Hazard Fear in Commodity Markets

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ABSTRACT

We introduce a commodity futures return predictor related to "fear" about weather, disease, geopolitical and economic hazards that distress the commodity supply or demand. Using Google search volume data by 149 hazards as keywords, we define a commodity hazard-fear characteristic that reflects the extent and direction of its past excess returns' comovement with the hazard-fear. Using this characteristic as trading signal in a long-short portfolio framework, we find a sizeable and significant commodity hazard-fear (CFEAR) premium. The CFEAR portfolio returns reflect some compensation for momentum, basis, skewness, basis-momentum, and illiquidity risks, but the risk-adjusted excess returns remain sizeable. Exposure to hazard-fear is strongly priced in the cross-section of individual commodity futures returns and commodity portfolios beyond known risk factors. We identify a significant role for investor sentiment in the CFEAR premia.

[*Word count*: 130]

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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) which contend that the fundamental backwardation-contango cycle, driven by supply and demand shocks, is the key driver of commodity futures prices.

The *theory of storage* explains the basis (or roll yield) – the difference between a spot and the contemporaneous futures price – in terms of interest foregone in storing a commodity (opportunity cost), warehousing costs, and a convenience yield from inventory. With low inventories there is upward pressure on the spot price as the high convenience yield exceeds all other costs and hence, the term structure curve is in backwardation (downward sloped) and the roll yield is positive. The futures price is then expected to increase with maturity; thus, long futures positions are profitable. The opposite setting, called contango (upward sloped curve), is typical of abundant inventories; here the futures price is expected to decrease with maturity and short positions are profitable.

The hedging pressure hypothesis stems from the *normal backwardation* theory of Keynes (1930) and Hicks (1939) which hinges on the interaction of hedgers (commercial traders) and speculators (non-commercial traders). The normal backwardation theory assumes that hedgers are net short, namely, commodity producers are hedging more than commodity consumers. The hedgers’ net short positions are matched off by speculators’ net long positions. Accordingly, futures prices are set low relative to the expected future spot price to entice speculators to take long positions; the subsequent increase in futures prices is interpreted as the “insurance” premium paid by hedgers to speculators. The *hedging pressure* hypothesis extends these ideas by allowing for the possibility of net-long hedging; accordingly, the futures price is set high relative to the expected spot price to entice speculators to take short positions; the subsequent fall in futures prices is the "insurance" premium accrued by short speculators. In sum, hedgers participate in the futures markets to manage the risk of price fluctuations but their risk management would not be possible without the participation of speculators – speculators fulfil the role of balancing the commodity futures market when long and short commercial positions do not match each other.

Building on the above mechanisms, namely, the dynamics of inventories and the inter-play of hedgers and speculators, we hypothesize that hazard fear contains predictive information about commodity futures returns. Admittedly, neither the theory of storage of Kaldor (1939) nor the hedging pressure hypothesis of Cootner (1960) explicitly state that hazard fear matters to commodity futures pricing. However, the fundamental interplay between hedgers and speculators portrayed by the hedging pressure hypothesis allows for a nexus between hazard fear and expected commodity futures returns, while the inherent asymmetry of inventories predicts a stronger hazard-fear effect when the underlying event is supply-reducing (or demand increasing) than vice versa.

Building on ideas from economic psychology, we argue that when economic agents feel "anxious" about a hazard – an event beyond their control that may abruptly alter the natural commodity backwardation-contango cycle – they search for information (Lemieux and Peterson, 2011). It has been shown also that the internet, through search engine tools such as *Google*, particularly, has become a handy way of finding information that market participants trust.[1] We proxy commodity hazard-fear by the volume of Google search queries by keywords representing weather, disease, geopolitical and economic hazards affecting the supply/demand.

Our contributions are threefold. Using *Google Trends* data on search volume by 149 commodity hazard-related keywords, we construct an index as proxy for aggregate commodity-

[1] According to *Smart Insights* (www.smartinsights.com) in 2017 the number of daily searches on Google is 3.5 billion which equates to 1.2 trillion searches per year worldwide and, in terms of search engines, Google dominates averaging a net share of 74.54%.

hazard fear (CFEAR). Instead of using the commodity names as keywords as most papers in the literature, our search terms reflect weather, agricultural disease, geopolitical and economic hazards inducing a shift in the commodity supply and/or demand curve. We obtain a commodity-specific trading signal by measuring the past response of individual commodity futures returns to the hazard fear; namely, using past data we gauge the strength and direction of the co-movement of individual commodity futures excess returns and CFEAR index changes. Ours is the first attempt to construct a commodity-market fear index and to translate it into a commodity-specific hazard fear signal.

