Fear of Hazards in Commodity Futures Markets

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ABSTRACT

This paper introduces a commodity futures return predictor related to fear of weather, disease, geopolitical or economic hazards, as proxied by internet search volume. A long-short portfolio strategy that sorts the cross-section of commodity futures contracts by their hazard-fear characteristic generates substantial excess returns and Sharpe ratios. The hazard-fear premium partially reflects compensation for hedging pressure, momentum, basis-momentum and illiquidity risk factors, but is not subsumed by them. Exposure to hazard-fear is strongly priced in the cross-section of individual commodity futures and commodity portfolios. We identify a strong role for general investor sentiment in the commodity hazard-fear premium.

[*Word count*: 98]

Keywords: Commodity futures; Fear; Hazards; Internet searches; Sentiment; Long-short portfolios.

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“Data are widely available, what is scarce is the ability to extract wisdom from them” (Hal Varian, Google Chief Economist, emeritus Professor at University of California, Berkeley.)

1. INTRODUCTION

THE COMMODITY FUTURES PRICING literature largely rests on two pillars known as the theory of storage (Kaldor, 1939; Working, 1949; Brennan, 1958) and the hedging pressure hypothesis (Cootner, 1960; Hirshleifer, 1988). The former pillar relates the long-short risk premium present in commodity futures markets to inventory levels and thus to the slope of the futures curve, while the latter pillar models the risk premium as a function of hedgers’ and speculators’ net positions. In support of these traditional theories, many studies[1] suggest that investors can benefit from taking long positions in backwardated futures (with downward-sloping term structure, net short hedging or net long speculation) and short positions in contangoed futures (with upward-sloping term structure, net long hedging or net short speculation).[2]

Our article hypothesizes that fear of rare and extreme events influences the pricing of commodity futures over and beyond the fundamental backwardation and contango risks. In this paper, commodity hazard-fear is defined as the economic agents’ concerns or apprehension induced by weather, agricultural disease, geopolitical and economic threats that affect a commodity supply or demand and thus its expected spot price. As economic agents assign too large probabilities of occurrence to these threats[3], we hypothesize that fear is priced no matter

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[1] Supportive evidence for the theory of storage can be found in Fama and French (1987), Erb and Harvey (2006), Gorton et al. (2012), Szymanowska et al. (2014) and Koijen et al. (2018) amongst many others. Studies baking the hedging pressure hypothesis include Bessembinder (1992), Basu and Miffre (2013) and Kang et al. (2019).

[2] Backwardation predicts a rise in commodity futures prices driven by scarce inventories (a downward-sloping term structure of futures prices), net short hedging or net long speculation. Conversely, contango predicts a drop in commodity futures prices driven by abundant inventories (an upward-sloping term structure), net long hedging or net short speculation.

[3] Goetzman et al. (2017) find evidence that retail and institutional investors ascribe a too high probability to rare, extreme events. It has been shown also that the realization of a low

how rare the events are (for example, a coffee producer could be apprehensive about frosts pre-harvests even though he never witnessed them but his fear is driven by the impact of other weather disasters on commodity prices). Our conjecture that the fear of rare hazards drives commodity futures prices is reminiscent of the *peso problem* in finance which arises when the possibility that some rare and extreme event may occur affects asset prices.

Let us first consider hazards that are supply-reducing (such as a frost that shifts the supply curve of coffee inwards) or demand-increasing (such as the risk of a heatwave that could induce an outward shift of the demand curve of natural gas). Fear of these hazards causes expectations of spot prices sharply increasing. These expectations, in turn, are likely to influence the hedging decisions of commodity market participants; namely, producers may take shorter hedges and consumers longer hedges than those they would typically adopt. The increase in net long hedging ought to be matched by an increase in net short speculation; however, short futures positions are seen as risky for speculators in a market bedevilled by supply-reducing or demand-increasing hazard fear (spot and futures prices are expected to rise if the hazard occurs).[4] Thus, to entice short speculation the current price of the futures contract relative to the expected future spot price has to be set higher than as solely dictated by fundamentals. Formally, the expected hazard-fear risk premium is the upward bias in the futures price as predictor of the future spot price in excess of what the futures price would be if there was no hazard-fear. Explicitly, the commodity futures premium in the presence of hazard-fear

probability event not only increases the subjective probabilities of occurrence of the same event but also inflates the subjective probabilities of unrelated events (Johnson and Tversky, 1983).

[4] J.P. Morgan's Global Commodities Research (22 Sept 2017) commentary: "Non-commercial investors have been reducing their net short position across the agricultural commodity complex over the last fortnight amid these weather-related production risks… We anticipate that non-commercial's will continue the wave of short covering through September, now that La Niña is a material threat, and oil prices are on the rise. This is particularly the case across markets with exposure to summer crop production in Latin America, namely CBOT Soybeans, CBOT Corn, ICE #11 Sugar and also ICE Arabica Coffee".

$E_t[Premium_{t,T}]$ equals $F_{t,T}^{CFEAR} - E_t[S_{t+T}] > 0$ with $F_{t,T}^{CFEAR} = F_{t,T} + Premium_{t,T}^{CFEAR+}$, where $F_{t,T}$ denotes the price at t of a futures contract with maturity T in the absence of fear and $Premium_{t,T}^{CFEAR+} > 0$ denotes the hazard-fear premium embedded in the futures price. The anticipated drop in the futures price as maturity approaches is the overall premium captured by short speculators which incorporates a fundamental and a hazard-fear component.

Let us now consider a hazard that is either supply-increasing (a lift of an oil embargo that shifts the supply curve of oil outward) or demand-reducing (a negative shock to the economy that shrinks the demand for commodities). Fear of these hazards causes expectations of spot prices sharply decreasing, and producers (consumers) may then take larger (smaller) hedges than they otherwise would. The increase in net short hedging requires a matching increase in net long speculation. In order to induce speculators to take more long positions in this setting, the futures price ought to be lower than it would be in "normal" conditions, $E_t[Premium_{t,T}] = F_{t,T}^{CFEAR} - E_t[S_{t+T}] < 0$ with $F_{t,T}^{CFEAR} = F_{t,T} + Premium_{t,T}^{CFEAR-}$ and $Premium_{t,T}^{CFEAR-} < 0$ is the supply-increasing or demand-reducing hazard-fear premium. The rise in the futures price with maturity (or the premium earned by long speculators) thus has a hazard-fear element.

Building on economic psychology, we hypothesize that economic agents' anxiety about potential events that could abruptly alter commodity prices induces them to search for information (Lemieux and Peterson, 2011). As proxy for the eagerness of market participants for news about impending hazards (e.g., the likelihood of a hurricane or the effect of past hurricanes on lumber prices), we use the volume of Google search queries by keywords representing 149 weather, agricultural disease, geopolitical and economic hazards. We conjecture that upsurges in the search queries reflect an increased level of fear. Thus, the more positively a commodity futures price co-moves with the level of fear, the more likely it is that the underlying commodity is subject to supply-reducing or demand-increasing hazard fear and therefore that its futures price embeds this fear component and hence, may fall over time. Vice versa, commodities whose futures prices co-move strongly but negatively with the level of fear are deemed to be subject to supply-increasing or demand-reducing fear; those futures prices are likely instead to be set low compared to fundamentals and thus they may rise over time.

Following the above intuition, the paper provides three contributions to the literature. Using the internet search volume by 149 commodity hazard-related keywords as proxy for hazard-fear, we adapt the setting of Da et al. (2015) to introduce a commodity hazard fear characteristic (hereafter CFEAR) that reflects how sensitive futures returns are to hazard-fear. Second, we construct a CFEAR-sorted portfolio of commodities to formally assess the out-of-sample predictive content of the CFEAR characteristic for commodity futures returns; namely, we test for the presence of a hazard-fear premium while through time-series spanning regressions we control for traditional commodity risk premia. Third, the paper contributes to the commodity pricing literature by providing cross-sectional tests for commodity portfolios (sorted on characteristics and sectors) and individual commodities to assess whether the CFEAR factor captures priced risk over and above traditional commodity risk factors.

We find that the long-short CFEAR portfolio captures an economically and statistically significant mean excess return of 8.23% per annum (t = 3.49). This sizeable CFEAR premium translates into a Sharpe ratio of 0.8888 that is very attractive compared to the Sharpe ratios of the well-known basis, hedging pressure and momentum portfolios. The CFEAR premium relates to momentum and hedging pressure but it is not subsumed by these risk factors. The results from cross-sectional tests further suggest that the CFEAR factor has significant pricing ability for both individual commodity futures and commodity portfolios after controlling for the role of traditional risk factors. These conclusions are not challenged by the inclusion of skewness, basis-momentum, illiquidity and volatility risk factors. Last but not least, the hazard-fear premium is more pronounced when the financial markets are pessimistic which reveals a significant role for sentiment in commodity futures markets through the hazard-fear channel.

This study is inspired by a nascent commodity markets literature which investigates the out-of-sample predictive linkages between investor attention (as proxied by internet searches) and commodity returns (Han et al., 2017a, 2017b; Vozlyublennaia, 2014). Through the lens of purely statistical criteria such as mean squared forecast errors, Han et al., (2017a) find that Google searches by oil-related keywords, such as *oil inventory*, *oil shortage*, *oil supply*, and real economy-related keywords, such as *crisis*, *recession*, *unemployment*, are good predictors of oil futures returns up to one week ahead relative to the historical average benchmark. Han et al. (2017b) find that the predictive ability of commodity return models that include various macroeconomic predictors notably fall by adding the Google search volume by 13 commodity names and combinations thereof with various terms (e.g. *cost*, *price*, *production* and *supply*). Using Google searches by *gold* and *oil indices*, Vozlyublennaia (2014) finds that more attention leads to less predictability (the ability of current/past returns to convey information about future returns) and interprets this result as suggesting that efficiency rises with attention.[5]

Second, through a different methodological lens our work emphasizes the contention by Gao and Süss (2015) that sentiment plays a role in commodity futures returns. Their regression analysis reveals that sentiment (investors' emotions) is an additional source of co-movement among commodity futures beyond the well-known macroeconomic and equity-related sources. Our finding that there is a significant hazard-fear premium in commodity futures markets, especially, when the financial market sentiment is pessimistic aligns with their contention.

Finally, we believe this study contributes to the increasing stream of literature on commodity futures pricing by showing that fear of weather, agricultural diseases, political or economic hazards affects pricing beyond known risk factors relating to momentum, basis,

[5] Internet search activity has been found to contain out-of-sample predictive information for equity returns (Da et al., 2011, 2015; Ben-Rephael et al., 2017; Dzielinski et al., 2018), sovereign credit spreads (Dergiades et al., 2015), and macroeconomic variables such as unemployment (D'Amuri and Marcucci, 2017; Niesert et al., 2019) inter alia.

hedging pressure, skewness, basis-momentum, market and funding illiquidity, or volatility (e.g., Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Miffre and Rallis, 2007; Basu and Miffre, 2013; Szymanowska et al., 2014; Bakshi et al., 2017; Fernandez-Perez et al., 2018 and Boons and Prado, 2019, amongst others). Thus, the paper not only sheds some light on commodity futures pricing but also informs the design of practical investment solutions.

The remainder of the paper is organized as follows. We introduce the commodity-specific CFEAR characteristic in Section 2 and test its role as pricing signal through time-series spanning tests and cross-sectional tests in Section 3. Section 4 examines potential drivers of the CFEAR effect. Section 5 provides extensions and robustness checks. Section 6 concludes. An online Annex provides details of further robustness checks and additional analyses.

2. COMMODITY HAZARD-FEAR CHARACTERISTIC

2.1. Google search volume data

Inspired by the extant literature that uses Google search volume as proxy for investor attention and information demand, our paper introduces a commodity hazard-fear (CFEAR) characteristic that is constructed from internet search volume data from *Google Trends*. Google organizes the searches by their origin (regions versus worldwide). We use the worldwide search data in the main empirical sections, and the US search data in the robustness tests section.

The Google searches are sampled at a weekly frequency with each observation capturing the search queries from Monday 00:00:00 to Sunday 23:59:59. The weekly frequency was chosen for the following reasons. A lower frequency is less pertinent to capture the dynamics of investor search behaviour as argued in Da et al. (2011) and Vozlyublennaia (2014) that also employ weekly search data. The daily searches employed by Da et al. (2015), Ben-Rephael et al. (2017) and Han et al. (2017b) are impractical in a portfolio framework since daily portfolio rebalancing is not in line with industry practice nor with extant research (Basu and Miffre, 2013; Szymanowska et al., 2014; Fernandez-Perez et al., 2018; Boons and Prado, 2019).

Using various sources (Iizumi and Ramankutty, 2015; Israel and Briones, 2013; United Nations Office for Disaster Risk Reduction, 2018; and reports from Material Risk Insights[6]), we compile a list of primary keywords that reflect commodity price risks associated with weather (WE), agricultural diseases (DI), geopolitical (GP), or economic (EC) threats. Next, as in Da et al. (2015), we refine the primary keywords by examining the top ten related searches (provided by *Google Trends*) and from these we filter out the irrelevant keywords.[7] Finally, we add to the latter the *risk* and *warning* terms, e.g. we consider *tsunami*, *tsunami risk* and *tsunami warning*. We thus end up with $J = 149$ keywords as listed in Table 1 by category: 113 weather (WE), 10 agricultural diseases (DI), 14 geopolitical (GP) and 12 economic (EC) hazards.

[Insert Table 1 around here]

A spell of *extreme cold* or a *frost* are examples of WE hazards that could damage the growth of cotton while simultaneously increase the demand of natural gas for heating purposes; extremely *dry weather* or *wet weather* may reduce the harvest of sugar and cocoa that thrive in the right mix of rain and sunshine. Among the DI hazards, an increase of *crop diseases* is likely to reduce the supply of grain commodities, and an outbreak of *La Roya* fungus is likely to reduce the supply of coffee. GE hazards such as the *Russian crisis* are threats to the supply of natural gas; likewise, a *Middle East conflict* may damage the oil provision. *Recession* or *crisis* are EC hazards that may reduce the demand for copper or oil due to a slowdown in business activity, while the demand for gold may simultaneously rise as gold is typically a safe-haven.

Let *j* denote a search keyword and *t* a sample week. *Google Trends* first obtains the ratio between the volume of queries associated with keyword *j* during week *t*, denoted $V_{j,t}$, and the entire volume of queries for any keyword in the same time period, denoted $V_{k,t}$. The ratio

[6] See www.materials-risk.com.

[7] For instance, one of the top related searches to *hail damage* is *hail storm* which we retain while we neglect searches by *flood lights* that is unrelated to the paper aim.

$V_{j,t}/V_{k,t}$ is subsequently divided by its historical maximum value and multiplied by a factor of 100 to scale it between 0 and 100. The resulting variable, $S_{j,t}$, is the Google Search Volume Index (GSVI) provided by *Google Trends* which has the interpretation of a search probability: $S_{j,t}$ equals 0 if the *j*th keyword is not searched at all on week *t* and equals 100 in the peak search week of the keyword. *Google Trends* compiles the GSVI data using a random subset of the actual historical search data and therefore the GSVI time-series downloaded on two different dates t_1 and t_2 can slightly differ, $\{S_{j,t}\}_{t1} \neq \{S_{j,t}\}_{t2}$. This well-known GSVI sample bias is, however, small as discussed in Da et al. (2011) and McLaren and Shanbhogue (2011) inter alia. Following these studies, we download GSVI series for each of the *J*=149 keywords on six different dates (6th, 7th, 9th, 15th, 16th and 17th February 2019) [8] and obtain the Google search volume time-series for the analysis as their average, i.e. $S_{j,t} \equiv \frac{1}{6}\sum_{d=1}^{6}\{S_{j,t}\}_d$.

As an illustration, Figure 1, Panel A shows the evolution of the Google search index $S_{j,t}$ for the keyword *hurricane*, and the average price of lumber futures (front-contract) in each sample month. We observe that the peaks in Google searches by *hurricane* precede the occurrence of most notorious hurricanes such as, for instance, Hurricane Irma on September 2017. A sharp increase in the Google searches tends to coincide or be immediately followed by an increase in lumber prices which later adjust downwards. Similar patterns are observed in Panels B and C. However, the opposite is observed in Panel D where increases in Google searches by *unemployment* (a demand-reduction related fear) are associated with decreases in the price of natural gas, which later gradually adjusts upwards. We cannot and do not assert that the agents behind these searches are exclusively commodity market participants; what is important for the

[8] The average pairwise correlation between the Google search series retrieved on the above 6 dates exceeds 90% for 55 out of the 149 search terms and the average correlation is 78%.

present purpose, as these graphical examples *prima facie* suggest, is that when agents are concerned about a threat (e.g. Hurricane Irma) they conduct hazard-related internet searches.

