 0.9, (1,1)) adopted in the main section of the paper is denoted in italics. $\widetilde{TONE}_{i,t}$ is the cross-sectionally standardized newswire tone signal, and likewise $\Delta\widetilde{TONE}_{i,t}$ for weekly tone changes. The analysis is based on data from January 3, 2000 to May 31, 2020.

	Tone-overlay portfolios							
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	Average
Panel A. Tone salience threshold (π, 1-π)								
0.01 - 0.99	0.3246	0.3880	0.2964	0.3564	0.3687	0.5288	0.1141	0.3396
0.05 - 0.95	0.8088	0.7986	0.5989	0.8814	0.7411	0.6955	0.7854	0.7585
0.10 - 0.90	*0.7618*	*0.8030*	*0.5309*	*0.6443*	*0.5961*	*0.7235*	*0.7474*	*0.6867*
0.15 - 0.85	0.6971	0.5650	0.5773	0.5935	0.7456	0.5432	0.7987	0.6458
0.20 - 0.80	0.5998	0.5756	0.4439	0.3746	0.7096	0.3955	0.6475	0.5352
0.25 - 0.75	0.4954	0.4031	0.2871	0.3820	0.4481	0.6509	0.3999	0.4381
Panel B. Traditional-signal tilting (τ)								
0.4	0.4189	0.5119	0.5967	0.6724	0.3215	0.4533	0.3747	0.4785
0.6	0.6739	0.6458	0.5665	0.7292	0.3545	0.5607	0.4768	0.5725
0.8	0.7300	0.6525	0.5972	0.7310	0.4766	0.6116	0.4933	0.6132
0.9	*0.7618*	*0.8030*	*0.5309*	*0.6443*	*0.5961*	*0.7235*	*0.7474*	*0.6867*
1	0.8535	0.6937	0.5644	0.7340	0.6492	0.7595	0.7318	0.7123
1.2	0.8419	0.6849	0.5019	0.7058	0.6395	0.7199	0.7265	0.6886
1.5	0.6308	0.6884	0.4105	0.5757	0.4867	0.6614	0.4578	0.5588
$\lvert\widetilde{TONE}_{it}\rvert$	0.8695	0.7841	0.4882	0.6059	0.4252	0.8170	0.7608	0.6787
$\lvert\Delta\widetilde{TONE}_{it}\rvert$	0.9402	0.7875	0.6135	0.7062	0.8848	0.8043	0.8365	0.7962
Panel C. Optimism vs pessimism (δ^{+}, δ^{-})								
(0, 1)	0.4764	0.4045	0.3219	0.3852	0.6028	0.6943	0.6671	0.5074
(0.2, 1)	0.6555	0.7619	0.5874	0.5871	0.7299	0.7505	0.8235	0.6994
(0.8, 1)	0.8384	0.6576	0.5234	0.7485	0.7166	0.6943	0.8292	0.7154
(1, 1)	*0.7618*	*0.8030*	*0.5309*	*0.6443*	*0.5961*	*0.7235*	*0.7474*	*0.6867*
(1, 0.8)	0.7436	0.6476	0.5473	0.7343	0.6195	0.5764	0.7751	0.6634
(1, 0.2)	0.7251	0.5597	0.6657	0.6900	0.4078	0.7103	0.6134	0.6246
(1, 0)	0.6693	0.5334	0.7434	0.8389	0.3253	0.8345	0.5506	0.6422

Online
ANNEX

Newswire Tone-Overlay Commodity Portfolios

Data Annex A.1. RavenPack News Analytics.

The commodity-level weekly $TONE_{i,t}$ measure, Eq. (3), utilizes several metadata that RavenPack News Analytics version 4 (RPNA4) assigns to news items – unscheduled (e.g., natural disasters and geopolitical events), scheduled (e.g., press conferences and macroeconomic data releases), discussions and opinion articles – from *Dow Jones Financial Wires*, *Wall Street Journal*, *Barron's* and *MarketWatch*.

RPNA4 generates one or more entity-level news records from each news item (also called *event*) according to the *entities* (commodities) mentioned in the story. Each entity-level news record is assigned 40 pieces of metadata or fields of which the relevant ones for our investigation are:

Entity name: an identifier of the entity discussed in the article. A news item is assigned multiple entity-level records if it mentions several entities.

Entity relevance: a score between 0 and 100 that indicates how intensively the story refers to each of the entities mentioned in the article. The score is assigned by a proprietary text processing algorithm that detects where the entity is mentioned in the article (i.e., headline, first paragraph, second paragraph, etc.), how often it is mentioned, and the overall number of other entities mentioned in the story. A higher relevance is assigned to an entity-level news record if it is mentioned in the headline, earlier on in the body of the story, when other entities are less mentioned.

Event novelty score*:* an index between 0 and 100 that indicates how novel a news story is across all news stories released with the same 24-hour time window. A high novelty score reflects early release (timing) within the window and highly novel or unprecedented information (uniqueness) through natural language processing (NLP) and semantic analysis techniques.

Event sentiment score: a 0-100 index that indicates the direction and strength of the short-term commodity price change anticipated by the story. Sentiment scores above 50 are positive or optimistic (price increase) and below 50 are negative or pessimistic (price decrease). A factor calculated by NLP algorithms according to categories of emotionally-charged words determines the strength or salience. Scores closer to 0 and 100 represent more salient pessimistic and optimistic sentiment, respectively.