Our second contribution is to the commodity risk factor investing literature by conducting time-series tests using various benchmarks in order to test the novel hypothesis that there is a CFEAR effect embedded in commodity futures prices. Specifically, we evaluate the performance of a long-short portfolio obtained by sorting 28 commodities according to the commodity-specific hazard fear signal. Our third and final contribution is to the relatively sparse commodity pricing literature by establishing through cross-sectional tests using a range of commodity portfolios (sorted on characteristics and sectors) or individual commodities that the CFEAR factor captures priced risk over and above that captured by traditional commodity pricing factors. Adding the CFEAR factor to the traditional four-factor model with the AVG, basis, hedging pressure and momentum factors provides a noticeable improvement in the cross-sectional fit.

The long-short CFEAR portfolio construction exercise mimics the decisions of an investor in real time (or in an out-of-sample sense). Specifically, at each portfolio formation time t which is each week-start (Monday end) in our analysis, the representative investor takes short (long) positions in those commodities whose excess returns have positively (negatively) co-moved with the CFEAR index and holds the resulting fully-collateralized long-short portfolio for one week. Repeating this process until the end of the sample period, we appraise the CFEAR-based strategy using a traditional pricing model that uses as risk factors the excess returns of a long-only (weekly rebalanced) portfolio of all commodities, and long-short basis, hedging pressure and momentum portfolios as the relevant risk factors. Employing separately two different sets of test assets (26 commodity portfolios and 28 individual commodities), we assess whether the CFEAR factor can price the cross-section of individual commodity futures returns and commodity futures portfolios over and above what can be regarded as a set of "traditional" commodity risk factors.

Empirically, we find that the long-short CFEAR portfolio captures an economically and statistically significant mean excess return of about 6.96% per annum ($t = 3.00$). The CFEAR premia translates to a Sharpe ratio of 0.7152 that is very attractive compared to the Sharpe ratio of traditional basis, hedging pressure and momentum portfolios over the same sample period. In time-series spanning regressions the CFEAR factor generates large alphas relative to a model with four traditional factors: an average commodity market factor (i.e., return of equal-weighted long-only portfolio of all commodities, AVG), basis factor, hedging pressure (HP) factor, and momentum (Mom) factors. The results from cross-sectional tests suggest that the CFEAR-based factor has significant pricing ability both for individual commodities and commodity portfolios after controlling for the role of the traditional risk factors.

Seeking to ascertain what the CFEAR premium relates to, a further analysis suggests that the CFEAR premia reflects positive exposure to commodity market skewness, but it is not subsumed by this risk. Further, we show that the CFEAR returns increase in lagged volatility and lagged illiquidity suggesting that speculators demand a greater premium to absorb imbalances in the supply and demand of futures contracts driven by hazard-fear when commodity futures markets are highly volatile or illiquid. The findings reveal that the CFEAR premium and alpha are notably higher in periods of bearish (pessimistic) investor sentiment as proxied by the VIX. Overall, we conclude that the CFEAR effect reflects exposure for commodity market risks but this is not the whole story; we identify a significant role for investor sentiment in the CFEAR premium.

Our paper is inspired by a recent literature that underscores the potential of internet search volume data to capture the actively-expressed beliefs and concerns of financial market participants and households (as opposed to indirect proxies such as the amount and tone of news and headlines). It has been shown that Google search queries can predict the mean and/or volatility of returns in equity markets (Da et al., 2011, 2014; Vozlyublennaia, 2015; Dimpfl and Jank, 2016; Ben Rhepael et al., 2017; Dzielinski et al., 2018), foreign exchange rate markets (Smith et al., 2012; Markiewicz et al., 2018), and for credit spreads in sovereign bond markets (Dergiades et al., 2015). Google search data has been found to be a useful out-of-sample predictor of changes in unemployment (see McLaren and Shanbogue, 2011, for the UK, D'Amuri and Marcucci, 2017, for the US and Niesert et al., 2019, for the UK, US, Canada, Germany and Japan) and other macroeconomic variables such as UK house prices (MacKaren and Shanbogue, 2011) and US private consumption (Vosen and Schmidt, 2011) beyond traditional indicators; e.g., internet searches by *Jobseeker's Allowance* are typically made by those who think that they may soon become unemployed.