[Insert Figure 1 here]

2.2. CFEAR characteristic

The goal is to define a commodity-specific characteristic that embeds hazard-fear expectations about subsequent futures prices. The approach unfolds in various steps. As in Da et al. (2015), the measure of interest is the weekly log change in the Google search volume for keyword *j* defined as $\Delta S_{j,t} \equiv \log(S_{j,t}/S_{j,t}), j = 1, \dots, J$. Working with logarithmic changes mitigates the possibility of a spurious relationship between searches and prices that is solely driven by stochastic trends (unreported unit root tests suggest that the time-series of log search changes, $\Delta S_{j,t}, t = 1, \dots, T$, like the commodity futures excess returns, are stationary, unlike the corresponding levels). Using search log changes also eliminates the look-ahead bias in GSVI induced by the aforementioned division of $V_{j,t}/V_{k,t}$ by its maximum historical value; this ensures that the hazard-fear characteristic is solely based on information available at the time of portfolio formation. Following Da et al. (2015), we then standardize the series $\Delta S_{j,t}$ to make them comparable $\Delta S^*_{j,t} \equiv \Delta S_{j,t}/\sigma^{\Delta S}_{j,t}$ across the $j = 1, \dots, 149$ keywords where $\sigma^{\Delta S}_{j,t}$ is the time *t* standard deviation of the time-series $\Delta S_{j,t}$ that comprises data from sample week 1 to week *t*.

We seek to focus on the most relevant hazards per commodity. To do this, as in Da et al. (2015), we let the data speak and run backward-looking regressions to ascertain the strength of the historical contemporaneous relationship between searches and commodity futures returns

$$r_{i,t-l} = \alpha + \beta^{CFEAR}_{i,j,t-l} \cdot \Delta S^*_{j,t-l} + \varepsilon_{t-l}, \quad l = 0, \dots, L-1 \tag{1}$$

for each of the $j = 1, \dots, 149$ keywords in the sample. We estimate Equation (1) by OLS and, for each commodity, we retain the keywords with the largest *t*-statistic $\left| t_{\hat{\beta}^{CFEAR}_{i,j,t-l}} \right|$. Finally, we construct the CFEAR characteristic for the *i*th commodity futures contract as follows

$$CFEAR_{i,t} \equiv \sum_{j=1}^{J} \hat{\beta}_{i,j,t-l}^{CFEAR} \times I\left(\left|t_{\hat{\beta}_{i,j,t-l}^{CFEAR}}\right| > \tau\right) \tag{2}$$

where τ is the two-sided 10% critical value from a standard normal distribution and $I(\cdot)$ is a binary indicator equal to 1 if $\left|t_{\hat{\beta}_{i,j,t-l}^{CFEAR}}\right| > \tau$, and 0 otherwise. Da et al. (2015) are concerned with the adverse sentiment (negative beliefs or pessimism) that induces *falling* equity prices and thus, retain the keywords with the most negative *t*-statistics. In the case of commodity futures, assets in zero net supply, falling prices are undesirable to long traders but desirable to short traders; accordingly, we retain the keywords *j* with $\left|t_{\hat{\beta}_{i,j,t-l}^{CFEAR}}\right| > 1.65$.

A large positive signal ($CFEAR_{i,t} > 0$) is taken to suggest that on the whole the futures price of commodity *i* co-moved positively with the hazard fear; that is, most of the hazards were supply-reducing or demand-increasing. If so, the futures contract is likely to be overpriced relative to the expected spot price which suggests that a short position is optimal at time *t*. A large negative signal ($CFEAR_{i,t} < 0$) indicates that the futures price of commodity *i* co-moved negatively with the hazard fear; that is, most of the relevant hazards were demand-decreasing or supply-enhancing. Accordingly, the futures contract is likely to be underpriced and thus, we take a long position at time *t*. To avoid a look-ahead bias, the analysis is conducted out-of-sample; namely, the buy or sell decisions at each week *t* in our sample period hinge on past data. Specifically, we deploy Equations (1) and (2) at each time *t* as in Da et al. (2015) using an initial lookback period of $L = 52$ weeks that is sequentially expanded one week at a time.[9]

[9] Da et al. (2015) deploy expanding-window regressions to maximize the statistical power of the keyword selection. The events (hazards) are, by definition, infrequent and therefore, a fixed-length (rolling) estimation window for Equation (1) of, say, one to five years is too short to produce accurate estimates of $\beta_{i,j,t-l}^{CFEAR}$. Using longer windows reduces considerably the sample of portfolio returns. We revisit this issue in the robustness tests section of the paper.

2.3 Data summary statistics

Table 2 describes the 28 commodity futures contracts used in our analysis which broadly resembles the cross-section of extant studies (e.g., Basu and Miffre, 2013; Bianchi et al., 2015; Boons and Prado, 2019): 17 agricultural (4 cereal grains, 4 oilseeds, 4 meats, 5 miscellaneous other softs), 6 energy, and 5 metals (1 base, 4 precious). The sample period, dictated by the availability of *Google Trends* search data, is from January 1, 2004 to December 31, 2018.

[Insert Table 2 around here]

The table reports summary statistics (mean, standard deviation, first-order autocorrelation and corresponding *t*-statistic) for the commodity futures returns which are calculated as $r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$ where $P_{i,t}$ is the Monday settlement price of front contracts in non-maturity months or that of second-nearest contracts otherwise. Commodity futures prices are obtained from *Thomson Reuters Datastream*. We note an absence of first-order autocorrelation in weekly futures returns consistent with no mean reversion. Table 2 also presents the mean and standard deviation of the weekly CFEAR characteristic, as defined in Equation (2) multiplied by 1,000.

3. **IS COMMODITY HAZARD-FEAR A PRICED FACTOR?**

The scope of this section is to shed light on the pricing ability of the CFEAR factor through both time-series spanning tests and cross-sectional tests. We begin by conducting a long-short portfolio analysis of the out-of-sample predictive ability of the CFEAR characteristic.

3.1 CFEAR portfolio analysis

Our representative investor forms at each portfolio formation time *t* (Monday-end) a long-short portfolio of commodity futures using $\theta_{i,t} \equiv (x_{i,t} - \bar{x}_t)/\sigma_t^x$ as sorting signal where $x_{i,t} = CFEAR_{i,t}$ is the hazard-fear characteristic obtained in Equation (2) with $\bar{x}_t$ and σ_t^x its cross-sectional mean and standard deviation at time *t*. At each portfolio formation time *t*, we sort the available cross-section of *N* commodity futures contracts according to $\theta_{i,t}$, take short positions in the $N/5$ (top quintile, Q5 hereafter) with the largest $\theta_{i,t} > 0$, and long positions in the bottom quintile, Q1, with the smallest $\theta_{i,t} < 0$. The constituents of the long (L) and short (S) portfolios are equally weighted, and the weights are appropriately scaled so that 100% of the investor mandate is invested ($\sum_i w_{i,t}^L = \sum_j \left|w_{j,t}^S\right| = 0.5$ for all *i* and *j*) at each *t*. We hold the long and short legs of this CFEAR portfolio for one week on a fully-collateralized basis; thus, the weekly excess return is half of the return of the longs minus half of the return of the shorts.

Table 3 summarizes the performance and risk profile of the CFEAR sorted quintiles and the long-short CFEAR portfolio. Since 52 past weeks of data are required to construct the first portfolio, the resulting weekly returns available are for the period January 2005 to December 2018. For comparison, Table 3 provides the same summary statistics for the equally-weighted long-only portfolio of the 28 commodity futures (AVG) and traditional long-short portfolios formed according to the basis, hedging pressure or momentum characteristics as the sorting signal. Appendix A provides details on the construction of these traditional benchmarks.

[Insert Table 3 around here]

We observe a monotonic decrease in the excess returns of the CFEAR-sorted quintiles from 5.42% (Q1) to -11.04% (Q5). The fully-collateralized Q1-Q5 portfolio captures an economically and statistically significant premium of 8.23% p.a. ($t = 3.49$). These measures suggest that the CFEAR signal contains useful out-of-sample predictive information for commodity excess returns. The CFEAR portfolio excess returns translate into a Sharpe ratio of 0.8888 which is higher than that of traditional portfolios at -0.2486 (AVG), 0.3387 (basis), 0.5926 (HP) and 0.1296 (Mom). The CFEAR portfolio also stands relatively well in terms of tail/crash risk as borne out, for instance, by a 99% VaR and maximum drawdown of 0.0314 and -0.1430, respectively, while the corresponding measures for the long-only and long-short traditional portfolios lie in the ranges [0.0331, 0.0562] and [-0.5392, -0.1828], respectively.

Looking at the excess returns of the long versus short legs of the hazard-fear mimicking portfolio evidences that the CFEAR premium is mostly driven by the substantial drop in price of the commodity futures contracts with the most positive $CFEAR_{i,t}$ characteristic; namely, the short positions achieve a large negative mean excess return of -11.04% p.a. (t = -2.24). This finding is consistent with the inherent asymmetry of inventories. Namely, inventories can in principle increase without bound but cannot be negative and hence, they are likely to be perceived by market participants as an easier lever to avoid sharp downward swings in commodity prices than sharp upward swings in commodity prices. Thus, supply-reducing or demand-increasing hazards may be seen as riskier by speculators than supply-increasing or demand-reducing hazards and hence, they command a greater premium for being short in markets exposed to the former hazards than for being long in markets facing the latter hazards.

Are a few specific commodities driving the performance of the CFEAR portfolio? Towards addressing this question, Figure 2 shows that the frequency with which a given commodity is included in the Q1 or Q5 portfolio is often below 50% revealing that the CFEAR strategy is diverse in composition. The *energy* commodities are more often in the short Q5 portfolio (than in the long Q1 portfolio) which indicates that on average the hazard fear they are exposed to is mostly of supply-reducing or demand increasing type. Soybean meals, live cattle, cocoa and coffee are more often in the long Q1 portfolio, suggesting that they are predominantly subject to fear associated with supply-increasing or demand-decreasing hazards.

[Insert Figure 2 around here]

Table 3, Panel B reports the pairwise correlations among the excess returns of the commodity CFEAR portfolio and the traditional basis, hedging pressure and momentum portfolios. The CFEAR portfolio is very mildly associated with the traditional portfolios as borne out by correlations ranging between -0.02 and 0.24. This result suggests that the predictive content the CFEAR signal only mildly overlaps with that of traditional signals.

Figure 3 plots the future value of $1 invested in the long-short CFEAR portfolio, traditional long-short commodity portfolios, and the long-only AVG portfolio. Confirming our earlier findings (c.f. Table 3), the graph suggests that the CFEAR strategy is relatively attractive.

[Insert Figure 3 around here]

3.2 Time-series spanning tests

The preceding analysis reveals that the CFEAR portfolio captures attractive mean excess returns in commodity markets. We test whether the CFEAR premium represents compensation for exposure to traditional risk factors by estimating the time-series spanning regression

$$r_{CFEAR,t} = \alpha_P + \beta_{AVG} r_{AVG,t} + \beta_{Basis} r_{Basis,t} + \beta_{HP} r_{HP,t} + \beta_{Mom} r_{Mom,t} + v_{P,t}, t = 1, \dots, T \quad (3)$$

using as regressors the excess returns of the AVG, Basis, HP and Mom portfolios. We test the significance of the intercept (or alpha) that is interpreted as the excess returns of the CFEAR portfolio that are not a compensation for the included risk factors. The betas (factor loadings) capture the risk exposures to each of the four factors. We consider the above four-factor specification, as employed by Fernandez-Perez et al. (2018) and Bianchi et al. (2015) inter alia, and parsimonious versions with one factor at a time. Table 4 reports the results.

[Insert Table 4 around here]

The betas of the HP and Mom factors are positive and that of the Basis factor is negative. These results are well aligned with the correlation structure shown in Table 3 (Panel B) and with the average characteristics (roll-yield, hedging pressure, momentum) of the CFEAR long and short quintiles (Q1 and Q5) reported in the online Annex Table A.1. The alpha of the CFEAR portfolio in Equation (3) is economically and statistically significant in all models averaging 7.94% p.a. ($t > 3$), slightly down from the raw 8.23% mean excess returns reported in Table 3, Panel A. This analysis suggests that risk exposure does not tell the whole story.

3.3 Cross-sectional pricing tests

The previous results suggest that the CFEAR factor is not subsumed by traditional risk factors and therefore, it may improve the cross-sectional pricing ability when added to a model that includes the benchmark factors. In order to test this conjecture, we carry out cross-sectional asset pricing tests employing, for consistency, the same benchmark factors as in the preceding time-series tests. We attempt to provide an answer to two main questions: (a) is exposure to the CFEAR factor priced? (b) is the CFEAR factor able to improve the explanatory power (and reduce the average pricing error) of existing commodity pricing models?

We employ two set of test assets. The first set are the 26 portfolios obtained as the quintiles of the individual commodity futures sorted according to the basis, HP, momentum, and CFEAR signals, and the six portfolios by sub-sector (see Table 1, column 2). As Daskalaki et al. (2014) inter alia argue, a bias may emerge as regards the significance of the prices of risk when the test assets are portfolios sorted by the same criterion used to construct the risk factors. Adding the sectoral portfolios alleviates this concern. In line with prior studies, the other set of test assets are the individual commodities ($N = 28$) that are harder to price and hence, represent a hurdle for any new factor (Daskalaki et al., 2014; Boons and Prado, 2019).

For the portfolio-level tests, as in Boons and Prado (2019), we first estimate full-sample betas through *time-series* OLS regressions of each portfolio excess returns on the risk factors

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i \cdot \boldsymbol{F}_t + \varepsilon_{i,t}, t = 1, \ldots, T \tag{4}$$

where $\boldsymbol{F}_t = (r_{CFEAR,t}, r_{AVG,t}, r_{Basis,t}, r_{HP,t}, r_{Mom,t})'$ are the factors on week *t* and $\varepsilon_{i,t}$ is an error term. As in Kan et al. (2013) and Boons and Prado (2019) inter alia, at step two we estimate the following cross-sectional regression of the average excess returns on the full-sample betas

$$\bar{r}_i = \lambda_0 + \boldsymbol{\lambda}\widehat{\boldsymbol{\beta}}_i + \epsilon_i, i = 1, \ldots, N \tag{5}$$

where $\boldsymbol{\lambda} = (\lambda_{CFEAR}, \lambda_{AVG}, \lambda_{Basis}, \lambda_{HP}, \lambda_{Mom})'$ are the prices of risk. Table 5 reports the OLS estimates $\{\hat{\lambda}_0, \ \hat{\boldsymbol{\lambda}}\}$, and *t*-tests for their significance based on Shanken (1992) standard errors

(t_S, to correct for error-in-variables in $\widehat{\boldsymbol{\beta}}$) and Kan et al. (2013) standard errors (t_{KRS}, to additionally correct for conditional heteroscedasticity and model misspecification).[10] We also report the explanatory power, adjusted-R^2(%), and mean absolute pricing error, $MAPE(\%) = \frac{100}{N}\sum_{i=1}^{N}|\hat{\epsilon}_i|$, of Equation (5) to assess the merit of adding the CFEAR factor to extant models.

For the 28 commodities as test assets (unbalanced panel) we adopt the traditional Fama and MacBeth (1973) approach, as in Boons and Prado (2019). Since the betas of individual commodities are notably time-varying, we obtain first the conditional commodity-level betas by estimating Equation (4) with one-year (or 52-week) rolling windows. At step two, with the betas $\widehat{\boldsymbol{\beta}}_{i,t-1}$ at hand, we estimate weekly *cross-sectional* OLS regressions

$$r_{i,t} = \lambda_t^0 + \boldsymbol{\lambda}_t\widehat{\boldsymbol{\beta}}_{i,t-1} + \epsilon_{i,t}, i = 1, \dots, N \tag{6}$$

where $\boldsymbol{\lambda}_t$ are the sequential prices of risk. We report the average prices of risk from step two alongside *t*-statistics computed with both the Fama-MacBeth (1973) standard errors, t_{FM}, and the Shanken (1992) corrected version, t_S. Likewise, we obtain the average cross-sectional adjusted-R^2(%) and MAPE(%) of Equation (6). Table 5 reports these measures.

[Insert Table 5 around here]

For the 26 portfolios, we observe in Panel A of Table 5 that hazard-fear risk is significantly positively priced at 8.02% p.a. in the single-factor Model 1. The cross-sectional fit of Model 1 (adjusted-R^2 of 50.45% and MAPE of 0.050%) is superior to that of the single-factor Models 2 to 5 with the traditional factors offering an adjusted-R^2 in the range 0.32% (AVG factor) to 31.05% (HP factor) and likewise for MAPE. When the AVG, basis, HP, momentum, and CFEAR factors are jointly considered (Model 7), the price of hazard-fear risk remains statistically and economically unchanged at 8.90% p.a. and the cross-sectional fit of this model

[10] Like Boons and Prado (2019), we use this approach for the portfolio-level tests so as to compute the Kan et al. (2013) *t*-statistics. The test results from the Fama-MacBeth approach with Shanken *t*-statistics, as shown in the online Annex Table A.2, are qualitatively similar.