The event sentiment score assigned by RPNA4 to each commodity-level record is obtained through an automated process that involves advanced NLP algorithms, machine learning (ML) algorithms and economic/financial experts' consensus. A simplified breakdown of this automated process is as follows: (1) *Text preprocessing*: tokenization, removing stop words, stemming or lemmatization, and handling special characters or formatting issues; (2) *Named entity recognition*: identification of commodities in the text and assigning relevance score through NLP algorithms; (3) *Sentiment analysis*: the text is processed with NLP algorithms to identify sentiment-bearing words, and syntactic structure to determine the emotional tone, sentiment polarity (positive, negative) and intensity of sentiment; ML models are trained and rigorously validated (cross validation, hyperparameter tuning and backtesting) using large historical datasets of labelled news articles where the sentiment (price impact) is known; (5) *Experts consensus*: each entity-level record is examined by experts with domain specific knowledge (finance and economics) and extensive experience and backgrounds in linguistics. Through a collection of surveys, the news items are rated by financial experts as having short-term positive or negative impact (and to which extent) on the commodity price; (6) *Integration*: the sentiment scores generated by ML are combined with the expert-provided scores through various methods (such as weighted averages) which are calibrated and backtested based on historical performance; (7) *Real-time sentiment scoring*: the trained and validated ML model, experts evaluation and integration method are deployed to process new entity-level records and assign them a sentiment score in real-time.

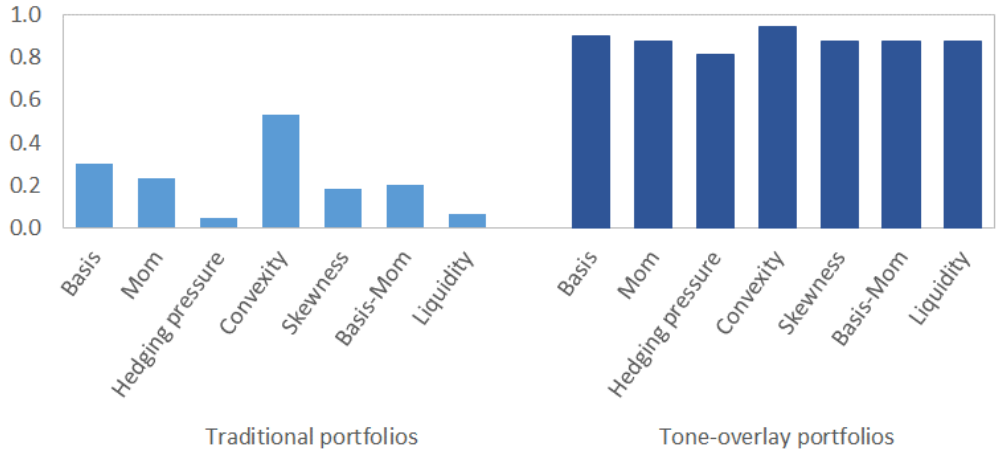


Figure A.1. Breakeven trading costs of tone-overlay portfolios.

The figure plots the roundtrip trading costs (in basis points) that nullify the mean excess returns of the tone-overlay and corresponding traditional portfolios. The tone-overlay model, Eq. (2), uses the baseline hyperparameter values $(\pi, \tau, (\delta^+, \delta^-)) = (0.1, 0.9, (1,1))$. The data covers the period January 3, 2000 to May 31, 2020.

Table A.1. Within- and across-sector correlations in commodity excess returns and tone.

The table illustrates the commodity dependence structure within the same sector (grey shaded area) and across sectors. Panel A reports the average pairwise correlations for the weekly commodity excess returns. Panel B reports the average pairwise correlations for the weekly newswire tone, $TONE_{i,t}$, calculated using Eq. (3) with a daily news-impact decay parameter $\gamma = 0.9$ and equal-weighting of intraday news $\phi_{k(d)} = \frac{1}{K_d}$. The analysis is based on data from January 3, 2000 to May 25, 2020.