(adjusted-R^2 of 75.90% and weekly MAPE of 0.035%) notably improves that of the traditional four-factor Model 6 with a counterpart adjusted-R^2 of 39.45% and MAPE of 0.053%. These findings are reaffirmed in Panel B when the 28 commodities are used as test assets.

4. WHAT DRIVES THE CFEAR EFFECT?

Having established that the CFEAR characteristic is able to predict commodity excess returns out-of-sample and that the CFEAR factor is priced, the goal of this section is to shed some light on the underlying economic forces behind the observed hazard-fear premium.

4.1 Does the CFEAR premium reflect skewness preferences?

The contracts in the short CFEAR quintile (Q5) exhibit, by construction, the most positive $CFEAR_{i,t}$ characteristic, as measured through Equation (2). According to Equation (1), these contracts pertain to those commodities that are relatively more strongly influenced by fears related to supply-reducing or demand-increasing hazards (upward price swings) and therefore, their returns ought to be more positively skewed on average. This is corroborated by the statistics shown in Table A.1 of the online Annex. Thus, one could ask whether the negative mean excess return of Q5 evidenced in Table 3, Panel A simply reflects investors' preference for positive skewness. We address this question by constructing the skewness risk factor documented by Fernandez-Perez et al. (2018) using $\theta_{i,t} \equiv (x_{i,t} - \bar{x}_t)/\sigma_t^x$ as sorting signal where $x_{i,t}$ is the time *t* realized skewness computed from historical daily commodity excess returns in the prior year. The skewness factor is summarized in the online Annex Table A.3.

Through time-series regressions we first test whether the CFEAR portfolio excess returns are compensation for exposure to the skewness risk factor. Second, in cross-sectional regressions we ask whether the CFEAR factor retains its pricing ability once we control for the pricing ability of the skewness risk factor. Table 6 reports the results. The time-series regression of CFEAR portfolio excess returns on the skewness risk factor (Panel A of Table 6; Model ii) suggests that the sign of the exposure of the CFEAR portfolio to the skewness risk factor is positive, as expected. However, the skewness beta is insignificant ($t = 0.80$) and the alpha of the CFEAR portfolio remains strongly significant at 7.70% p.a ($t = 3.48$).

[Insert Table 6 around here]

We now turn to the cross-sectional regressions based on the same set of 26 portfolios as test assets, for comparison with our prior findings. Table 6, Panel B, reports the results. We observe that exposure to the skewness risk factor does not capture a statistically significant positive price of risk in Model 1 at 0.0797 ($t_S = 1.17$). When we add the CFEAR factor to the five-factor commodity pricing model with the skewness factor (Model 2) we observe that the CFEAR factor is significantly priced and the cross-sectional fit improves notably as borne out by an adjusted-R^2 of 77.47% in Model 2 versus 42.49% in Model 1, or a MAPE that falls substantially from 0.051 to 0.032. The cross-sectional regression results using the 28 individual commodities do not qualitatively alter the findings pertaining to the pricing of the CFEAR factor, even though the skewness risk factor is now priced positively; details are provided in the online Annex Table A.4. These results reinforce the insights from the time-series pricing tests; namely, the CFEAR risk is not merely a skewness risk in disguise.

4.2 Is CFEAR risk subsumed by basis-momentum, illiquidity and volatility risks?

Boons and Prado (2019) show that a signal related to the slope and curvature of the commodity futures curve, referred to as basis-momentum (BM), predicts commodity excess returns. Theoretically, the BM factor is consistent with imbalances in supply and demand of futures contracts that materialize when the market-clearing ability of speculators and financial intermediaries is impaired (e.g., during episodes when overall commodity market volatility or illiquidity is high). Since the hazards under study may create fear-induced imbalances in the supply and demand of commodity futures, we test whether the CFEAR premium is merely compensation for exposure to the BM factor. The BM signal, as sorting criteria to construct the long-short BM portfolio, is the cross-sectionally standardized difference between the average past returns of first- and second-nearby futures contract over a one-year (or 52-week) lookback period. Summary statistics for the BM factor are shown in the online Annex Table A.3.

The pricing tests with the additional BM risk factor are shown in Table 6. The CFEAR excess returns reflect compensation for exposure to the BM factor as borne out by a significantly positive BM beta in Model iii of Panel A. However, the alpha of the CFEAR strategy in the traditional four-factor Model i at 7.80% p.a. ($t = 3.53$) decreases very little (at 6.98% p.a.) and remains significant ($t = 3.07$) after controlling for the BM factor. The cross-sectional regressions of Model 3 in Table 6, Panel B, indicate that the pricing power of the CFEAR factor is not challenged in an augmented model that also includes the BM factor (significant CFEAR price of 7.58% p.a. in Model 4 of Table 6, Panel B), suggesting that CFEAR risk is not subsumed by BM risk. Conversely, the BM factor, which is significantly priced when added to the traditional four-factor model (Model 3), no longer commands a positive price of risk in an augmented model that also includes the CFEAR factor (Model 4). This suggests that BM risk is to a large extent subsumed by CFEAR risk.

Next, we test whether the CFEAR risk is directly related to market and funding illiquidity risks. The first benchmark for this purpose, inspired by Marshall et al. (2012) and Szymanowska et al. (2014), is a tradeable risk factor constructed as the excess returns of a long-short portfolio based on Amihud's (2002) illiquidity measure (defined at each portfolio formation time as the average of the absolute daily excess return over dollar daily-volume during the prior 2 months; $x_{i,t} \equiv \frac{1}{D}\sum_{j=0}^{D-1}\frac{|r_{i,t-j}|}{\$Volume_{i,t-j}}$, with D the number of days). We buy the most illiquid quintile (Q5) as signalled by the highest cross-sectionally standardized $x_{i,t}$, and short the least illiquid quintile (Q1) as signalled by the lowest cross-sectionally standardized $x_{i,t}$. As in Nagel (2016) and Koijen et al. (2018) inter alia, we additionally consider the first-difference in the TED spread (three-month Treasury bill minus three-month LIBOR in US dollars) to proxy for innovations to funding illiquidity. Table 6 reports the results.

The time-series results in Panel A (Models iv and v) suggest that the CFEAR portfolio is significantly negatively exposed to illiquidity shocks. Specifically, the negative beta of the tradeable illiquidity risk factor suggests that the commodities in Q5 (those with the most positive CFEAR) are relatively illiquid.[11] In other words, fear of hazards that reduce the commodity supply or increase the commodity demand affects predominantly the most illiquid futures contracts. This might be a reflection of the fact that trading exchanges (c.f. Table 2) increase the margins as a way to guard from large upward swings in commodity futures prices. However, the intercepts of Models iv and v of Table 6 remain economically large and significant at 7.75% p.a. ($t > 3$).[12] Thus, although the CFEAR portfolio is exposed to illiquidity risk, it still captures a significant premium that is not explained by this risk.

The cross-sectional tests in Panel B suggest that illiquidity risk is negatively priced. This result concurs with Boons and Prado (2019) notwithstanding differences in our commodity portfolios, as test assets, and sample periods. In line with their argument, the negative price of risk may suggest that investors are willing to pay for insurance against positive shocks to illiquidity. Interestingly, when we control for the CFEAR factor the price of illiquidity risk decreases notably in magnitude and becomes statistically insignificant. This suggests that the CFEAR factor is priced partly because it exposes investors to illiquidity shocks.

Last but not least, we test whether the CFEAR premium captures imbalances in the supply and demand of futures contracts related to commodity market volatility. To do this, as in Boons and Prado (2019), using past 22-daily excess return data we compute at each portfolio formation time: *i*) aggregate market volatility, $AggrVar$, as the annualized variance of the

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[11] As shown in Table A.1 of the online Annex the average of Amihud's illiquidity measure across constituents of each CFEAR quintile and over time confirms that the Q5 constituents are more illiquid than the Q1 constituents at the 1% significance level.

[12] As the TED spread is not a traded risk factor, the intercept of Model v cannot be treated as a measure of abnormal performance or alpha.

excess returns of the AVG portfolio (equally-weighted portfolio of all 28 commodities) and *ii*) average market volatility, $AvgVar$, as the average of the annualized variances of the excess returns of the 28 commodities. We adopt the first difference in each of the two measures as proxy for innovations in commodity market volatility. Table 6 reports the results.

The time-series regressions suggest that the CFEAR portfolio excess return (Models vi and vii in Table 6, Panel A) is unrelated to commodity market volatility risk and hence, the intercept remains essentially unchanged after controlling for this exposure. The cross-sectional regressions reveal that the significant negative price of volatility risk (as proxied by $\Delta AvgVar$) vanishes when we account for the CFEAR factor but yet again, the price of CFEAR risk remains positive and statistically significant within models that account for shocks to either $\Delta AggVar$ or $\Delta AvgVar$. The similarity of findings for the volatility and illiquidity risks is not surprising given that volatility acts as proxy for state variables driven by market liquidity or by the ability of speculators to clear the market.

We also consider the "kitchen-sink" pricing model for the times-series spanning tests, Model viii in Table 6, Panel A, and the cross-sectional tests, Models 13 and 14 of Table 6, Panel B. The conclusions are unchanged. The intercept of the time-series "kitchen sink" regression remains positive at 7.04% p.a. (*t*-statistic of 3.20) and the CFEAR factor is cross-sectionally priced at the 1% level. We obtain qualitatively similar results as regards the pricing ability of the CFEAR factor in the cross-sectional regression when the test assets are *i*) individual commodities (*N*=28, online Annex Table A.4) and *ii*) commodity quintiles sorted by the CFEAR, basis, hedging pressure, momentum, basis-momentum and Amihud illiquidity signals together with the six sub-sector portfolios (*N*=41, online Annex Table A.5).

4.3. CFEAR premium and VIX

We now address the question of whether the CFEAR premium relates to broad financial investor sentiment or fear as gauged by the CBOE implied volatility index, VIX, that measures the expected price fluctuations of the S&P 500 options 30 days ahead. The US equity-based VIX is widely used in the literature as proxy for fluctuations in investors' risk aversion and/or financial market sentiment given that the US equity market is still the largest and most liquid equity market in the world; for instance, Gao and Süss (2015) adopt it as proxy for broad financial market sentiment in their analysis of commodity futures markets.[13]

We estimate the following regressions using the VIX as dummy and in levels, respectively

$$r_{CFEAR,t} = \alpha_0^F + \alpha_{VIX}^F \, D_{t-1}^{VIX} + \boldsymbol{\beta}_i \cdot \boldsymbol{F}_t + v_t, \; t = 1, \dots, T \tag{7}$$

$$r_{CFEAR,t} = \delta_0^F + \delta_{VIX}^F \, VIX_{t-1} + \boldsymbol{\beta}_i \cdot \boldsymbol{F}_t + v_t, \; t = 1, \dots, T \tag{8}$$

where $r_{CFEAR,t}$ is the excess return of the CFEAR portfolio from week $t-1$ to week t, and $\boldsymbol{F}_t$ is the vector of traditional risk factors (AVG, Basis, HP, Mom). For the present purposes, the key explanatory variable in Equation (7) is D_{t-1}^{VIX}, a VIX-sentiment dummy equal to 1 if the VIX level at $t-1$ is higher than its full sample average and 0 otherwise. Accordingly, the CFEAR alpha in the high- and low-sentiment regimes is captured by the parameters $\alpha_0^F + \alpha_{VIX}^F$ and α_0^F, respectively. We denote by $\alpha_0 + \alpha_{VIX}$ and α_0, respectively, the parameters of the restricted Equation (7) with $\boldsymbol{\beta}_i = \boldsymbol{0}$ that capture the CFEAR premium (mean excess return of the CFEAR portfolio) in the high- and low-sentiment regimes, respectively. The key regressor in Equation (8) is the VIX level and thus the relevant coefficient is δ_{VIX}^F, while we use the notation δ_{VIX} for the sentiment coefficient in the restricted Equation (8) with $\boldsymbol{\beta}_i = \boldsymbol{0}$. To ease the interpretation of the coefficient estimates, we normalize the VIX level in Equation (8).

Table 7, Panel A, reports the CFEAR premium (and alpha) in the high versus low sentiment weeks with Newey-West *t*-statistics for their individual significance and for the significance of the CFEAR premium differential $H_0\!: r_{CFEAR}^{high} = r_{CFEAR}^{low}$ vs $H_1\!: r_{CFEAR}^{high} \neq r_{CFEAR}^{low}$. As a

[13] The CBOE applies its proprietary VIX methodology to create indices that reflect expected volatility for options on crude oil, silver, gold and energy ETFs but the time-series available are short (starting 2007 at the earliest) and there are no commodity market-wide implied volatility indices available to date.

benchmark for the discussion, Panel B reports similar statistics for the traditional basis, hedging pressure and momentum portfolios. The mean excess return and alpha of the CFEAR portfolio are much higher when the VIX levels are high; i.e., when risk-aversion is high or when sentiment is adverse. Specifically, the CFEAR premium is a sizeable 15.81% per annum ($t = 3.70$) in high VIX weeks versus an insignificant 4.10% ($t = 1.50$) in low VIX weeks, and the differential 11.71% is economically sizeable and significant ($t = 2.33$). This finding is reaffirmed by the CFEAR alpha of 15.31% (high VIX) versus 3.77% (low VIX) using the traditional risk factor model, with a significant differential ($t = 2.45$) and by the significantly positive slopes δ_{VIX} and δ_{VIX}^{F} in Equation (8). An increase of one standard deviation in VIX translates into a 5.26% p.a. increase in the risk-adjusted excess returns of the CFEAR portfolio.

[Insert Table 7 around here]

These results suggest that time-varying risk aversion and/or broad financial market sentiment influence(s) the CFEAR premium.[14] A rationale is that speculators may demand a higher premium in high VIX periods when their risk-bearing ability is impaired (due to either funding liquidity constraints or to their reluctance to take risks in bad times) or because their investment decisions are influenced by sentiment (pessimism). Given that risk aversion and sentiment are likely to co-vary over time, it is challenging to tell the two explanations apart. Towards the latter, we conduct an identical analysis for the traditional commodity premia; if the significantly larger CFEAR premium in high VIX weeks was purely the result of higher risk aversion, we would expect this effect to be present in the traditional premia too. The results in Table 7, Panel B suggest that the basis, hedging pressure and momentum premia are not related to VIX, which contrasts sharply with what we observe for the CFEAR premium.

[14] It has been shown that the fluctuations in the VIX are often too large to be fully rationalized as changes in economic uncertainty and global risk-aversion (e.g., Bloom, 2014).

Therefore, the more pronounced CFEAR premium observed in high VIX weeks is likely to be a sentiment-induced effect; the commodity hazard-fear is exacerbated by investors' pessimism.

The effect of sentiment on asset prices is known to be greater in markets where arbitrage is more difficult (Stambaugh et al., 2012). In this vein, the theoretical model for commodity futures markets of Gao and Süss (2015) suggests that, when arbitrage through short-selling is difficult, sentiment offers an additional premium to futures returns which is associated with investors' risk tolerance. Since inventories cannot be negative, speculators may be more reluctant to go short in markets exposed to fear of supply-reducing or demand-increasing hazards than to go long in markets exposed to fear of demand-reducing or supply-increasing hazards. The reason is that inventories are a weaker lever to cushion price swings in the former case; namely, when spot prices are expected to rise. Accordingly, the influence of sentiment can be conjectured as particularly strong in the short quintile (Q5) of the CFEAR portfolio. To address this question we repeat the previous analysis in a disaggregated manner for the Q1 and Q5 portfolios. The results are shown in Table 7, last two columns. The premium demanded by speculators to take short futures positions in the Q5 commodities which are, by construction, those most subject to supply-reducing or demand-increasing hazards is much larger when sentiment is pessimistic; the mean excess return of Q5 is -30.79% p.a. ($t = -3.01$) in high VIX periods versus a negligible -0.27% p.a. ($t = -0.06$) in low VIX periods. By contrast, the long Q1 quintile is unrelated to VIX. Thus, the way in which financial sentiment influences the CFEAR premium appears consistent with the asymmetry of inventories.

5. EXTENSIONS AND ROBUSTNESS CHECKS

The purpose of this section is to appraise the CFEAR premium after transaction costs, to cycle through several aspects of the CFEAR factor construction, and to deploy a placebo test.

5.1. Turnover and transaction costs

We measure the turnover (TO) of a given portfolio as the average of all the trades incurred

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

where $t = 1, \ldots, T$ denotes the portfolio formation times, $w_{i,t}$ is the weight assigned to the *i*th commodity as dictated by a given strategy at week *t*, $w_{i,t^+} \equiv w_{i,t} \times e^{r_{i,t+1}}$ is the actual portfolio weight right *before* the next rebalancing at $t+1$, $r_{i,t+1}$ is the weekly return of the *i*th commodity from week t to week $t+1$. Thus the *TO* measure captures also the mechanical evolution of the weights due to within-week price dynamics (*e.g.*, $w_{i,t}$ increases to w_{i,t^+} when $r_{i,t+1} > 0$). We calculate the time *t* net return of the long-short portfolio *P* as

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

using proportional trading costs *TC*=8.6 bps (Marshall et al., 2012). Figure 4 shows the results.

[Insert Figure 4 around here]

The CFEAR portfolio (*TO*=0.14) is notably less trading intensive than the basis (*TO*=0.38), momentum (0.27), skewness (0.21), and basis-momentum (0.23) portfolios, but slightly more than the illiquidity (0.10) and HP (0.06) portfolios. In line with this finding, the Sharpe ratio values confirm that transaction costs subsume only a small part of the returns of the CFEAR portfolio and accordingly, it still affords a very attractive performance.

5.2. Alternative approaches to measure the CFEAR characteristic

This section provides robustness tests by cycling through different aspects of the CFEAR signal construction. First, we do not pre-filter the keywords via statistical tests (which require making probability distributional assumptions); instead, we define the CFEAR signal as the sum of the $\beta_{i,j,t-l}^{CFEAR}$ coefficients from Equation (1) across all $j = 1, \ldots, 149$ keywords. Given the standardization of the Google search changes ($\Delta S_{j,t-l}^{*}$), the $\hat{\beta}_{i,j,t-l}^{CFEAR}$ estimates obtained in Equation (1) are comparable across keywords and hence, a CFEAR signal obtained by aggregating all $\beta_{i,j,t-l}^{CFEAR}$ coefficients shall be fairly accurate as irrelevant keywords should be mirrored in relatively small coefficients $\hat{\beta}_{i,j,t-l}^{CFEAR}$. Second, we define CFEAR as the mean of the significant slope coefficients in Equation (1) to isolate the quality (leaving out the quantity or number) of significant hazards. Third, we consider US Google searches by the users' IP address as criteria. Fourth, as in Da et al. (2015) we winsorize the Google search changes by shrinking the extreme $\Delta S_{j,t}$ towards $\overline{\Delta S}_{j,t} \pm 1.96\sigma_{j,t}^{\Delta S}$ where $\overline{\Delta S}_{j,t}$ is the mean of the time-series associated with the search term j up to time t and $\sigma_{j,t}^{\Delta S}$ its standard deviation. Fifth, we deseasonalize the searches $\Delta S_{j,t}$ by regressing them on month dummies and retain the residuals, also as in Da et al. (2015). The rationale for omitting these transformations in the main analysis is that our goal is to exploit surges in Google searches and therefore, by filtering out the large hazard-search changes by winsorization we may disregard relevant information. Likewise, many weather hazards (e.g., hurricanes, frosts, torrential rain) are seasonal and so the fear (proxied by the search activity) may capture seasonality that has valuable predictive content.

[Insert Table 8 around here]

Table 8, Panel A, summarizes the performance and risk of these alternative CFEAR portfolios. Panel B reports the price of the CFEAR risk factor in a cross-sectional regression that includes the traditional AVG, basis, hedging pressure and momentum factors for the 26 commodity portfolios employed above, as well as the increase in adjusted-R^2(%) when the CFEAR risk factor is included. Overall the main findings are robust to these alternative definitions of the CFEAR characteristic. But there are nuances in the results. Column (1) suggests, for example, that using all keywords (letting the magnitude of $\hat{\beta}_{i,j,t-l}^{CFEAR}$ determine the relatively importance of the keyword j) as opposed to pre-filtering them statistically provides, if anything, a more informative CFEAR signal as borne out by a higher premium of 9.28% p.a. ($t = 3.35$) versus 8.23% ($t = 3.49$) in the baseline case of Table 3. Defining the CFEAR signal as the mean of the significant slopes results, as shown in column (2), in a still significant yet slightly smaller premium which suggests that the number of hazards matters. The results in column (3) show that the CFEAR signal extracted from US searches is informative, albeit slightly less than the one extracted from world searches. Finally, the winsorization and deseasonalization of the Google searches somewhat decreases the magnitude of the CFEAR premium, as shown in columns (4) and (5), respectively, confirming our above intuition.

5.3. Alternative portfolio construction methods

Further we deploy the CFEAR portfolios: *a*) considering a fixed-length rolling window of 10 years ($L = 520$ weeks) for the estimation of Equation (2), *b*) weighting the Q1 and Q5 constituents by the magnitude of the standardized CFEAR signal, *c*) forming the long-short CFEAR portfolio with the entire cross section (N/2 each) of commodities weighted either by 1/N, standardized rankings, standardized signals, or winsorized and standardized signals, and *d*) considering at each portfolio formation time the 0.8N commodities with the largest open interest on the prior week to further ensure that the results are not driven by illiquidity. The results, gathered in the Online Annex Table A.6, suggest that the CFEAR premium remains sizeable ranging from 4.35% p.a. (when N/2 equally-weighted commodities are included in the long and short portfolios) to 10.17% p.a. (0.8N most liquid commodities in the cross-section).

For completeness, we construct the CFEAR portfolio using the more widespread approach of forming a long-short portfolio at each month-end and holding it for one month. We keep the other aspects of the CFEAR portfolio construction as above. For consistency, we re-deploy the AVG, and the traditional long-short portfolios (benchmarks) using the same approach. The results in Table A.7 of the online Annex indicate that the CFEAR premium remains economically sizeable and statistically significant at 7.63% ($t = 3.20$) translating into a Sharpe ratio of 0.8329 that is attractive relative to that of the alternative strategies. Thus, we assert that our findings are not an artifact of the weekly portfolio formation frequency.

5.4. Placebo test

This section conducts a placebo test to ascertain whether our finding of a significant hazard-fear premia in commodity futures markets is an artefact of the methodology used. For this purpose, we deploy the same methodology for cross-sections of equity index, fixed income and currency futures. The rationale is that it is implausible that fear of weather events (e.g., frosts) or crop diseases (e.g., La Roya fungus) has any meaningful influence on the prices of say, currencies or fixed income futures. Thus, the finding of a significant hazard-fear premium in these alternative futures markets may be interpreted as evidence that the commodity hazard-fear premium we have identified is spurious.[15]

In order to increase the power of this placebo test, the geopolitical (GP) and economic (EC) hazards are filtered out since they are likely to influence the pricing generally across futures classes; i.e., we obtain the CFEAR signal using the 123 keywords/hazards in the weather (WE) and crop disease (DI) categories that are especially linked to commodities. We re-construct the long-short CFEAR portfolio of commodity futures using the 123 WE/DI keywords and form similar portfolios with the equity index, fixed income and currency futures. For this analysis, we obtain daily settlement prices from *Thomson Reuters Datastream* for 40 futures on equity indices, 13 futures on fixed income and 19 futures on currencies; see details in Table A.8 of the online Annex. The placebo test results are reported in Table 9.

[Insert Table 9 around here]

The fear premium remains sizeable and statistically significant at 6.63% p.a. ($t = 2.82$) in commodity futures markets when the keywords are restricted to the WE/DI hazards. Reassuringly, and in line with our above intuition, the WE/DI hazard-fear premium in financial futures markets is negligible at 0.14% p.a. (t=0.15) in equity index futures markets, 0.67% p.a. (t=0.98) in fixed income futures markets and -3.78% p.a. (t=-0.94) in currency futures markets. This suggests that the CFEAR premium in commodity futures is unlikely to be spurious.

[15] We are mindful, however, of a literature that links rare disasters (including weather ones) and equity prices (see e.g., Barro, 2006; Hong et al., 2019, Choi et al., 2019, to name a few). Although rare events do impact the pricing of individual stocks (for example, a frost raises the valuation of producers), we expect that effect to be diversified away at the level of equity index futures (the same frost simultaneously decreases the valuation of refiners).

6. CONCLUSIONS

Does fear of rare disasters – such as extreme weather, agricultural pests or financial crises – that shift the supply or demand of commodities impact commodities futures prices? This paper addresses this question through a portfolio analysis that provides evidence of a hazard-fear effect with asset pricing implications. First, we find that commodity hazard-fear, as proxied by the volume of Google searches by 149 hazard-related keywords, has out-of-sample predictability for commodity futures returns. A long-short portfolio that utilizes the hazard-fear as sorting signal for a cross-section of 28 commodity futures contracts earns a sizeable premium of 8.23% per annum that cannot be rationalized as compensation for exposure to known commodity futures risk factors. Second, we find that exposure to hazard-fear is a key determinant of the cross-sectional variation in the excess returns of individual commodities and commodity portfolios. The findings are robust to transaction costs and to alternative signal measurement and portfolio construction methods. A placebo test that deploys the same methodology for the weather and crop diseases (specific to commodities) as search keywords in the context of equity index, fixed income and currency futures reveals that there is no CFEAR premium in these markets, which suggests that our finding of a significant hazard-fear premium in commodity futures market is unlikely to be an artefact of the methodology.

We show that the CFEAR premium is significantly more pronounced during periods of pessimistic investor sentiment as proxied by the VIX (the “fear gauge” in financial markets). This finding stands in sharp contrast to the commodity basis, hedging pressure and momentum premia that show no such strong relation with the VIX. We thus argue that the emotion known as investor sentiment exacerbates the commodity hazard-fear. Overall, we conclude that, over and above the fundamental backwardation and contango cycle, commodity futures are influenced by the fear of weather, agricultural diseases, geopolitical or economic disasters.

Appendix A. Traditional risk factors

The commodity market factor (AVG) is obtained as the excess returns of a long-only, equally-weighted and weekly-rebalanced portfolio of all commodities (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Bakshi et al., 2017) to reflect general commodity price movements.

The other three risk factors reflect the backwardation and contango cycle. They are obtained as the excess returns of long-short portfolios using as sorting signals the roll-yield (Erb and Harvey, 2006; Gorton et al., 2012; Szymanowska et al., 2014; Bakshi et al., 2017), momentum (Erb and Harvey, 2006; Miffre and Rallis, 2007; Bakshi et al., 2017) and hedging pressure (Basu and Miffre, 2013; Bianchi et al., 2015), respectively. The roll-yield (or basis) characteristic of commodity *i* is measured as $Roll_{i,t} \equiv \ln\left(F_{i,t,T_1}\right) - \ln\left(F_{i,t,T_2}\right)$, with F_{i,t,T_1} and F_{i,t,T_2} the time *t* price of the futures contract with respective maturities T_1 and T_2 ($T_1 < T_2$). The momentum signal is the average of weekly excess returns in the prior year; $Mom_{i,t} \equiv \frac{1}{52}\sum_{j=0}^{51} r_{i,t-j}$. The hedging pressure (HP) signal is $HP_{i,t} \equiv \left(\frac{1}{52}\right)\sum_{j=0}^{51} \frac{Long_{i,t-j}-Short_{i,t-j}}{Long_{i,t-j}+Short_{i,t-j}}$, with $Long_{i,t}$ and $Short_{i,t}$, the week *t* long and short open interests of large speculators, respectively, as reported by the CFTC in its Futures-Only Legacy Commitments of Traders report.

As with the CFEAR characteristic in the main analysis, for each of these *k*=3 characteristics we sort the futures contracts at each Monday-end by the standardized signals $\theta_{i,k,t} \equiv (x_{i,k,t} - \bar{x}_{k,t})/\sigma_{k,t}^{x}$), buy the quintile with the highest $\theta_{i,k,t}$, short the quintile with the lowest $\theta_{i,k,t}$, assign equal weights to the constituents and hold the fully-collateralized positions for a week.

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Table 1. Google search keywords

This table lists all the search keywords (J=149) used to obtain the CFEAR characteristic. The terms are grouped according to the type of hazard or vulnerability. An asterisk indicates queries carried out specifically within the weather category of *Google Trends*.

Weather (WE; 113 keywords)
Adverse weather conditions, adverse weather warning, adverse weather, blizzard risk, blizzard warning, blizzard*, catastrophic events, catastrophic weather, catastrophic weather events, climate change, climate disturbance, cold spell, cold weather, cold*, cyclogenesis, cyclone, cyclone risk, cyclone warning, drought risk, drought warning, drought, droughts, dry weather, el Niño weather, extreme cold temperatures, extreme cold, extreme heat, extreme rain, extreme temperatures, extreme weather, extreme wind, flood risk, flood warning, flood, flooding, floods, forest fire, forest fires, freeze warning, frost*, frosts*,frost risk, frost warning, global warming, gust*, gusts*, hail, hail risk, hail warning, hail damage, hail storm, hail storm warning, Harmattan wind, heat*,heatwaves, heatwave, heat waves, heat wave, heavy rain*, heavy rain fall, heavy rain risk, heavy rain warning, high temperature, high temperatures, hot weather, hurricane, hurricanes*, hurricane risk, hurricane warning, natural disaster, natural hazard, rain*, severe heat, severe weather, severe weather risk, snow*, snow risk, snow warning, snow storm warning, storm*, storm risk, storm warning, strong wind, strong wind gust, tornado, tornado risk, tornado warning, torrent rain, tropical cyclone, tropical cyclone risk, tropical cyclone warning, tropical storm, tropical storm risk, tropical storm warning, tropical weather, typhoon, typhoon risk, typhoon warning, weather blizzard warning, weather risk, weather warning, wet weather, wildfire*, wildfires, wildfire risk, wildfire warning, wind*, wind gust, wind gusts, wind risk, wind speed, wind storm, wind warning.
Agricultural diseases (DI; 10 keywords)
Crop diseases, crop pest, crop pests, crop pest risk, ebola, insect pest, la roya, pest control, pest risk, rust coffee.
Geopolitical (GP; 14 keywords)
Africa instability, Africa terrorism, Libya crisis, Middle East conflict, Middle East instability, Middle East terrorism, oil crisis, oil embargo, oil outage, Russia crisis, Syrian war, terrorism, terrorist attack, terrorist attacks.
Economic (EC; 12 keywords)
Crisis, financial crisis, economic crisis, recession, the recession, economic recession, recession 2008, recession depression, unemployment, unemployment rate, US recession, US unemployment

Table 2. Sample of commodity futures

This table lists the 28 futures contracts, main trading exchanges, first and last observation date, summary statistics for excess returns (annualized mean, annualized standard deviation (StDev), first-order autocorrelation (AC1) and associated *t*-statistic in parentheses) and summary statistics for the CFEAR characteristics (mean and standard deviation).