Sector	Commodity	Panel A. Excess return						Panel B. Newswire tone					
		Energy	Grains	Livestock	Metals	Oilseeds	Softs	Energy	Grains	Livestock	Metals	Oilseeds	Softs
Energy	Heating oil	0.69	0.13	0.06	0.29	0.22	0.12	0.25	-0.01	0.00	0.03	-0.01	0.00
	Natural gas	0.41	0.10	0.04	0.10	0.12	0.07	0.26	-0.01	0.02	0.02	0.01	0.05
	RBOB gasoline	0.54	0.15	0.10	0.33	0.23	0.13	0.47	0.03	0.01	0.02	0.01	0.00
	Unleaded gasoline	0.47	-0.01	0.00	0.08	0.04	0.03	0.47	0.03	0.01	0.02	0.01	0.00
	WTI crude oil	0.67	0.13	0.05	0.30	0.21	0.12	0.32	0.05	-0.02	0.09	0.04	0.04
	Average	*0.56*	*0.10*	*0.05*	*0.22*	*0.16*	*0.09*	*0.36*	*0.02*	*0.01*	*0.04*	*0.01*	*0.02*
Grains	Corn	0.15	0.59	-0.01	0.21	0.47	0.14	0.02	0.37	0.00	-0.01	0.10	0.05
	Oats	0.09	0.50	0.02	0.13	0.32	0.12	0.04	0.37	-0.02	-0.02	0.13	0.10
	Rough rice	0.07	0.40	0.00	0.12	0.19	0.08	0.00	0.30	0.04	-0.02	0.01	0.02
	Wheat	0.09	0.55	0.02	0.17	0.35	0.12	0.01	0.35	0.06	-0.04	0.15	0.06
	Average	*0.10*	*0.51*	*0.01*	*0.16*	*0.33*	*0.11*	*0.02*	*0.35*	*0.02*	*-0.03*	*0.10*	*0.06*
Livestock	Feeder cattle	0.10	-0.06	0.55	0.08	0.03	0.07	-0.01	0.03	0.27	-0.02	0.01	0.03
	Lean hogs	-0.01	0.01	0.46	0.03	0.03	0.00	0.06	0.02	0.28	0.00	0.00	0.03
	Live cattle	0.10	0.06	0.55	0.08	0.09	0.09	0.01	0.06	0.29	0.01	0.12	0.01
	Frozen pork bellies	0.00	0.01	0.40	0.01	0.01	0.02	-0.02	-0.04	0.27	-0.05	0.04	0.01
	Average	*0.05*	*0.01*	*0.49*	*0.05*	*0.04*	*0.04*	*0.01*	*0.02*	*0.28*	*-0.02*	*0.04*	*0.02*
Metals	Copper	0.26	0.19	0.08	0.50	0.27	0.16	0.07	0.09	0.00	0.24	0.02	0.04
	Gold	0.16	0.13	0.00	0.61	0.15	0.12	0.03	-0.01	-0.03	0.28	-0.01	0.02
	Palladium	0.19	0.13	0.09	0.58	0.20	0.15	0.02	-0.03	0.01	0.23	-0.04	0.02
	Platinum	0.25	0.15	0.06	0.64	0.21	0.16	0.02	-0.07	-0.02	0.21	-0.12	0.00
	Silver	0.22	0.18	0.02	0.66	0.20	0.16	0.04	-0.11	-0.03	0.28	-0.02	0.02
	Average	*0.22*	*0.16*	*0.05*	*0.60*	*0.21*	*0.15*	*0.04*	*-0.03*	*-0.02*	*0.25*	*-0.03*	*0.02*
Oilseeds	Soybeans	0.18	0.42	0.05	0.22	0.72	0.15	0.02	0.09	0.04	-0.04	0.33	0.03
	Soybean meal	0.10	0.36	0.01	0.13	0.63	0.10	0.00	0.10	0.07	-0.06	0.34	0.03
	Soybean oil	0.24	0.36	0.06	0.29	0.60	0.17	0.00	0.13	0.02	-0.05	0.37	0.06
	Average	*0.17*	*0.38*	*0.04*	*0.21*	*0.65*	*0.14*	*0.01*	*0.11*	*0.04*	*-0.05*	*0.35*	*0.04*
Softs	Cocoa	0.15	0.12	0.06	0.23	0.15	0.32	0.00	0.11	0.00	-0.02	0.13	0.26
	Coffee	0.11	0.18	0.04	0.19	0.20	0.34	0.04	0.06	0.02	0.03	0.07	0.26
	Cotton	0.13	0.19	0.05	0.19	0.14	0.45	0.02	0.07	0.04	0.00	0.07	0.37
	Frozen orange juice	0.02	0.07	0.02	0.09	0.10	0.30	0.04	-0.01	0.06	0.04	-0.08	0.20
	Lumber	0.08	0.09	0.05	0.09	0.11	0.29	0.00	0.08	0.00	0.02	0.07	0.25
	Average	*0.10*	*0.13*	*0.04*	*0.16*	*0.14*	*0.34*	*0.02*	*0.06*	*0.03*	*0.02*	*0.05*	*0.27*

Table A.2. Traditional commodity futures characteristics and newswire tone.

Panel A reports Pearson correlations between the traditional signals used in long-short commodity allocations and the newswire tone signal, $TONE_{i,t}$ from Eq. (3). Panel B presents correlations between the excess returns of traditional long-short portfolios and a long-short portfolio formed by $TONE_{i,t}$ alone as sorting signal. The analysis is based on data from January 3, 2000 to May 25, 2020.

Sector	Commodity	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
		Panel A. Individual commodity futures						
Energy	Heating oil	0.20	0.09	0.10	0.06	-0.02	0.11	-0.01
	Natural gas	0.15	0.17	0.03	-0.04	0.00	0.05	-0.05
	RBOB gasoline	0.04	0.10	-0.22	-0.03	-0.03	-0.07	0.04
	Unleaded gasoline	0.05	-0.20	-0.28	-0.03	0.09	-0.22	-0.18
	WTI crude oil	-0.01	-0.02	0.01	0.02	-0.02	0.05	-0.06
Grains	Corn	-0.08	-0.01	-0.05	-0.02	-0.10	-0.01	0.16
	Oats	-0.22	-0.10	0.11	-0.24	-0.10	-0.27	-0.09
	Rough rice	-0.03	-0.12	-0.06	0.02	-0.01	-0.04	-0.03
	Wheat	-0.06	0.08	0.10	-0.12	-0.07	-0.14	0.01
Livestock	Feeder cattle	0.07	0.10	0.11	0.01	0.27	-0.04	0.07
	Lean hogs	-0.04	0.00	-0.03	-0.01	-0.07	-0.01	0.09
	Live cattle	0.01	-0.06	0.04	0.02	-0.15	-0.04	-0.16
	Frozen pork bellies	0.03	0.14	0.10	0.01	-0.07	0.19	0.03
Metals	Copper	0.02	0.03	0.00	-0.02	0.04	-0.03	0.05
	Gold	0.09	-0.02	0.01	-0.02	0.03	0.06	-0.07
	Palladium	0.02	0.03	0.00	0.05	0.02	-0.05	-0.10
	Platinum	-0.05	-0.06	0.01	-0.10	0.01	0.00	0.05
	Silver	0.05	-0.05	-0.15	-0.09	-0.01	0.09	-0.16
Oilseeds	Soybeans	-0.15	0.01	-0.09	0.00	-0.05	0.05	-0.16
	Soybean meal	-0.08	-0.11	-0.06	-0.01	-0.05	-0.15	0.04
	Soybean oil	-0.24	-0.21	-0.16	-0.02	-0.10	-0.15	0.06
Softs	Cocoa	0.08	0.06	0.12	-0.06	-0.03	-0.15	0.03
	Coffee	0.07	0.00	-0.10	0.06	0.12	0.20	0.00
	Cotton	-0.07	0.07	0.08	-0.15	0.08	0.02	-0.04
	Frozen orange juice	0.23	0.32	0.21	-0.09	-0.08	0.03	0.03
	Lumber	-0.04	-0.12	0.14	-0.02	-0.05	-0.15	0.09
	Average	0.00	0.00	0.00	-0.03	-0.01	-0.03	-0.01
	Min	-0.24	-0.21	-0.28	-0.24	-0.15	-0.27	-0.18
	Max	0.23	0.32	0.21	0.06	0.27	0.20	0.16
		Panel B. Factor mimicking portfolios						
	TONE	0.05	0.00	0.03	0.07	-0.06	0.07	-0.04