			First obs	Last obs	Excess return				CFEAR	
Commodity	Sub-sector	Exchanges	YYYYMMDD	YYYYMMDD	Mean	StDev	AC1		Mean	StDev
I. Agricultural sector (N=17)										
Corn	Cereal grains	CBOT	20040105	20181231	-0.0671	0.2912	-0.0021	(-0.04)	0.0031	0.0145
Oats	Cereal grains	CBOT	20040105	20181231	0.0120	0.3475	-0.0339	(-1.05)	-0.0195	0.0128
Rough rice	Cereal grains	CBOT	20040105	20181231	-0.0819	0.2488	0.0101	(0.23)	-0.0159	0.0303
Wheat CBT	Cereal grains	CBOT	20040105	20181231	-0.1227	0.3152	0.0129	(0.34)	-0.0227	0.0116
Cotton no.2	Oilseeds	NYMEX/ICE	20040105	20181231	-0.0220	0.2872	0.0085	(0.23)	0.0139	0.0238
Soybeans	Oilseeds	CBOT	20040105	20181231	0.0525	0.2486	0.0256	(0.66)	-0.0042	0.0115
Soybean meal	Oilseeds	CBOT	20040105	20181231	0.1092	0.2872	0.0462	(1.14)	-0.0339	0.0219
Soybean oil	Oilseeds	CBOT	20040105	20181231	-0.0467	0.2460	-0.0176	(-0.46)	0.0241	0.0107
Feeder cattle	Meats	CME	20040105	20181231	0.0270	0.1659	-0.0479	(-1.30)	0.0090	0.0199
Lean hogs	Meats	CME	20040105	20150706	-0.0662	0.2377	0.0650	(1.27)	0.0334	0.0102
Live cattle	Meats	CME	20040105	20181231	-0.0075	0.1602	-0.0618	(-2.05)	-0.0388	0.0099
Frozen pork bellies	Meats	CME	20040105	20110705	-0.0228	0.2979	-0.0570	(-0.93)	-0.0324	0.0137
Cocoa	Misc. other softs	NYMEX/ICE	20040105	20181231	0.0253	0.2948	-0.0237	(-0.68)	-0.0435	0.0329
Coffee C	Misc. other softs	NYMEX/ICE	20040105	20181231	-0.0551	0.3115	0.0115	(0.27)	-0.0246	0.0170
Frozen Orange juice	Misc. other softs	ICE/NYMEX	20040105	20181231	0.0176	0.3414	0.0344	(0.93)	-0.0077	0.0156
Sugar no.11	Misc. other softs	NYMEX/ICE	20040105	20181231	-0.0417	0.3141	-0.0351	(-0.87)	-0.0067	0.0144
Lumber	Misc. other softs	CME	20040105	20181231	-0.1229	0.3087	0.0074	(0.21)	0.0103	0.0234
II. Energy sector (N=6)										
Light crude oil	Energy	NYMEX	20040105	20181231	-0.0753	0.3400	-0.0200	(-0.41)	0.0046	0.0224
Electricity JPM	Energy	NYMEX	20040105	20150727	-0.1454	0.4428	0.0619	(0.97)	0.0270	0.0318
Gasoline RBOB	Energy	NYMEX	20051010	20181231	-0.0305	0.3227	0.0404	(0.72)	0.1407	0.1388
Heating oil	Energy	NYMEX	20040105	20181231	-0.0125	0.3095	0.0227	(0.50)	-0.0155	0.0257
Natural gas	Energy	NYMEX	20040105	20181231	-0.3633	0.4224	-0.0102	(-0.26)	0.0332	0.0250
NY unleaded gas	Energy	NYMEX	20040105	20070102	0.1768	0.3686	-0.0146	(-0.21)	0.0344	0.0118
III. Metals (N=5)										
Copper (High Grade)	Base metals	COMEX	20040105	20181231	0.0682	0.2720	0.0188	(0.32)	-0.0175	0.0260
Gold 100oz (CMX)	Precious metals	COMEX	20040105	20181231	0.0560	0.1785	-0.0090	(-0.24)	0.0025	0.0228
Palladium	Precious metals	NYMEX	20040105	20181231	0.0988	0.3148	0.0220	(0.52)	-0.0117	0.0250
Platinum	Precious metals	NYMEX	20040105	20181231	-0.0114	0.2302	0.0167	(0.48)	-0.0151	0.0125
Silver 5000 oz	Precious metals	COMEX	20040105	20181231	0.0421	0.3196	0.0117	(0.27)	-0.0054	0.0289

Table 3. CFEAR factor and traditional commodity risk factors

The table summarizes the long-short CFEAR portfolio, the equally-weighted long-only portfolio of all 28 commodities (AVG), and the long-short basis, hedging pressure, and momentum (Mom) portfolios. Q1 (Q5) is the commodities quintile with the most negative (positive) $CFEAR_{i,t}$ characteristics. Newey-West robust *t*-statistics are shown in parentheses. Panel B reports the correlations and corresponding significance *p*-values in curly brackets. CER denotes certainty equivalent return based on power utility. The time period is January 2005 (week 1) to December 2018 (week 4).

	CFEAR						AVG	Basis	Hedging pressure	Mom
	Long (Q1)	Q2	Q3	Q4	Short (Q5)	Q1-Q5				
Panel A: Summary statistics										
Mean	0.0542	-0.0171	-0.0466	-0.0571	-0.1104	0.0823	-0.0332	0.0346	0.0598	0.0151
	(1.26)	(-0.35)	(-0.97)	(-1.19)	(-2.24)	(3.49)	(-0.86)	(1.27)	(2.32)	(0.51)
StDev	0.1637	0.1788	0.1687	0.1695	0.1761	0.0926	0.1336	0.1021	0.1009	0.1168
Downside volatility (0%)	0.0534	0.0611	0.0553	0.0571	0.0587	0.0285	0.0461	0.0323	0.0294	0.0363
Skewness	-0.3572	-0.3498	-0.2933	-0.2750	-0.2260	-0.0884	-0.4596	-0.1454	0.0318	-0.1676
	(-3.94)	(-3.86)	(-3.24)	(-3.04)	(-2.49)	(-0.98)	(-5.07)	(-1.60)	(0.35)	(-1.85)
Excess Kurtosis	1.5096	1.3070	1.5708	0.9296	0.8903	0.7668	1.7672	0.5940	0.6147	0.7764
	(8.33)	(7.21)	(8.67)	(5.13)	(4.91)	(4.23)	(9.75)	(3.28)	(3.39)	(4.28)
JB normality test *p*-value	0.0010	0.0010	0.0010	0.0010	0.0010	0.0013	0.0010	0.0044	0.0070	0.0010
AC(1)	0.0175	-0.0073	0.0555	0.0215	0.0175	-0.0235	0.0501	0.0152	-0.0511	-0.0379
99% VaR (Cornish-Fisher)	0.0647	0.0708	0.0682	0.0650	0.0676	0.0314	0.0562	0.0356	0.0331	0.0421
% of positive months	52%	49%	48%	48%	46%	55%	50%	54%	54%	50%
Maximum drawdown	-0.4712	-0.5332	-0.5433	-0.6956	-0.8222	-0.1430	-0.5392	-0.1905	-0.1828	-0.2872
Sharpe ratio	0.3308	-0.0957	-0.2763	-0.3372	-0.6272	0.8888	-0.2486	0.3387	0.5926	0.1296
Sortino ratio	1.0141	-0.2800	-0.8431	-1.0012	-1.8805	2.8921	-0.7197	1.0720	2.0331	0.4173
Omega ratio	1.1263	0.9654	0.9050	0.8841	0.7967	1.3817	0.9130	1.1297	1.2342	1.0472
CER (power utility)	-0.0141	-0.0993	-0.1198	-0.1310	-0.1909	0.0607	-0.0790	0.0084	0.0343	-0.0192
Panel B: Correlation structure										
AVG						-0.02				
						{0.56}				
Basis						-0.02	0.05			
						{0.59}	{0.20}			
Hedging pressure						0.14	0.09	0.27		
						{0.00}	{0.01}	{0.00}		
Momentum						0.24	0.02	0.36	0.33	
						{0.00}	{0.66}	{0.00}	{0.00}	

Table 4. Time-series spanning tests: Alpha of the long-short CFEAR portfolio

The table reports estimation results from time-series regressions to test whether the CFEAR portfolio provides alpha in the context of a four-factor benchmark model that includes the AVG, basis, hedging pressure, and momentum factors (Fernandez-Perez et al., 2018; Bianchi et al., 2015), and individual factor models. Alongside the alpha, we report the betas (risk exposures) with Newey West h.a.c. *t*-statistics in parentheses, and adjusted-R^2. The time period is January 2005 (week 1) to December 2018 (week 4).

	Annualized alpha	AVG	Basis	Hedging pressure	Momentum	Adj.-R^2 (%)
Model 1	0.0818	-0.0150				-0.09
	(3.51)	(-0.46)				
Model 2	0.0829		-0.0180			-0.10
	(3.49)		(-0.39)			
Model 3	0.0748			0.1254		1.73
	(3.14)			(2.58)		
Model 4	0.0794				0.1914	5.70
	(3.47)				(4.74)	
Model 5	0.0780	-0.0193	-0.1239	0.0809	0.2075	7.34
	(3.53)	(-0.66)	(-2.39)	(1.58)	(4.50)	

Table 5. Cross-sectional pricing tests

The table presents cross-sectional pricing tests using the four-factor model of Fernandez-Perez et al. (2018) and Bianchi et al. (2015) inter alia with the average commodity factor (AVG), basis factor, hedging pressure factor (HP) and momentum factor (Mom). The test assets are the 26 portfolios (quintiles from sorting the 28 individual commodities by the roll-yield, hedging pressure, momentum and CFEAR signals, and the six sub-sector portfolios) in Panel A, and the 28 individual commodities in Panel B. For the portfolio-level tests, we report the (annualized) prices of risk from a cross-sectional regression of average portfolio excess returns on full-sample betas with Shanken (1992) errors-in-variables corrected *t*-statistics in parentheses, and Kan et al. (2013) corrected (for additional model misspecification and heteroscedasticity) *t*-statistics in curly brackets. For the commodity-level tests, we report the (annualized) average prices of risk from sequential (weekly) cross-sectional regressions on sequential betas with Fama-MacBeth (1973) *t*-statistics in curly brackets and Shanken (1992) *t*-statistics in parentheses. The time period is January 2005 to December 2018.

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Adj.-R^2 (%)	MAPE (%)
			Panel A: Commodity portfolios (N=26 test assets)					
Model 1	-0.0006	0.0802					50.45	0.050
	(-0.87)	(2.59)						
	{-0.76}	{2.54}						
Model 2	-0.0004		-0.0132				0.32	0.069
	(-0.42)		(-0.22)					
	{-0.39}		{-0.18}					
Model 3	-0.0007			0.0496			14.17	0.059
	(-1.02)			(1.55)				
	{-0.80}			{1.56}				
Model 4	-0.0008				0.0659		31.05	0.053
	(-1.16)				(2.07)			
	{-0.86}				{2.02}			
Model 5	-0.0007					0.0719	28.64	0.058
	(-0.96)					(2.04)		
	(-0.73)					{2.18}		
Model 6	0.0001		-0.0356	0.0207	0.0589	0.0556	39.45	0.053
	(0.06)		(-0.59)	(0.68)	(1.91)	(1.62)		
	{0.06}		{-0.53}	{0.68}	{1.83}	{1.66}		
Model 7	-0.0011	0.0890	0.0240	0.0451	0.0604	0.0243	75.90	0.035
	(-1.18)	(3.00)	(0.40)	(1.58)	(1.96)	(0.76)		
	{-1.25}	{2.87}	{0.40}	{1.68}	{1.94}	{0.82}		

(Cont.) **Table 5. Cross-sectional pricing tests**

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Adj.-R^2 (%)	MAPE (%)
	Panel B: Individual commodities (N=28 test assets)							
Model 1	-0.0008	0.0889					6.03	2.559
	{-1.09}	{3.09}						
	(-1.03)	(2.92)						
Model 2	-0.0004		-0.0223				5.95	2.547
	{-0.58}		{-0.51}					
	(-0.58)		(-0.51)					
Model 3	-0.0009			0.0075			5.44	2.576
	{-1.30}			{0.20}				
	(-1.30)			(0.20)				
Model 4	-0.0008				0.0466		5.87	2.557
	{-1.10}				{1.59}			
	(-1.09)				(1.57)			
Model 5	-0.0006					0.0220	6.58	2.548
	{-0.85}					{0.61}		
	(-0.85)					(0.61)		
Model 6	0.0003		-0.0578	0.0020	0.0587	0.0347	19.25	2.208
	{0.34}		{-1.23}	{0.05}	{2.00}	{0.94}		
	(0.32)		(-1.17)	(0.05)	(1.90)	(0.90)		
Model 7	0.0001	0.1032	-0.0530	0.0255	0.0508	-0.0021	23.07	2.099
	{0.17}	{3.70}	{-1.14}	{0.67}	{1.73}	{-0.06}		
	(0.15)	(3.26)	(-1.00)	(0.59)	(1.67)	(-0.05)		

Table 6. CFEAR risk versus skewness, basis-momentum, illiquidity and volatility risks

Panel A reports the alpha and risk exposures of the CFEAR portfolio in the context of the traditional four-factor model augmented with factors related to skewness (Fernandez-Perez et al. 2018), basis-momentum (BM) (Boons and Prado, 2019), illiquidity (Amihud, 2002), funding illiquidity (ΔTED) and volatility ($\Delta AggrVar$ and $\Delta AvgVar$). It also considers a "kitchen-sink" model that includes all factors. Newey West t-statistics are shown in parentheses. Panel B reports cross-sectional pricing tests for the same 26 commodity portfolios as in Table 5, Panel A. We report the (annualized) prices of risk with Shanken (1992) t-statistics corrected for error-in-variables in parentheses, and Kan et al. (2013) t-statistics additionally corrected for model misspecification and heteroskedasticity in curly brackets. The time period is January 2005 to December 2018.

Panel A: Time-series tests

	alpha	AVG	Basis	Hedging pressure	Mom	Skewness	BM	Illiquidity	ΔTED	ΔAggrVar	ΔAvgVar	Adj.-R^2
Model i	0.0780	-0.0193	-0.1239	0.0809	0.2075							7.34
	(3.53)	(-0.66)	(-2.39)	(1.58)	(4.50)							
Model ii	0.0770	-0.0194	-0.1289	0.0715	0.2087	0.0386						7.37
	(3.48)	(-0.67)	(-2.50)	(1.33)	(4.53)	(0.80)						
Model iii	0.0698	-0.0140	-0.1465	0.0940	0.1584		0.1743					10.04
	(3.07)	(-0.49)	(-2.91)	(1.94)	(3.58)		(3.83)					
Model iv	0.0773	-0.0122	-0.0927	0.0809	0.1712			-0.1972				11.22
	(3.63)	(-0.44)	(-1.87)	(1.65)	(3.88)			(-5.14)				
Model v	0.0779	-0.0213	-0.1237	0.0804	0.2074				-0.0018			7.25
	(3.54)	(-0.71)	(-2.39)	(1.57)	(4.50)				(-0.63)			
Model vi	0.0780	-0.0213	-0.1243	0.0796	0.2061					-0.0593		7.30
	(3.55)	(-0.74)	(-2.40)	(1.57)	(4.52)					(-0.64)		
Model vii	0.0780	-0.0211	-0.1219	0.0773	0.2058						-0.0270	7.34
	(3.54)	(-0.73)	(-2.36)	(1.53)	(4.53)						(-1.03)	
Model viii	0.0704	-0.0122	-0.1149	0.0880	0.1316	0.0049	0.1480	-0.1777	-0.0016	-0.0375	-0.0112	12.78
	(3.20)	(-0.43)	(-2.31)	(1.84)	(3.11)	(0.11)	(3.33)	(-4.36)	(-0.50)	(-0.36)	(-0.42)	

(*Cont.*) Table 6. CFEAR risk versus skewness, basis-momentum, illiquidity and volatility risks

Panel B: Cross-sectional tests (Test assets: 26 commodity portfolios)

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Skewness	BM	Iliquidity	ΔTED	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0003		-0.0191	0.0198	0.0479	0.0511	0.0797						42.49	0.051
	(-0.27)		(-0.31)	(0.65)	(1.67)	(1.52)	(1.17)							
	{-0.29}		{-0.28}	{0.63}	{1.65}	{1.50}	{0.87}							
Model 2	-0.0013	0.0881	0.0349	0.0441	0.0524	0.0217	0.0702						77.47	0.032
	(-1.38)	(2.98)	(0.58)	(1.54)	(1.84)	(0.68)	(1.02)							
	{-1.44}	{2.88}	{0.56}	{1.67}	{1.80}	{0.72}	{0.94}							
Model 3	-0.0011		0.0228	0.0439	0.0584	0.0224		0.2169					72.74	0.035
	(-1.07)		(0.36)	(1.53)	(1.87)	(0.71)		(2.60)						
	{-1.10}		{0.34}	{1.56}	{1.82}	{0.73}		{2.20}						
Model 4	-0.0013	0.0758	0.0327	0.0483	0.0596	0.0184		0.1227					80.01	0.032
	(-1.31)	(2.82)	(0.53)	(1.70)	(1.93)	(0.58)		(1.40)						
	{-1.36}	{2.71}	{0.53}	{1.80}	{1.90}	{0.62}		{1.27}						
Model 5	0.0000		-0.0349	0.0415	0.0618	0.0272			-0.1001				64.42	0.041
	(0.03)		(-0.57)	(1.46)	(2.00)	(0.86)			(-2.16)					
	{0.04}		{-0.55}	{1.56}	{1.88}	{0.90}			{-1.97}					
Model 6	-0.0009	0.0785	0.0126	0.0478	0.0611	0.0203			-0.0466				77.68	0.035
	(-0.96)	(2.97)	(0.21)	(1.69)	(1.98)	(0.64)			(-0.99)					
	{-1.00}	{2.85}	{0.21}	{1.89}	{1.95}	{0.70}			{-0.93}					
Model 7	-0.0002		-0.0232	0.0209	0.0572	0.0487				-0.0515			47.41	0.051
	(-0.19)		(-0.37)	(0.68)	(1.82)	(1.44)				(-1.59)				
	{-0.21}		{-0.42}	{0.92}	{1.79}	{1.48}				{-1.75}				
Model 8	-0.0011	0.0860	0.0258	0.0439	0.0596	0.0232				-0.0228			77.17	0.035
	(-1.20)	(2.96)	(0.43)	(1.53)	(1.93)	(0.73)				(-0.78)				
	{-1.26}	{3.20}	{0.43}	{1.98}	{1.88}	{0.81}				{-0.86}				
Model 9	-0.0002		-0.0244	0.0195	0.0570	0.0564					-0.0009		39.77	0.054
	(-0.16)		(-0.38)	(0.65)	(1.86)	(1.65)					(-0.40)			
	{-0.08}		{-0.22}	{0.61}	{1.59}	{1.68}					{-0.14}			
Model 10	-0.0010	0.0880	0.0182	0.0459	0.0615	0.0237					0.0004		75.99	0.034
	(-0.99)	(3.03)	(0.29)	(1.63)	(2.01)	(0.74)					(0.17)			
	{-0.87}	{2.81}	{0.27}	{1.70}	{1.97}	{0.81}					{0.13}			
Model 11	-0.0019		0.0667	0.0391	0.0655	0.0387						-0.0142	60.36	0.042
	(-1.24)		(0.76)	(1.33)	(1.99)	(1.14)						(-1.72)		
	{-1.33}		{0.80}	{1.29}	{1.91}	{1.15}						{-1.80}		
Model 12	-0.0015	0.0821	0.0476	0.0474	0.0623	0.0235						-0.0046	77.20	0.034
	(-1.25)	(2.94)	(0.65)	(1.67)	(2.02)	(0.73)						(-0.72)		
	{-1.32}	{2.65}	{0.65}	{1.74}	{1.98}	{0.79}						{-0.67}		
Model 13	-0.0016		0.0509	0.0445	0.0533	0.0219	0.0529	0.2040	-0.0384	0.0110	-0.0024	-0.0050	74.64	0.034
	(-1.15)		(0.63)	(1.58)	(1.90)	(0.70)	(0.65)	(1.69)	(-0.67)	(0.29)	(-0.80)	(-0.58)		
	(-0.84)		(0.47)	(1.67)	(1.86)	(0.74)	(0.48)	(1.27)	(-0.49)	(0.20)	(-0.47)	(-0.36)		
Model 14	-0.0019	0.0774	0.0659	0.0473	0.0535	0.0175	0.0865	0.0876	0.0017	-0.0137	0.0001	-0.0030	81.38	0.031
	(-1.44)	(2.98)	(0.86)	(1.69)	(1.92)	(0.56)	(1.12)	(0.66)	(0.03)	(-0.36)	(0.02)	(-0.38)		
	(-1.12)	(2.97)	(0.67)	(1.72)	(1.93)	(0.59)	(0.90)	(0.56)	(0.02)	(-0.31)	(0.01)	(-0.24)		

Table 7. Commodity portfolio performance in high- versus low-VIX periods

This table reports in Panel A the annualized mean excess return and annualized alpha of the CFEAR portfolio in high and low VIX weeks with significance *t*-statistics in parentheses. Alpha is measured relative to the traditional pricing model with AVG, basis, hedging pressure and momentum risk factors. The last row reports *t*-statistics for the significance of the high- versus low-VIX premium and alpha differentials. $\delta_{VIX}(\delta_{VIX}^{F})$ are the VIX slopes in Equation (8) without (with) the traditional risk factors. Panel B reports the same analysis for these risk factors. The last two columns show the mean excess return, separately, of the long and short legs of the portfolios and corresponding *t*-statistics. Newey-West standard errors are used throughout. The time period is January 2005 (week 1) to December 2018 (week 4).

	Excess return	Alpha	δ_{VIX}	δ_{VIX}^{F}	Q1 (long)	Q5 (short)
Panel A: CFEAR portfolio						
I. High	0.1581	0.1531	0.0009	0.0010	0.0082	-0.3079
	(3.70)	(3.83)	(1.94)	(2.53)	(0.09)	(-3.01)
II. Low	0.0410	0.0377			0.0793	-0.0027
	(1.50)	(1.47)			(1.77)	(-0.06)
t-stat (H_0: diff=0)	2.3332	2.4519			-0.6837	-2.7345
Panel B: Traditional benchmarks						
Basis portfolio						
I. High	0.0223		-0.0001		-0.0460	-0.0906
	(0.45)		(-0.15)		(-0.40)	(-0.94)
II. Low	0.0418				0.0166	-0.0670
	(1.32)				(0.28)	(-1.30)
t-stat (H_0: diff=0)	-0.3345				-0.4908	-0.2145
Hedging pressure portfolio						
I. High	0.1207		0.0008		0.0494	-0.1921
	(2.43)		(1.14)		(0.42)	(-2.12)
II. Low	0.0283				-0.0179	-0.0744
	(1.00)				(-0.35)	(-1.60)
t-stat (H_0: diff=0)	1.6376				0.5228	-1.1450
Momentum portfolio						
I. High	-0.0102		-0.0008		-0.0445	-0.0242
	(-0.17)		(-1.00)		(-0.36)	(-0.23)
II. Low	0.0274				-0.0102	-0.0650
	(0.82)				(-0.18)	(-1.11)
t-stat (H_0: diff=0)	-0.5333				-0.2517	0.3311

Table 8. Robustness tests: Alternative CFEAR signal construction methods

The table summarizes the performance and risks of the long-short CFEAR portfolio based on a trading signal constructed using the approach described in Section 2.2 without filtering the keywords, by averaging the significant betas from Equation (1), by restricting the Google searches to a US origin, and by winsorizing or deseasonalizing the search data $\Delta S_{j,t}$. The significance of the mean excess return is tested with Newey-West t-statistics (in parentheses). Panel B reports the annualized CFEAR risk price from cross-sectional regressions with the AVG, basis, hedging pressure and momentum factors for the same 26 commodity portfolios as in Table 5, Panel A, and the increase in adjusted-R^2 when the CFEAR factor is added. Shanken (1992) t-statistics are shown in parentheses and Kan et al. (2013) t-statistics in curly brackets. The time period is January 2005 (week 1) to December 2018 (week 4).

	(1)	(2)	(3)	(4)	(5)
	w/o hazard filtering	**Mean (betas)**	**US searches**	**Winsorized searches**	**Deseasonalized searches**
Panel A: Summary statistics					
Mean	0.0928	0.0597	0.0495	0.0795	0.0647
	(3.35)	(2.50)	(2.23)	(2.96)	(2.66)
StDev	0.1030	0.0922	0.0833	0.1034	0.0964
Downside volatility (0%)	0.0312	0.0259	0.0244	0.0315	0.0282
Skewness	-0.1307	0.1725	0.0088	-0.0990	-0.0615
Excess Kurtosis	0.4012	0.5568	0.3605	0.6454	0.3550
JB normality test p -value	0.0320	0.0047	0.1246	0.0038	0.1055
99% VaR (Cornish-Fisher)	0.0341	0.0285	0.0268	0.0350	0.0315
% of positive months	57%	52%	54%	57%	55%
Maximum drawdown	-0.1882	-0.2040	-0.1682	-0.1432	-0.1566
Sharpe ratio	0.9011	0.6473	0.5949	0.7695	0.6711
Panel B: Cross-sectional asset pricing tests					
λ_{CFEAR}	0.0938	0.1145	0.0849	0.0913	0.1183
	(2.52)	(3.09)	(2.30)	(2.52)	(3.01)
	{2.43}	{2.45}	{2.25}	{2.39}	{2.76}
ΔAdj.-R^2 (%)	33.25	22.59	25.02	33.97	29.12

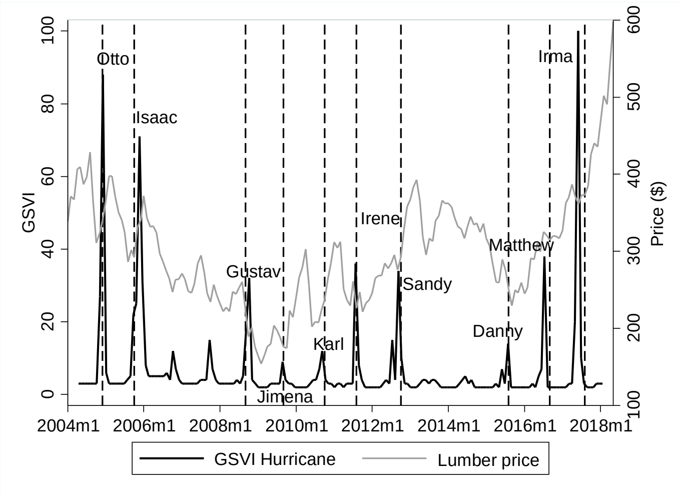
Table 9. Placebo test

The table reports summary statistics for the long-short hazard-fear based portfolio with the trading signal obtained according to the methodology described in Section 2.2 but using instead only the 123 search terms in the weather (WE) and agricultural diseases (DI) categories (c.f. Table 1). The cross sections are as detailed in Table 2 (28 commodity futures) and in the online Annex A.8 (40 equity index futures, 13 fixed income futures, 19 currency futures). The time period is January 2005 (week 1) to December 2018 (week 4).

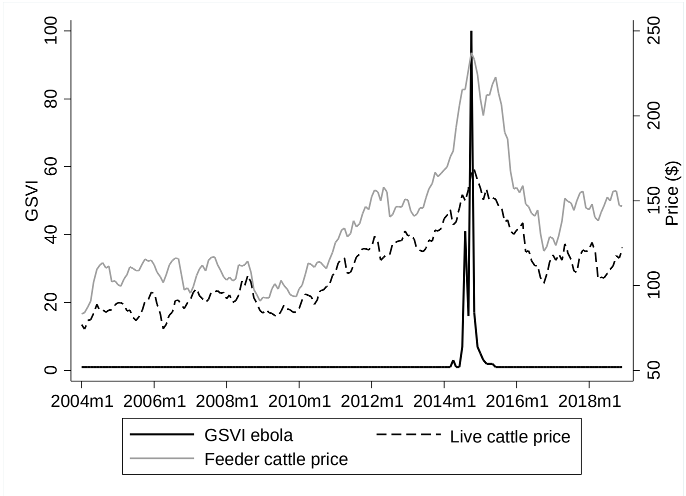
	Commodity	Equity index	Fixed income	Currency
Mean	0.0663	0.0014	0.0067	0.0043
	(2.82)	(0.15)	(0.98)	(0.46)
StDev	0.0939	0.0406	0.0271	0.0390
Downside volatility (0%)	0.0268	0.0137	0.0091	0.0140
Skewness	0.0862	-0.2060	-0.1551	-0.1010
	(0.95)	(-2.27)	(-1.71)	(-1.12)
Excess Kurtosis	0.3447	2.5047	2.3857	5.6401
	(1.90)	(13.82)	(13.17)	(31.13)
JB normality test *p* -value	0.0946	0.0010	0.0010	0.0010
99% VaR (Cornish-Fisher)	0.0292	0.0171	0.0111	0.0200
% of positive months	54%	50%	51%	52%
Maximum drawdown	-0.1300	-0.1374	-0.0725	-0.1435
Sharpe ratio	0.7054	0.0355	0.2475	0.1107
Sortino ratio	2.4767	0.1049	0.7343	0.3090
Omega ratio	1.2854	1.0135	1.1004	1.0448
CER (power utility)	0.0442	-0.0027	0.0049	0.0005

Figure 1. Google searches and commodity prices.
The graphs plots the evolution of monthly intensity of the Google Search Volume Index (GSVI; denoted $S_{j,t}$) by a hazard keyword, alongside the monthly average of the daily commodity futures price.

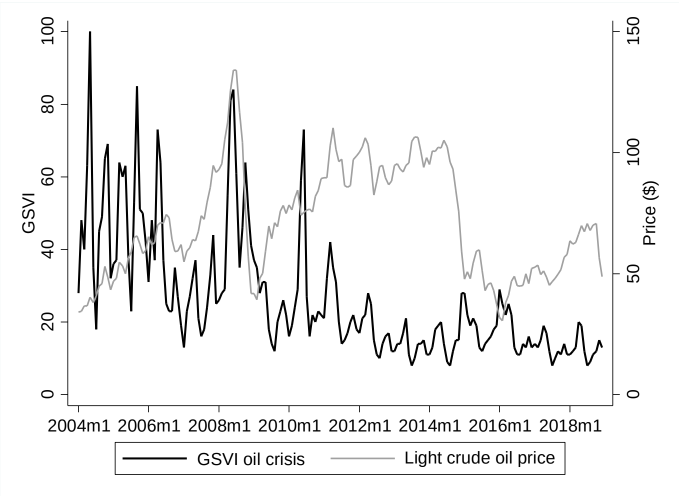
Panel A: *Hurricane* (WE) searches vs lumber price



Panel B: *Ebola* (DI) searches vs feeder/live cattle prices



Panel C: *Oil crisis* (GP) searches vs light crude oil price



Panel D: *Unemployment* (EC) searches vs natural gas price

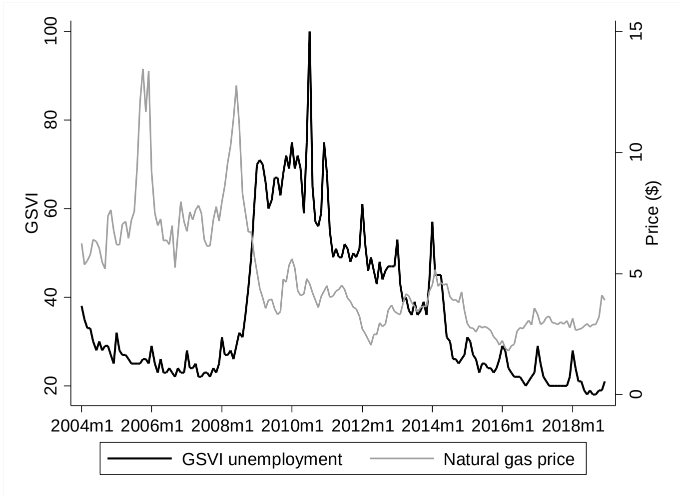


Figure 2. Composition of Q1 and Q5 portfolios in hazard-fear commodity sorts

This graph plots the percentage of sample weeks from January 2005 (week 1) to December 2018 (week 4) when each of the *N*=28 commodities is within the top *N*/5 commodities or bottom *N*/5 commodities ranked on the CFEAR signal. The results are organized by sector.

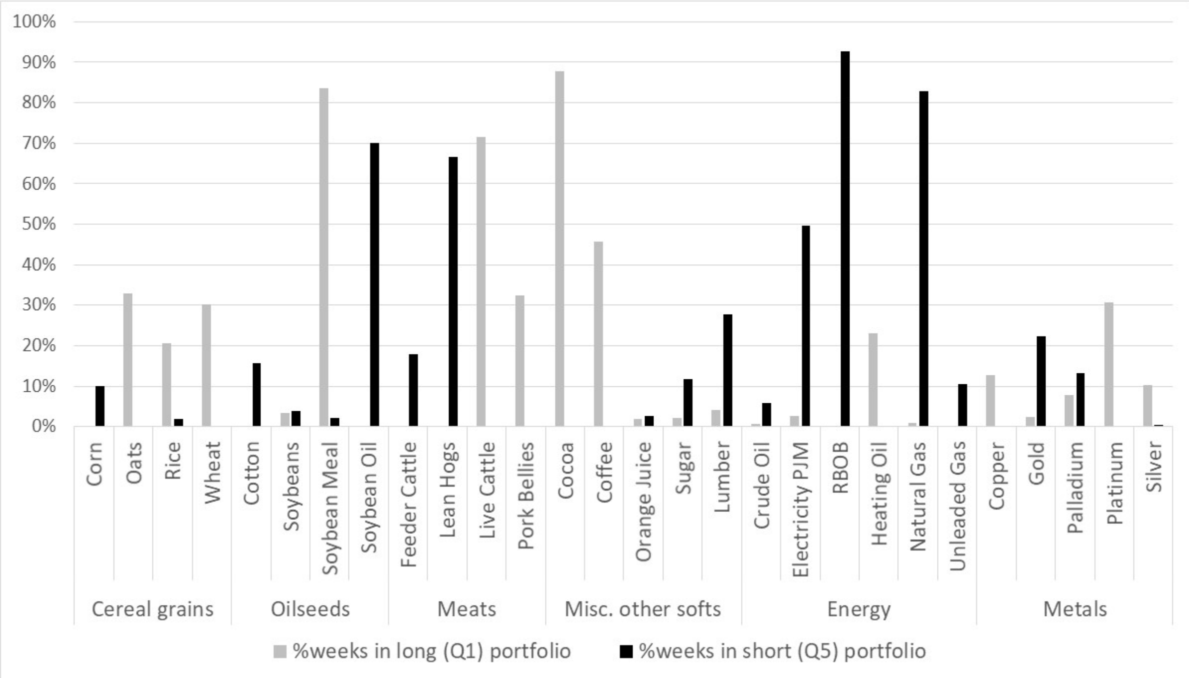


Figure 3. Future value of $1 invested in commodity portfolios

The graph shows the evolution of $1 invested in the long-only portfolio that equally weights all commodities (AVG), and the long-short basis, momentum (Mom), hedging pressure (HP) and CFEAR portfolios. The graph is based on the total returns (excess returns plus the 1-month U.S. Treasury bill rate) and the portfolio rebalancing frequency is weekly.