Table A.3. Tone-overlay outperformance and broad market sentiment.

The table reports estimation results of time-series regressions of the tone-overlay portfolio excess returns (orthogonalized with respect to the corresponding traditional portfolio) on contemporaneous (Panel A) or one-week lagged (Panel B) market-wide sentiment proxied by CBOE's VIX, Baker-Wurgler sentiment index (Baker and Wurgler, 2006), FRB of St. Louis news sentiment index (Shapiro et al., 2020), University of Michigan consumer sentiment index, American Association of Individual Investors (AAII) sentiment index, and Photo news pessimism index (Obaid and Pukthuanthong, 2022). The regressions include an unreported intercept. Newey-West robust *t*-statistics are shown in parentheses. The analysis is based on data from January 3, 2000, to May 25, 2020.

	Orthogonalized tone-overlay portfolio returns													
	Panel A. Contemporaneous market-wide sentiment (pricing model)							Panel B. Lagged market-wide sentiment (predictive model)						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
VIX	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.93)	(0.31)	(-0.03)	(0.41)	(0.11)	(0.55)	(0.30)	(-0.06)	(0.10)	(-0.26)	(-0.23)	(-0.28)	(-0.03)	(-0.89)
Adjusted R^2	-0.0002	-0.0012	-0.0012	-0.0009	-0.0012	-0.0008	-0.0011	-0.0012	-0.0012	-0.0012	-0.0012	-0.0011	-0.0012	-0.0003
BW	-0.0010	-0.0008	-0.0004	0.0001	-0.0007	-0.0002	-0.0004	-0.0009	-0.0006	-0.0004	0.0000	-0.0007	-0.0001	-0.0004
	(-0.83)	(-0.65)	(-0.38)	(0.05)	(-0.76)	(-0.19)	(-0.29)	(-0.71)	(-0.51)	(-0.30)	(0.02)	(-0.77)	(-0.11)	(-0.31)
Adjusted R^2	-0.0004	-0.0007	-0.0011	-0.0012	-0.0006	-0.0012	-0.0011	-0.0006	-0.0009	-0.0011	-0.0012	-0.0006	-0.0012	-0.0011
FED news	-0.0008	-0.0001	-0.0025	-0.0006	-0.0009	-0.0006	-0.0009	-0.0004	0.0003	-0.0022	0.0001	-0.0009	-0.0001	-0.0002
	(-0.43)	(-0.05)	(-1.43)	(-0.30)	(-0.50)	(-0.36)	(-0.43)	(-0.23)	(0.15)	(-1.27)	(0.05)	(-0.48)	(-0.06)	(-0.09)
Adjusted R^2	-0.0010	-0.0012	0.0010	-0.0011	-0.0009	-0.0011	-0.0010	-0.0012	-0.0012	0.0005	-0.0012	-0.0009	-0.0012	-0.0012
Michigan	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.62)	(1.27)	(0.74)	(0.89)	(0.79)	(0.99)	(1.37)	(0.73)	(1.52)	(1.03)	(0.99)	(0.84)	(1.15)	(1.35)
Adjusted R^2	-0.0008	0.0007	-0.0006	-0.0001	-0.0003	0.0001	0.0009	-0.0006	0.0015	0.0000	0.0003	-0.0002	0.0006	0.0008
AAII	0.0000	0.0032	0.0000	-0.0006	0.0002	-0.0018	0.0009	0.0011	0.0005	-0.0013	-0.0007	-0.0019	-0.0026	-0.0003
	(0.00)	(0.86)	(0.01)	(-0.16)	(0.07)	(-0.48)	(0.25)	(0.28)	(0.17)	(-0.39)	(-0.18)	(-0.64)	(-0.72)	(-0.09)
Adjusted R^2	-0.0012	-0.0003	-0.0012	-0.0012	-0.0012	-0.0009	-0.0012	-0.0011	-0.0012	-0.0011	-0.0012	-0.0008	-0.0006	-0.0012
Photo pes	0.0004	0.0006	0.0007	0.0002	0.0000	0.0003	0.0003	0.0004	-0.0003	-0.0001	0.0000	-0.0007	-0.0001	-0.0003
	(0.78)	(1.19)	(1.39)	(0.42)	(0.09)	(0.59)	(0.53)	(0.55)	(-0.42)	(-0.22)	(-0.06)	(-1.11)	(-0.15)	(-0.50)
Adjusted R^2	-0.0005	0.0003	0.0007	-0.0011	-0.0012	-0.0009	-0.0009	-0.0006	-0.0009	-0.0012	-0.0012	0.0015	-0.0012	-0.0008

Table A.4. Predicting commodity futures returns with optimistic versus pessimistic tone.