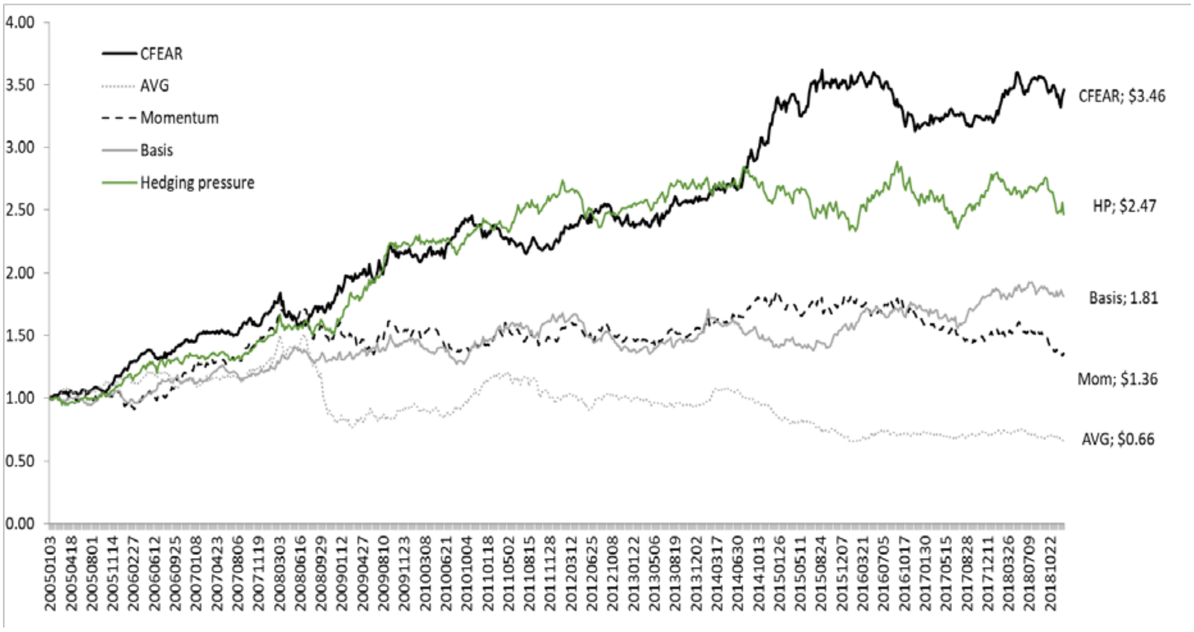
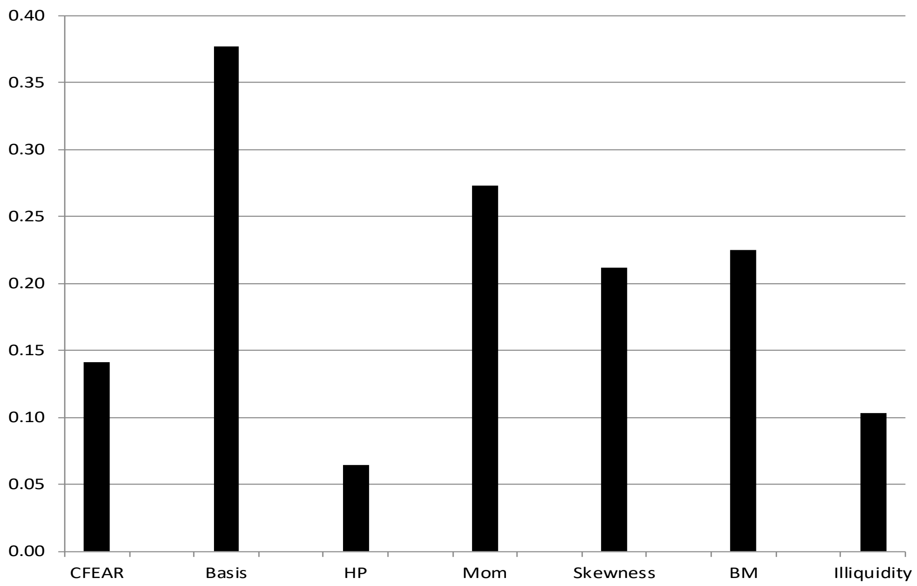


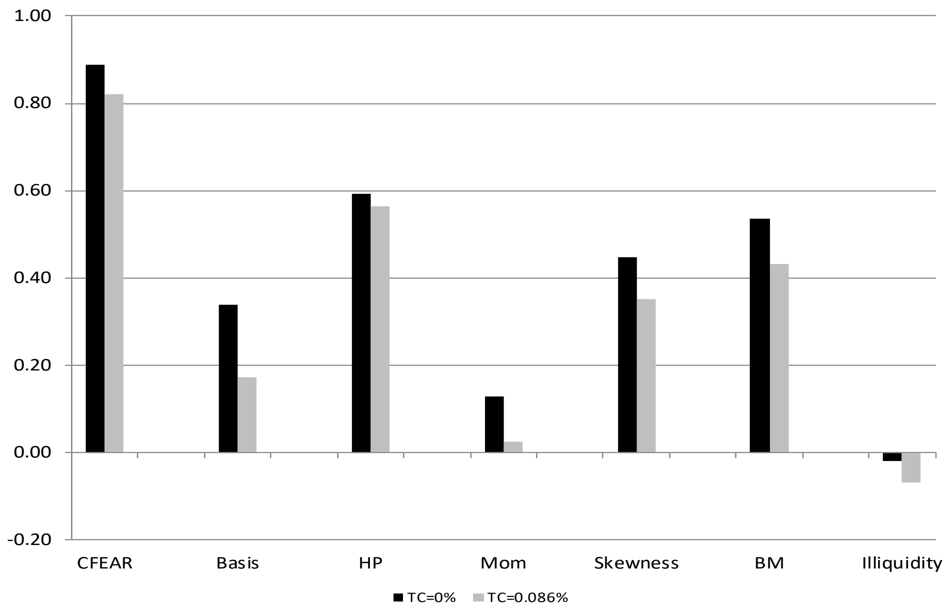
Figure 4. Turnover and net performance of commodity portfolios

Panel A plots the turnover of each of the long-short commodity portfolios formed according to the CFEAR, basis, hedging pressure (HP), momentum (Mom), skewness, basis-momentum (BM) and illiquidity signals. Panel B plots the Sharpe ratios of each of the portfolios before and after proportional trading costs of 8.6 bps (Marshall et al., 2012).

Panel A: Turnover



Panel B: Sharpe ratio



ONLINE ANNEX

Fear of Hazards in Commodity Futures Markets

September 11, 2019

Table A.1 Characteristics of the CFEAR-sorted commodity quintiles

The table reports the average of each commodity characteristic across time and constituents of the CFEAR-sorted quintiles. The last column reports the mean of the differential average Q1-Q5 characteristic. Newey-West robust significance *t*-statistics are shown in parentheses. The observations are from January 2004 (week 1) to December 2018 (week 4).

	CFEAR					
Signal	**Long (Q1)**	**Q2**	**Q3**	**Q4**	**Short (Q5)**	**Q1-Q5**
CFEAR	-0.0419	-0.0196	-0.0064	0.0083	0.0543	-0.0962
	(-20.53)	(-14.72)	(-8.59)	(14.50)	(21.42)	(-25.04)
Roll-yield	-0.0052	-0.0121	-0.0081	-0.0068	-0.0141	0.0089
	(-4.31)	(-14.05)	(-7.21)	(-7.19)	(-6.13)	(3.51)
Hedging pressure	0.3110	0.2542	0.3054	0.3088	0.2193	0.0917
	(32.51)	(17.00)	(23.91)	(29.41)	(27.37)	(8.46)
Momentum	0.0229	-0.0097	-0.0091	-0.0197	-0.1231	0.1460
	(1.48)	(-0.52)	(-0.47)	(-1.21)	(-5.81)	(8.62)
Skewness	0.0055	0.0019	0.1268	0.1314	0.0327	-0.0273
	(0.26)	(0.08)	(5.92)	(4.84)	(2.33)	(-1.31)
Basis-Mom	0.0002	-0.0001	-0.0001	-0.0002	-0.0003	0.0006
	(3.47)	(-1.17)	(-1.35)	(-4.91)	(-5.62)	(6.20)
Illiquidity	3.5675	2.2553	7.4814	10.5769	36.2314	-32.6640
	(3.83)	(3.99)	(2.61)	(3.15)	(4.41)	(-3.93)
Average Variance (22-day)	0.0510	0.0226	0.0596	0.0506	0.1377	-0.0867
	(3.81)	(6.64)	(4.40)	(3.77)	(8.95)	(-5.37)

Table A.2 Portfolio pricing tests based on weekly cross-sectional regressions

The table presents cross-sectional pricing tests using the four-factor model of Fernandez-Perez et al. (2018) and Bianchi et al. (2015) inter alia with the average commodity factor (AVG), and the basis, hedging pressure and momentum (Mom) factors. The test assets are the 26 portfolios (quintiles from sorting the 28 commodity futures by the roll-yield, hedging pressure, momentum and CFEAR signals, and the six sub-sector portfolios). We report the (annualized) average prices of risk from weekly cross-sectional regressions on full-sample betas with Fama-MacBeth (1973) *t*-statistics in curly brackets and Shanken (1992) *t*-statistics in parentheses. The time period is January 2005 (week 1) to December 2018 (week 4).

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	adj.-R^2 (%)	MAPE (%)
Model 1	-0.0008	0.0754					8.80	1.230
	{-1.07}	{2.76}						
	(-1.03)	(2.65)						
Model 2	-0.0010		0.0073				8.02	1.244
	{-1.22}		{0.15}					
	(-1.22)		(0.15)					
Model 3	-0.0009			0.0252			7.81	1.242
	{-1.24}			{0.86}				
	(-1.23)			(0.86)				
Model 4	-0.0009				0.0451		9.13	1.222
	{-1.33}				{1.62}			
	(-1.31)				(1.60)			
Model 5	-0.0008					0.0371	10.35	1.215
	{-1.15}					{1.17}		
	(-1.14)					(1.16)		
Model 6	-0.0004		-0.0226	0.0192	0.0538	0.0368	25.25	1.028
	{-0.47}		{-0.43}	{0.68}	{1.88}	{1.15}		
	(-0.45)		(-0.41)	(0.66)	(1.83)	(1.12)		
Model 7	-0.0007	0.0774	-0.0087	0.0355	0.0488	0.0260	30.04	0.963
	{-0.76}	{2.95}	{-0.16}	{1.29}	{1.74}	{0.86}		
	(-0.71)	(2.75)	(-0.15)	(1.20)	(1.63)	(0.80)		

Table A.3 Skewness, basis-momentum and illiquidity risk factors

The table summarizes the performance and risks of the long-short skewness, basis-momentum (BM) and illiquidity portfolios. Newey-West robust h.a.c. *t*-statistics are shown in parentheses. CER stands for certainty equivalent return based on a power utility function. Panel B reports the pairwise correlations (with significance *p*-values in curly brackets) between the CFEAR portfolio and the skewness, basis-momentum and illiquidity portfolios. The time period is January 2005 (week 1) to December 2018 (week 4).

	Skewness	**BM**	**Illiquidity**
Panel A: Summary statistics			
Mean	0.0444	0.0519	-0.0019
	(1.62)	(1.93)	(-0.07)
StDev	0.0991	0.0967	0.0963
Downside volatility (0%)	0.0266	0.0283	0.0292
Skewness	0.2256	-0.0180	0.0084
	(2.49)	(-0.20)	(0.09)
Excess Kurtosis	0.3258	0.6157	0.9454
	(1.80)	(3.40)	(5.22)
JB normality test *p* -value	0.0134	0.0071	0.0010
AC(1)	-0.0015	0.0133	0.0673
99% VaR (Cornish-Fisher)	0.0296	0.0323	0.0340
% of positive months	51%	52.8%	48%
Maximum drawdown	-0.2955	-0.2376	-0.5200
Sharpe ratio	0.4481	0.5368	-0.0194
Sortino ratio	1.6714	1.8340	-0.0640
Omega ratio	1.1707	1.2097	0.9930
CER (power utility)	0.0200	0.0285	-0.0251
Panel B: Correlation structure			
CFEAR	0.06	0.22	-0.25
	{0.11}	{0.00}	{0.00}

Table A.4 CFEAR pricing ability with skewness, basis-momentum, illiquidity and volatility factors: 28 individual commodities

The table reports the outcome of cross-sectional pricing tests using the 28 individual commodities as test assets. We report the (annualized) average prices of risk obtained in sequential (weekly) cross-sectional regressions on sequential betas with Fama-MacBeth (1973) *t*-statistics in curly brackets and Shanken (1992) corrected *t*-statistics in parentheses. The time period is January 2005 (week 1) to December 2018 (week 4).

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Skewness	BM	Illiquidity	ΔTED	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 1	0.0006		-0.0735	-0.0072	0.0506	0.0170	0.0735						22.18	2.115
	{0.69}		{-1.50}	{-0.19}	{1.74}	{0.45}	{2.17}							
	(0.64)		(-1.39)	(-0.17)	(1.61)	(0.42)	(2.01)							
Model 2	0.0005	0.1020	-0.0711	0.0119	0.0415	-0.0203	0.0738						25.67	2.007
	{0.60}	{3.64}	{-1.46}	{0.31}	{1.44}	{-0.52}	{2.17}							
	(0.52)	(3.16)	(-1.27)	(0.27)	(1.25)	(-0.45)	(1.89)							
Model 3	-0.0001		-0.0398	-0.0131	0.0596	0.0136		0.0315					22.83	2.109
	{-0.10}		{-0.82}	{-0.33}	{2.00}	{0.35}		{0.95}						
	(-0.10)		(-0.78)	(-0.31)	(1.90)	(0.33)		(0.91)						
Model 4	-0.0002	0.0856	-0.0359	0.0158	0.0547	-0.0113		0.0318					26.05	2.009
	{-0.24}	{3.04}	{-0.75}	{0.40}	{1.85}	{-0.29}		{0.95}						
	(-0.22)	(2.77)	(-0.68)	(0.36)	(1.69)	(-0.27)		(0.87)						
Model 5	0.0000		-0.0427	0.0216	0.0567	0.0231			-0.0198				22.37	2.105
	{-0.04}		{-0.92}	{0.56}	{1.95}	{0.61}			{-0.69}					
	(-0.04)		(-0.88)	(0.54)	(1.88)	(0.58)			(-0.66)					
Model 6	-0.0002	0.1069	-0.0349	0.0330	0.0462	-0.0046			-0.0029				25.84	2.001
	{-0.28}	{3.78}	{-0.74}	{0.86}	{1.58}	{-0.12}			{-0.10}					
	(-0.25)	(3.36)	(-0.66)	(0.76)	(1.40)	(-0.11)			(-0.09)					
Model 7	0.0005		-0.0701	0.0053	0.0620	0.0446				0.0166			21.05	2.134
	{0.64}		{-1.45}	{0.14}	{2.14}	{1.21}				{1.52}				
	(0.58)		(-1.32)	(0.12)	(1.93)	(1.10)				(1.38)				

(*Cont.*) Table A.4 CFEAR pricing ability with skewness, basis-momentum, illiquidity and volatility factors: 28 individual commodities

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Skewness	BM	Illiquidity	ΔTED	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 8	0.0005	0.1066	-0.0698	0.0284	0.0523	0.0032				0.0085			24.80	2.027
	{0.60}	{3.79}	{-1.47}	{0.73}	{1.80}	{0.08}				{0.79}				
	(0.53)	(3.32)	(-1.29)	(0.64)	(1.58)	(0.07)				(0.69)				
Model 9	0.0002		-0.0550	0.0092	0.0592	0.0372					0.0004		21.31	2.131
	{0.26}		{-1.17}	{0.24}	{2.03}	{0.99}					{0.87}			
	(0.24)		(-1.10)	(0.22)	(1.91)	(0.93)					(0.82)			
Model 10	0.0000	0.1083	-0.0484	0.0329	0.0533	-0.0018					0.0005		25.05	2.022
	{0.06}	{3.86}	{-1.02}	{0.84}	{1.84}	{-0.05}					{1.12}			
	(0.05)	(3.33)	(-0.88)	(0.73)	(1.59)	(-0.04)					(0.96)			
Model 11	0.0001		-0.0481	-0.0030	0.0544	0.0349						-0.0009	21.54	2.127
	{0.07}		{-1.02}	{-0.08}	{1.86}	{0.93}						{-0.69}		
	(0.07)		(-0.98)	(-0.07)	(1.77)	(0.89)						(-0.66)		
Model 12	-0.0001	0.1082	-0.0422	0.0222	0.0490	-0.0031						0.0001	25.11	2.021
	{-0.11}	{3.83}	{-0.90}	{0.56}	{1.68}	{-0.08}						{0.09}		
	(-0.09)	(3.41)	(-0.80)	(0.50)	(1.50)	(-0.07)						(0.08)		
Model 13	0.0002		-0.0536	0.0255	0.0462	0.0179	0.0594	0.0631	0.0014	0.0111	0.0001	-0.0005	33.87	1.690
	{0.21}		{-1.03}	{0.57}	{1.55}	{0.42}	{1.55}	{1.77}	{0.04}	{0.91}	{0.12}	{-0.37}		
	(0.20)		(-0.96)	(0.53)	(1.46)	(0.39)	(1.45)	(1.66)	(0.04)	(0.86)	(0.12)	(-0.35)		
Model 14	0.0001	0.1012	-0.0495	0.0403	0.0479	0.0181	0.0636	0.0682	0.0092	0.0060	0.0002	0.0000	36.27	1.592
	{0.10}	{3.42}	{-0.94}	{0.88}	{1.61}	{0.40}	{1.67}	{1.88}	{0.27}	{0.49}	{0.24}	{-0.02}		
	(0.09)	(3.09)	(-0.85)	(0.80)	(1.46)	(0.36)	(1.52)	(1.70)	(0.25)	(0.44)	(0.22)	(-0.02)		

Table A.5 CFEAR factor pricing with skewness, basis-momentum, illiquidity and volatility risk factors: 41 commodity portfolios.