The table reports estimation results for panel fixed effects (FE) regressions of weekly commodity futures returns on four lags of commodity-specific newswire tone, and their interactions with a pessimistic tone dummy ($I_{i,t-j}^{TONE-} = 1$ if $TONE_{i,t-j} < 50$, and $I_{i,t-j}^{TONE-} = 0$ otherwise), lagged market-wide sentiment, lagged commodity futures characteristics (basis, momentum, hedging pressure, convexity, basis-momentum, skewness, liquidity, and excess return). Broad market sentiment is proxied by the FRB of San Francisco news index (Shapiro et al., 2020). All regressors are standardized at the panel level. The coefficients of $TONE_{i,t-j}$ are scaled by 100. Significance *t*-statistics are shown in parentheses. The first Wald (two-sided) test is for $H_0: \beta_1 + \beta_2 = 0$ where β_1 and β_2 are the coefficients of $TONE_{i,t-j}, j = 1,2$. The second Wald (two-sided) test is for $H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$ where δ_j is the coefficient of $TONE_{i,t-j} \times I_{i,t-j}^{TONE-}, j = 1,..,4$. The inferences are based on two-way (commodity and year-week) clustered standard errors. The sample period is January 3, 2000 to May 25, 2020.

	Commodity excess returns				
	(1)	(2)	(3)	(4)	(5)
$TONE_{i,t-1}$	0.146	0.144	0.147	0.143	0.141
	(2.718)	(2.640)	(3.157)	(2.685)	(2.605)
$TONE_{i,t-2}$	-0.106	-0.108	-0.078	-0.108	-0.11
	(-2.257)	(-2.305)	(-1.561)	(-2.317)	(-2.365)
$TONE_{i,t-3}$	-0.023	-0.025	-0.011	-0.021	-0.023
	(-0.469)	(-0.495)	(-0.233)	(-0.432)	(-0.460)
$TONE_{i,t-4}$	0.060	0.058	0.034	0.064	0.062
	(1.115)	(1.065)	(0.739)	(1.190)	(1.137)
$TONE_{i,t-1} \times I_{i,t-1}^{TONE-}$	-0.043	-0.037	-0.066	-0.038	-0.031
	(-0.484)	(-0.407)	(-0.907)	(-0.430)	(-0.350)
$TONE_{i,t-2} \times I_{i,t-2}^{TONE-}$	0.047	0.051	0.017	0.050	0.054
	(0.648)	(0.704)	(0.231)	(0.693)	(0.753)
$TONE_{i,t-3} \times I_{i,t-3}^{TONE-}$	0.005	0.009	-0.034	-0.000	0.004
	(0.044)	(0.079)	(-0.298)	(-0.001)	(0.037)
$TONE_{i,t-4} \times I_{i,t-4}^{TONE-}$	-0.025	-0.020	0.037	-0.034	-0.028
	(-0.218)	(-0.168)	(0.350)	(-0.294)	(-0.240)
$Sentiment_{t\text{-}1}$				0.004	0.004
				(1.528)	(1.521)
$Sentiment_{t\text{-}2}$				0.002	0.002
				(0.461)	(0.460)
$Sentiment_{t\text{-}3}$				-0.003	-0.003
				(-0.712)	(-0.709)
$Sentiment_{t\text{-}4}$				-0.002	-0.003
				(-0.866)	(-0.876)
Controls $\boldsymbol{Z}_{t\text{-}1}$	Yes	Yes	Yes	Yes	Yes
Commodity FE	No	Yes	Yes	No	Yes
Year-Week FE	No	No	Yes	No	No
Observations	25,428	25,428	25,428	25,428	25,428
Adjusted R^2	0.002	0.002	0.163	0.004	0.004
Wald test p-value (β)	0.522	0.563	0.172	0.563	0.608
Wald test p-value (δ)	0.967	0.964	0.907	0.963	0.960

Table A.5. Tone-overlay portfolios with hyperparameter cross validation.

The table summarizes in Panel A the traditional portfolios and in Panel B the corresponding tone-overlay portfolios based on the biweekly cross validation of the tone-overlay hyperparameters $\boldsymbol{\theta} = (\pi, \tau, (\delta^+, \delta^-))$ as described in Appendix B of the manuscript. Mean excess return, standard deviation (StDev) and semi deviation are annualized. $\Delta SR = SR_{overlay} - SR_{trad}$ is the Sharpe ratio gain of the tone-overlay (vs. traditional) portfolios and $\Delta CER = CER_{overlay} - CER_{trad}$ is the certainty equivalent return gain based on power utility and relative risk aversion $\nu = 5$. The Ledoit and Wolf (2008) test p-value in italics is for H_0: $\Delta SR \leq 0$ versus H_A: $\Delta SR > 0$. The p-value of the GMM test of Anderson and Cheng (2016) in italics is for H_0: $\Delta CER = 0$ vs H_A: $\Delta CER \neq 0$. The t-statistics, shown in parentheses, are based on Newey-West standard errors. The sequential one-week rebalanced portfolios are implemented on data from January 2, 2000 to May 31, 2020. As dictated by the estimation window length for the tone-overlay model (L=260 weeks), and the hyperparameter cross-validation window length (S = 52 weeks), the weekly OOS portfolio excess return sequence commences on January 3, 2006.

	Panel A. Traditional portfolios							Panel B. Cross-validated tone-overlay portfolios						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
Mean	0.0257	0.0242	0.0593	0.0403	0.0208	0.0702	0.0095	0.0877	0.0892	0.1150	0.0909	0.0901	0.1110	0.0939
	(0.93)	(0.84)	(2.12)	(1.56)	(0.75)	(3.04)	(0.31)	(4.09)	(4.28)	(5.71)	(4.10)	(3.50)	(5.32)	(4.02)
StDev	0.1046	0.1173	0.1099	0.0933	0.1103	0.0957	0.1062	0.0836	0.0856	0.0799	0.0858	0.0922	0.0870	0.0851
Skewness	-0.6030	-0.0842	-0.3729	-0.1693	-0.7890	-0.0660	-0.1709	-0.0234	-0.0814	0.0172	0.1608	-0.3778	0.0425	-0.0177
	(-6.32)	(-0.95)	(-4.09)	(-1.90)	(-7.94)	(-0.74)	(-1.92)	(-0.26)	(-0.92)	(0.19)	(1.81)	(-4.13)	(0.48)	(-0.20)
Excess kurtosis	4.4858	2.1790	2.2315	3.5429	7.2274	3.1016	0.5941	0.3810	0.4491	1.4304	1.5074	2.5440	1.6016	1.1449
	(9.10)	(6.48)	(6.57)	(8.23)	(10.84)	(7.75)	(2.77)	(1.96)	(2.23)	(5.08)	(5.25)	(7.03)	(5.44)	(4.41)
Semi deviation	0.0728	0.0805	0.0782	0.0634	0.0819	0.0643	0.0710	0.0531	0.0543	0.0511	0.0536	0.0641	0.0564	0.0543
1% VaR	-0.0333	-0.0374	-0.0343	-0.0293	-0.0352	-0.0295	-0.0341	-0.0253	-0.0259	-0.0236	-0.0260	-0.0280	-0.0259	-0.0257
Max drawdown	-0.2819	-0.3881	-0.1803	-0.2479	-0.3453	-0.1821	-0.3743	-0.1045	-0.1513	-0.1134	-0.1217	-0.1929	-0.0972	-0.1287
Sharpe ratio	0.2454	0.2061	0.5400	0.4324	0.1886	0.7337	0.0897	1.0497	1.0418	1.4386	1.0590	0.9778	1.2757	1.1032
ΔSR								0.8044	0.8357	0.8986	0.6267	0.7892	0.5420	1.0135
Ledoit-Wolf test p-value								*0.0061*	*0.0031*	*0.0016*	*0.0191*	*0.0007*	*0.0111*	*0.0009*
Sortino ratio	0.3428	0.2907	0.7781	0.6284	0.2608	1.1137	0.1253	1.6581	1.6379	2.3925	1.7067	1.4895	2.0751	1.7422
Omega ratio	1.0924	1.0784	1.2204	1.1719	1.0743	1.3119	1.0328	1.4541	1.4482	1.6855	1.4657	1.4353	1.5958	1.4807
CER	0.0219	0.0194	0.0552	0.0373	0.0166	0.0670	0.0056	0.0853	0.0866	0.1128	0.0884	0.0872	0.1084	0.0914
ΔCER								0.0634	0.0672	0.0576	0.0511	0.0706	0.0414	0.0858
GMM test p-value								*0.0049*	*0.0011*	*0.0076*	*0.0044*	*0.0020*	*0.0250*	*0.0020*

Table A.6. Net performance of traditional portfolios and corresponding tone-overlay portfolios.

The table summarizes the net performance of traditional portfolios in Panel A, and tone-overlay portfolios with hyperparameters set at $\pi = 0.10$ (salience), $\tau = 0.9$ (tilting), and $\delta^{+} = \delta^{-} = 1$ (optimism/pessimism) in Panel B. The analysis is based on the 8.6bp roundtrip transaction cost estimate of Marshall et al. (2012). Mean excess return, standard deviation (StDev) and semi deviation are annualized. $\Delta SR = SR_{overlay} - SR_{trad}$ is the Sharpe ratio gain of the tone-overlay (vs. traditional) portfolios and $\Delta CER = CER_{overlay} - CER_{trad}$ is the certainty equivalent return gain based on power utility and relative risk aversion $\nu = 5$. The Ledoit and Wolf (2008) test p-value is for $H_0: \Delta SR \leq 0$ versus $H_A: \Delta SR > 0$. The p-value of the GMM test of Anderson and Cheng (2016) is for $H_0: \Delta CER = 0$ vs $H_A: \Delta CER \neq 0$. The t-statistics, shown in parentheses, use Newey-West standard errors. The sequential one-week rebalanced portfolios are implemented on data from January 2, 2000 to May 31, 2020. The OOS returns start on January 3, 2005 as dictated by the estimation window ($L = 260$ weeks) of the tone-overlay.