The table reports the outcome of cross-sectional pricing tests using N=41 commodity portfolios as test assets. The portfolios are defined as the quintiles sorted on the CFEAR, basis, hedging pressure, momentum, skewness, basis-momentum and Amihud's (2002) illiquidity signals, and the 6 sectoral portfolios. We report the (annualized) prices of risk from a cross-sectional regression of the average portfolio excess returns on the full-sample betas with Shanken (1992) t-statistics in parentheses corrected for errors-in-variables, and Kan et al. (2013) t-statistics in curly brackets additionally corrected for model misspecification and heteroscedasticity. The time period is January 2005 (week 1) to December 2018 (week 5).

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Skewness	BM	Iliquidity	ΔTED	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0003		-0.0166	0.0288	0.0406	0.0618	0.0537						40.51	0.049
	(-0.33)		(-0.28)	(0.93)	(1.34)	(1.76)	(1.80)							
	{-0.34}		{-0.25}	{0.90}	{1.34}	{1.75}	{1.58}							
Model 2	-0.0014	0.0902	0.0422	0.0532	0.0447	0.0282	0.0518						69.61	0.038
	(-1.57)	(3.00)	(0.71)	(1.82)	(1.48)	(0.86)	(1.73)							
	{-1.58}	{2.93}	{0.69}	{1.92}	{1.50}	{0.91}	{1.69}							
Model 3	-0.0005		-0.0048	0.0320	0.0550	0.0387		0.0824					51.11	0.045
	(-0.58)		(-0.08)	(1.04)	(1.72)	(1.17)		(2.78)						
	{-0.61}		{-0.07}	{1.03}	{1.67}	{1.20}		{2.60}						
Model 4	-0.0014	0.0849	0.0390	0.0532	0.0550	0.0207		0.0585					70.66	0.036
	(-1.50)	(2.90)	(0.65)	(1.81)	(1.72)	(0.64)		(2.12)						
	{-1.50}	{2.78}	{0.64}	{1.98}	{1.71}	{0.69}		{1.96}						
Model 5	-0.0002		-0.0233	0.0451	0.0521	0.0489			-0.0426				42.53	0.049
	(-0.20)		(-0.39)	(1.54)	(1.64)	(1.50)			(-1.41)					
	{-0.21}		{-0.37}	{1.62}	{1.56}	{1.53}			{-1.19}					
Model 6	-0.0013	0.0925	0.0360	0.0572	0.0545	0.0296			-0.0150				66.97	0.039
	(-1.46)	(3.32)	(0.61)	(1.98)	(1.71)	(0.92)			(-0.52)					
	{-1.46}	{3.43}	{0.60}	{2.20}	{1.70}	{0.98}			{-0.46}					
Model 7	-0.0003		-0.0176	0.0331	0.0549	0.0606				-0.0442			42.51	0.049
	(-0.29)		(-0.28)	(1.06)	(1.70)	(1.71)				(-1.87)				
	{-0.30}		{-0.25}	{1.26}	{1.62}	{1.65}				{-1.83}				

(*Cont.*) Table A.5 CFEAR factor pricing with skewness, basis-momentum, illiquidity and volatility risk factors: 41 commodity portfolios.

	Constant	CFEAR	AVG	Basis	Hedging pressure	Mom	Skewness	BM	Iliquidity	ΔTED	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 8	-0.0014	0.0899	0.0384	0.0559	0.0550	0.0290				-0.0272			69.23	0.038
	(-1.46)	(2.99)	(0.63)	(1.90)	(1.71)	(0.88)				(-1.23)				
	{-1.43}	{2.89}	{0.63}	{2.02}	{1.69}	{0.92}				{-1.07}				
Model 9	-0.0002		-0.0233	0.0323	0.0535	0.0656					-0.0004		35.65	0.051
	(-0.19)		(-0.38)	(1.05)	(1.68)	(1.85)					(-0.27)			
	{-0.15}		{-0.30}	{1.04}	{1.59}	{1.81}					{-0.14}			
Model 10	-0.0013	0.0923	0.0343	0.0576	0.0546	0.0295					0.0001		66.99	0.039
	(-1.42)	(3.09)	(0.58)	(1.98)	(1.71)	(0.90)					(0.04)			
	{-1.34}	{2.97}	{0.53}	{2.17}	{1.70}	{0.94}					{0.03}			
Model 11	-0.0009		0.0158	0.0409	0.0575	0.0567						-0.0060	39.85	0.049
	(-0.86)		(0.24)	(1.37)	(1.79)	(1.64)						(-1.25)		
	{-0.77}		{0.20}	{1.29}	{1.67}	{1.54}						{-1.14}		
Model 12	-0.0012	0.0949	0.0269	0.0562	0.0535	0.0304						0.0014	67.24	0.039
	(-1.10)	(3.24)	(0.41)	(1.93)	(1.69)	(0.93)						(0.33)		
	{-1.11}	{3.02}	{0.40}	{2.07}	{1.66}	{0.98}						{0.27}		
Model 13	-0.0010		0.0175	0.0357	0.0506	0.0313	0.0460	0.0663	-0.0224	-0.0387	-0.0004	-0.0021	59.58	0.040
	(-0.95)		(0.27)	(1.25)	(1.70)	(0.98)	(1.56)	(2.48)	(-0.79)	(-1.72)	(-0.24)	(-0.45)		
	{-1.08}		{0.23}	{1.36}	{1.82}	{1.10}	{1.33}	{2.65}	{-0.63}	{-1.75}	{-0.21}	{-0.38}		
Model 14	-0.0012	0.0871	0.0310	0.0459	0.0510	0.0220	0.0492	0.0537	-0.0058	-0.0307	0.0009	0.0026	76.16	0.032
	(-1.20)	(3.24)	(0.48)	(1.62)	(1.71)	(0.69)	(1.67)	(2.04)	(-0.21)	(-1.36)	(0.52)	(0.58)		
	{-1.22}	{3.15}	{0.45}	{1.67}	{1.77}	{0.74}	{1.68}	{2.01}	{-0.18}	{-1.28}	{0.38}	{0.46}		

Table A.6 Robustness tests: Alternative CFEAR portfolio construction methods

The table summarizes in Panel A the CFEAR factor obtained through alternative long-short portfolio construction methods where: (1) the lookback period is a fixed-length rolling window of 10 years ($L = 520$ weeks); (2) the long Q1 and short Q5 quintile constituents are weighted by the strength of the standardized signals; (3)-(6) the long Q1 and short Q5 portfolios include $N/2$ commodities each which are weighted equally, by standardized rankings, by standardized signals, and by winsorized and standardized signals; (7) at each portfolio formation time we consider only the $0.8N$ of the commodities with the largest open interest on the prior week. Panel B reports the price of the CFEAR factor in the model with AVG, basis, hedging pressure, and momentum factors for the same 26 commodity portfolios as in Table 5, Panel A, with Shanken (1992) t-statistics in parentheses and Kan et al. (2013) t-statistics in curly brackets. The last row of Panel B reports the increase in adj.-R^2 when the CFEAR factor is added. The portfolio returns are from January 2005 (week 1) to December 2018 (week 5), except in column (1) which are from January 2014 (week 1).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Rolling windows (L=10 years)	Quintiles Std. signals	Binary weights	Std. rankings	Std. signals	Winsor. Std. signals	80% most liquid comm
Panel A: Summary statistics							
Mean	0.0633	0.0775	0.0435	0.0601	0.0575	0.0596	0.1017
	(1.78)	(2.77)	(3.09)	(3.60)	(2.55)	(2.72)	(3.84)
StDev	0.0876	0.1056	0.0561	0.0669	0.0861	0.0845	0.1005
Downside volatility (0%)	0.0277	0.0312	0.0169	0.0191	0.0248	0.0244	0.0289
Skewness	-0.2332	0.0290	-0.0203	0.0658	0.0889	0.0851	0.1047
Excess Kurtosis	0.6623	0.8056	0.7328	0.3208	0.7676	0.7192	0.6414
JB normality test p-value	0.0306	0.0010	0.0021	0.1455	0.0012	0.0020	0.0038
99% VaR (Cornish-Fisher)	0.0308	0.0350	0.0187	0.0206	0.0280	0.0273	0.0314
% of positive months	55%	54%	54%	53%	52%	52%	58%
Maximum drawdown	-0.1066	-0.1554	-0.0997	-0.0886	-0.1283	-0.1279	-0.1388
Sharpe ratio	0.7228	0.7342	0.7750	0.8996	0.6675	0.7060	1.0112
Panel B: Cross-sectional asset pricing tests							
λ_{CFEAR}	0.0706	0.0960	0.0481	0.0578	0.0732	0.0719	0.1024
	(1.17)	(2.79)	(2.44)	(2.69)	(2.61)	(2.63)	(2.88)
	{1.30}	{2.66}	{2.42}	{2.65}	{2.46}	{2.48}	{2.68}
ΔAdj.-R^2 (%)	19.66	38.13	28.03	35.11	35.61	35.64	34.77

Table A.7 Long-short portfolios with monthly rebalancing

The table reports the performance and risks of the CFEAR quintiles and long-short portfolio, alongside the benchmarks using end-of-month sorting and one-month holding periods. Q1 (Q5) is the quintile with the most negative (positive) CFEAR characteristic. Newey-West robust h.a.c. *t*-statistics are shown in parentheses. Panel B reports the pairwise correlations among all the tradeable commodity risk factors with significance *p*-values in curly brackets. CER is the certainty equivalent return based on power utility. The time period is January 2005 to December 2018.

	CFEAR								Hedging				
	Long (Q1)	Q2	Q3	Q4	Short (Q5)	Q1-Q5	AVG	Basis	pressure	Mom	Skewness	BM	Illiquidity
Panel A: Summary statistics													
Mean	0.0411	-0.0153	-0.0312	-0.0509	-0.1115	0.0763	-0.0330	0.0516	0.0516	0.0068	0.0457	0.0411	0.0072
	(0.83)	(-0.28)	(-0.55)	(-1.00)	(-1.93)	(3.20)	(-0.72)	(1.62)	(1.99)	(0.24)	(1.97)	(1.36)	(0.24)
StDev	0.1806	0.1868	0.1825	0.1853	0.1732	0.0916	0.1471	0.1030	0.0923	0.1108	0.0961	0.1023	0.1012
Downside volatility (0%)	0.1389	0.1360	0.1496	0.1376	0.1320	0.0571	0.1170	0.0587	0.0516	0.0677	0.0550	0.0712	0.0742
Skewness	-0.7318	-0.4016	-0.8094	-0.6879	-0.6055	-0.1432	-0.8037	0.3772	0.1402	0.2467	0.1845	-0.4079	-0.4276
Excess Kurtosis	2.4650	1.7736	1.0318	3.4902	1.7342	1.6190	3.1259	1.5263	0.3367	0.7557	0.2993	1.3369	1.4942
JB normality test *p*-value	0.0010	0.0013	0.0014	0.0010	0.0010	0.0032	0.0010	0.0027	0.4535	0.0488	0.3922	0.0042	0.0025
99% VaR (Cornish-Fisher)	0.1655	0.1617	0.1562	0.1899	0.1612	0.0678	0.1474	0.0656	0.0568	0.0729	0.0585	0.0815	0.0848
% of positive months	52%	46%	55%	43%	45%	58%	50%	55%	55%	50%	54%	58%	55%
Maximum drawdown	-0.4767	-0.5630	-0.5189	-0.6144	-0.8191	-0.1389	-0.5394	-0.1977	-0.2070	-0.2533	-0.1975	-0.2600	-0.4237
Sharpe ratio	0.2277	-0.0816	-0.1710	-0.2748	-0.6438	0.8329	-0.2244	0.5015	0.5592	0.0618	0.4753	0.4018	0.0714
Sortino ratio	0.2962	-0.1122	-0.2087	-0.3702	-0.8450	1.3361	-0.2822	0.8797	0.9996	0.1011	0.8299	0.5777	0.0974
Omega ratio	1.1937	0.9384	0.8762	0.8048	0.6065	1.8728	0.8357	1.4558	1.5001	1.0480	1.4238	1.3517	1.0567
CER (power utility)	-0.0499	-0.1114	-0.1266	-0.1537	-0.2018	0.0546	-0.0943	0.0257	0.0304	-0.0235	0.0229	0.0143	-0.0191
Panel B: Correlation structure													
AVG						0.14							
						{0.08}							
Basis						-0.07	0.14						
						{0.34}	{0.08}						
Hedging pressure						0.27	0.11	0.17					
						{0.00}	{0.16}	{0.03}					
Momentum						0.31	0.21	0.26	0.41				
						{0.00}	{0.01}	{0.00}	{0.00}				
Skewness						0.06	0.09	0.07	0.49	0.21			
						{0.45}	{0.26}	{0.33}	{0.00}	{0.01}			
BM						0.20	0.12	0.01	0.03	0.35	0.22		
						{0.01}	{0.12}	{0.85}	{0.69}	{0.00}	{0.00}		
Illiquidity						-0.40	0.04	0.13	-0.09	-0.14	-0.08	-0.21	
						{0.00}	{0.58}	{0.09}	{0.23}	{0.06}	{0.28}	{0.01}	

Table A.8 Cross sections of financial futures contracts

The table details the futures contracts employed in the placebo tests of Section 5.4 of the paper. The observation period is January 2004 (week 1) to December 2018 (week 4).

Panel A: Equity index futures (N=40)	Panel B: Fixed Income and interest rates futures (N=13)	Panel C: Currency futures (N=19)
Dow-Jones Industrial Average	1-Month Eurodollar	Australian Dollar
E-mini Dow-Jones Industrial Average	30-Day FED Funds	Brazilian Real
E-mini MSCI EAFE	3-Month Eurodollar	Canadian Dollar
E-mini MSCI Emerging Markets	2-Year U.S. Treasury Note	Chinese Renmimbi
E-mini Russell 2000	3-Year U.S. Treasury Note	Czech Koruna
E-Mini S&P500	5-Year Eurodollar Bundle	Euro
Euro Stoxx 50	5-Year U.S. Treasury Note	Hungarian Forint
MSCI Asia	10-Year U.S. Treasury Note	Israeli Shekel
MSCI Emerging Markets Latin America	30-Year U.S. Treasury Bond	Japanese Yen
MSCI India	Barclays Capital U.S. Aggregate	Korean Won
MSCI Russia	Municipal Bond Index	Mexican Peso
MSCI Taiwan	Ultra 10-Year U.S. Treasury Note	New Zealand Dollar
MSCI Thailand	Ultra Treasury Bond Index	Norwegian Krona
MSCI USA		Polish Zloty
MSCI World		Russian Rouble
Nasdaq 100		South African Rand
Nasdaq Biotechnology		Sterling
Nikkei 225		Swedish Krona
NYSE composite		Swiss Franc
Russell 1000		
Russell 1000 Growth		
Russell 1000 Value		
Russell 2000 Growth		
Russell 2000 Value		
Russell 3000		
S&P Citigroup Growth		
S&P Citigroup Value		
S&P Consumer Discretionary		
S&P Consumer Staples		
S&P Energy		
S&P Finance		
S&P Health		
S&P Industrial		
S&P Information Technology		
S&P Materials		
S&P Small Capitalization		
S&P Utilities		
S&P400 Mid Capitalization		
S&P500		
Value Line		