	Panel A. Traditional portfolios							Panel B. Tone-overlay portfolios						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
Mean	0.0111	0.0115	0.0484	0.0319	0.0227	0.0588	0.0161	0.0483	0.0465	0.0631	0.0593	0.0607	0.0720	0.0570
	(0.41)	(0.42)	(1.89)	(1.28)	(0.85)	(2.57)	(0.56)	(2.33)	(2.29)	(3.24)	(2.80)	(2.58)	(3.58)	(2.55)
StDev	0.1040	0.1170	0.0995	0.0920	0.1088	0.0960	0.1039	0.0842	0.0865	0.0801	0.0858	0.0922	0.0875	0.0849
Skewness	-0.5925	-0.0803	-0.6290	-0.1852	-0.7745	-0.0897	-0.1677	-0.0251	-0.0959	0.0132	0.1498	-0.2914	-0.0343	-0.0109
	(-6.44)	(-0.94)	(-6.78)	(-2.15)	(-8.08)	(-1.05)	(-1.95)	(-0.29)	(-1.12)	(0.15)	(1.74)	(-3.34)	(-0.40)	(-0.13)
Excess kurtosis	4.2912	1.9990	3.3958	3.5403	7.2166	2.8593	0.6153	0.3357	0.3740	1.3670	1.4453	2.5958	1.6263	1.0920
	(9.22)	(6.38)	(8.33)	(8.49)	(11.17)	(7.68)	(2.93)	(1.82)	(1.99)	(5.09)	(5.27)	(7.32)	(5.66)	(4.41)
Semi deviation	0.0718	0.0799	0.0742	0.0627	0.0802	0.0649	0.0693	0.0533	0.0552	0.0512	0.0539	0.0637	0.0578	0.0540
1% VaR	-0.0333	-0.0375	-0.0312	-0.0291	-0.0347	-0.0298	-0.0332	-0.0262	-0.0270	-0.0246	-0.0266	-0.0286	-0.0269	-0.0263
Max drawdown	-0.3152	-0.4065	-0.1783	-0.2877	-0.3686	-0.1920	-0.3567	-0.1276	-0.2034	-0.1193	-0.1733	-0.1769	-0.1043	-0.2195
Sharpe ratio	0.1069	0.0986	0.4868	0.3461	0.2085	0.6126	0.1550	0.5738	0.5371	0.7877	0.6911	0.6580	0.8220	0.6720
ΔSR								0.4669	0.4385	0.3009	0.3450	0.4495	0.2094	0.5171
Ledoit-Wolf test p-value								*0.0242*	*0.0241*	*0.0462*	*0.0432*	*0.0389*	*0.0634*	*0.0121*
Sortino ratio	0.1473	0.1378	0.6847	0.4970	0.2895	0.9136	0.2180	0.8599	0.7963	1.2196	1.0671	0.9764	1.2602	1.0138
Omega ratio	1.0391	1.0367	1.1990	1.1350	1.0821	1.2535	1.0572	1.2267	1.2100	1.3307	1.2844	1.2766	1.3504	1.2702
CER	0.0074	0.0068	0.0450	0.0289	0.0186	0.0556	0.0124	0.0459	0.0439	0.0609	0.0568	0.0577	0.0693	0.0545
ΔCER								0.0547	0.0718	0.0285	0.0545	0.0583	0.0497	0.0469
GMM test p-value								*0.0374*	*0.0180*	*0.0696*	*0.0363*	*0.0346*	*0.0425*	*0.0370*

Table A.7. Tone-overlay outperformance and "kitchen sink" factor spanning.

The table shows estimation results of factor spanning time-series regressions for the tone-overlay portfolio excess returns orthogonalized with respect to the corresponding traditional portfolio. The risk factors include those in the main analysis (see Panel A of Table 5) and additional factors such as value, speculative pressure, open interest change, inflation beta, USD beta, and volatility. The signals used to construct the factors are detailed in Appendix A. Reported alphas are annualized. Newey-West robust *t*-statistics are shown in parentheses. The analysis is based on data from January 3, 2000, to May 25, 2020.

	Orthogonalized tone-overlay portfolio returns						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
α	0.0749	0.0774	0.0625	0.0841	0.0616	0.0946	0.0665
	(3.76)	(4.00)	(3.30)	(4.30)	(3.72)	(5.03)	(3.47)
β_{Basis}	_	0.0671	-0.0036	0.0098	0.0675	0.0342	-0.0055
		(1.77)	(-0.09)	(0.30)	(2.29)	(0.85)	(-0.14)
β_{Mom}	-0.0077	_	-0.0011	-0.0104	-0.0190	-0.0025	0.0081
	(-0.21)		(-0.03)	(-0.27)	(-0.64)	(-0.07)	(0.22)
$\beta_{Hedging\ pressure}$	-0.0538	-0.0445	_	-0.0525	-0.0147	-0.0422	-0.0435
	(-1.15)	(-1.08)		(-1.33)	(-0.43)	(-1.08)	(-1.16)
$\beta_{Convexity}$	0.0228	-0.0238	0.0714	_	-0.0203	0.0195	0.0693
	(0.61)	(-0.67)	(1.36)		(-0.52)	(0.45)	(1.07)
$\beta_{Skewness}$	-0.0202	-0.0237	0.0091	-0.0107	_	0.0019	0.0101
	(-0.54)	(-0.76)	(0.31)	(-0.33)		(0.06)	(0.24)
$\beta_{Basis\text{-}Mom}$	0.0905	0.0579	0.0607	0.0568	0.0555	_	0.1186
	(2.46)	(1.73)	(1.64)	(1.59)	(1.63)		(2.71)
$\beta_{Liquidity}$	0.0380	0.0264	0.0377	0.0162	0.0238	0.0243	_
	(1.09)	(0.74)	(1.20)	(0.47)	(0.82)	(0.64)	
β_{Value}	0.0196	0.0225	0.0247	0.0191	0.0270	0.0134	0.0412
	(0.72)	(0.88)	(0.76)	(0.66)	(1.05)	(0.48)	(1.42)
$\beta_{Speculative\ pressure}$	-0.0243	0.0012	0.0111	-0.0409	-0.0148	-0.0310	-0.0221
	(-0.86)	(0.04)	(0.33)	(-1.46)	(-0.56)	(-1.10)	(-0.87)
$\beta_{Open\ interest\ change}$	-0.0016	-0.0107	-0.0226	-0.0076	0.0096	-0.0210	0.0013
	(-0.05)	(-0.33)	(-0.71)	(-0.21)	(0.32)	(-0.60)	(0.04)
$\beta_{Inflation\ beta}$	0.0084	-0.0103	-0.0006	0.0233	0.0029	0.0034	-0.0011
	(0.30)	(-0.34)	(-0.02)	(0.78)	(0.13)	(0.12)	(-0.04)
$\beta_{USD\ beta}$	-0.0138	-0.0015	0.0061	-0.0455	0.0124	-0.0276	-0.0187
	(-0.53)	(-0.06)	(0.22)	(-1.56)	(0.53)	(-1.05)	(-0.69)
$\beta_{Volatility}$	-0.0331	-0.0183	-0.0002	-0.0022	-0.0186	-0.0020	0.0021
	(-1.21)	(-0.75)	(-0.01)	(-0.08)	(-0.87)	(-0.08)	(0.09)
Adjusted R^2	0.0059	0.0016	0.0051	0.0010	0.0060	-0.0071	0.0221

Table A.8. Tone-overlay strategy versus EWI strategy for signal combination.

The table reports the equal-weight style-integrated portfolios (EWI; Fernandez-Perez et al., 2019) for each traditional signal and the $TONE_{i,t}$ signal (Panel A) and tone-overlay portfolios (Panel B). The top (long) and bottom (short) quintiles are based on equally-weighted commodities throughout. Mean excess return, standard deviation (StDev) and semi deviation are annualized. $\Delta SR = SR_{overlay} - SR_{trad}$ is the Sharpe ratio gain of the tone-overlay (vs. traditional) portfolios and $\Delta CER = CER_{overlay} - CER_{trad}$ is the certainty equivalent return gain based on power utility and relative risk aversion $\nu = 5$. The Ledoit and Wolf (2008) test p-value is for $H_0: \Delta SR \leq 0$ versus $H_A: \Delta SR > 0$. The p-value of the GMM test of Anderson and Cheng (2016) is for $H_0: \Delta CER = 0$ vs $H_A: \Delta CER \neq 0$. The t-statistics, shown in parentheses, are based on Newey-West standard errors. The tone-overlay portfolios are deployed with hyperparameters fixed at $(\pi, \tau, (\delta^+, \delta^-)) = (0.1, 0.9, (1,1))$. The portfolios are implemented on data from January 2, 2000 to May 31, 2020 period. The first OOS return for the tone-overlay portfolios is on January 3, 2005, as dictated by the estimation window length ($L = 260$ weeks). The EWI portfolios are appraised over the same period.

	Panel A. EWI strategy							Panel B. Tone-overlay strategy						
	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity	Basis	Mom	Hedging pressure	Convexity	Skewness	Basis-Mom	Liquidity
Mean	0.0461	0.0444	0.0678	0.0641	0.0473	0.0688	0.0337	0.0868	0.0861	0.0914	0.1046	0.0804	0.1195	0.0800
	(1.99)	(1.76)	(2.94)	(2.66)	(2.03)	(2.83)	(1.37)	(4.17)	(4.23)	(4.58)	(5.05)	(3.66)	(6.34)	(3.78)
StDev	0.0967	0.1029	0.0968	0.0938	0.1000	0.1007	0.0895	0.0890	0.0893	0.0839	0.0877	0.0932	0.0862	0.0862
Skewness	-0.2021	-0.1998	-0.3701	-0.6436	-0.7103	-0.7668	-0.4849	-0.0046	-0.1866	-0.1536	0.2475	-0.4678	-0.0332	0.1437
	(-2.34)	(-2.31)	(-4.19)	(-6.91)	(-7.52)	(-8.01)	(-5.38)	(-0.05)	(-2.16)	(-1.78)	(2.85)	(-5.21)	(-0.39)	(1.67)
Excess kurtosis	0.6394	1.1898	1.5641	8.0951	5.3242	5.6490	1.9729	0.3921	0.5874	1.3604	2.1643	2.8219	0.2424	2.0447
	(3.02)	(4.66)	(5.53)	(11.59)	(10.04)	(10.26)	(6.33)	(2.07)	(2.83)	(5.08)	(6.66)	(7.63)	(1.40)	(6.46)
Semi deviation	0.0642	0.0704	0.0693	0.0678	0.0738	0.0743	0.0632	0.0561	0.0596	0.0556	0.0531	0.0652	0.0530	0.0534
1% VaR	-0.0303	-0.0323	-0.0299	-0.0290	-0.0314	-0.0312	-0.0282	-0.0271	-0.0272	-0.0253	-0.0263	-0.0285	-0.0255	-0.0263
Max drawdown	-0.1949	-0.3024	-0.2249	-0.2568	-0.2543	-0.2032	-0.3523	-0.1156	-0.1710	-0.0869	-0.1008	-0.1756	-0.1077	-0.2351
Sharpe ratio	0.4765	0.4311	0.7007	0.6831	0.4731	0.6828	0.3768	0.9752	0.9634	1.0889	1.1922	0.8631	1.3860	0.9277
ΔSR								0.4988	0.5323	0.3882	0.5092	0.3900	0.7032	0.5509
Ledoit-Wolf test *p*-value								*0.0217*	*0.0063*	*0.0398*	*0.0078*	*0.0112*	*0.0027*	*0.0086*
Sortino ratio	0.6945	0.6217	1.0202	0.9961	0.6713	0.9848	0.5321	1.5299	1.4659	1.6990	1.9772	1.2846	2.2992	1.4711
Omega ratio	1.1857	1.1703	1.2929	1.2904	1.1950	1.2894	1.1468	1.4132	1.4083	1.4794	1.5379	1.3676	1.6318	1.3968
CER	0.0428	0.0407	0.0646	0.0610	0.0439	0.0653	0.0310	0.0841	0.0833	0.0890	0.1019	0.0774	0.1169	0.0774
ΔCER								0.0412	0.0426	0.0244	0.0409	0.0335	0.0517	0.0464
GMM test *p*-value								*0.0067*	*0.0166*	*0.0572*	*0.0195*	*0.0294*	*0.0095*	*0.0200*