More related to our study for commodity markets, internet search activity has been shown to contain predictive information for returns in various commodity markets (Han et al., 2017a, 2017b; Guo and Ji, 2013; Ji and Guo, 2015; Vozlyublennaia, 2014).[2] We should note at this point that studies documenting the opposite finding, namely, that commodity returns or their volatility have predictive power for search volume changes, like that of Vozlyublennaia (2014), use commodity names as the Google search keywords (see also Baur and Dimpf (2016) for gold and silver). Stating

[2] Using *WTI crude oil*, *corn price*, *heating oil* and *gold price* as keywords, Ji and Guo (2015) establish a predictive link between Google searches and the subsequent prices of these commodities using weekly data. Han et al., (2017a) show that Google searches by 85 oil-related and real economy-related keywords can predict oil futures prices in- and out-of-sample using weekly and daily data. For 13 commodities, Han et al. (2017b) show that daily Google searches (by the commodity names as keywords (and combinations of them with the words *price*, *futures*, *production* and *supply*) can predict futures prices after controlling for several macroeconomic predictors. Guo and Ji (2013) show that market concerns revealed through Google searches by *Libyan war*, *financial/economic/global crisis*, *economic recession* influence the oil futures volatility. Vozlyublennaia (2014) analyses the link between gold/WTI crude oil index performance and investor attention and finds that commodity excess returns are influenced by search volume changes and vice versa.

that the commodity price evolution can predict the search volume changes when the search terms are instead hazards/catastrophe related would be a far-fetched contention.

Our paper extends a scant literature that using case studies for coffee, corn or natural gas shows that the uncertainty surrounding an impending weather event increases systematically the commodity futures price during the pre-harvest season in the case of coffee and corn and in the run-up to the winter season in the case of natural gas (Di Tomasso and Till, 2000; Till, 2000; Till and Eagleeye, 2006). The commodity futures price is cast as "too high" when an analysis of historical data shows that significant profits can be made from taking short positions during the relevant uncertainty period. Inspired by these isolated case studies and by the extant evidence that search activity conveys market participants' beliefs and concerns, we generalize the notion of "weather fear" to fear about *weather*, *disease*, *geopolitical* and *economic* events as proxied by Google search queries to construct a trading signal for each of 28 commodities.

Our paper speaks to a fast growing empirical literature on risk-factor investing that suggests long-short strategies to capture premia in commodity futures markets. Consistent with the theory of storage of Kaldor (1939), Working (1949) and Brennan (1958), and the hedging pressure theory of Keynes (1930), Hicks (1939) and Cootner (1960), respectively, long-short strategies based on the roll yield, or the net positions of either hedgers (or speculators) relative to their total positions, have been shown to be profitable as they capture fundamental risks related to the inexorable backwardation-contango cycle. Momentum profitability in commodity futures markets has also been linked to the backwardation-contango cycle. In essence, the most backwardated commodity futures contracts, as proxied by high roll-yields, net long speculative positions, and good past performance, outperform the most contangoed futures contracts as proxiec by low roll-yields, net short speculative positions, and poor past performance; see e.g., Basu and Miffre (2013), Erb and Harvey (2006), Gorton and Rouwenhorst (2006) and Miffre and Rallis (2007).

Finally, our work is related to that of Gao and Süss (2015) who establish through univariate and multivariate regression analyses of commodity futures returns on various sentiment candidate proxies that sentiment exposure is present in commodity futures returns. Our focus is instead on hazard fear, and the finding that this is priced in commodity futures markets and that the effect is significantly pronounced when investor sentiment is bearish aligns with their key finding.

The remainder of the paper unfolds as follows. In section 2 we motivate the empirical analysis and formulate testable hypothesis. Section 3 describes the methodology and data, and in Sections 4 and 5 the empirical results are discuss. The paper ends with a summary and conclusions.

2. THEORETICAL MOTIVATION AND TESTABLE PREDICTIONS

The theoretical motivation for this study hinges on the interplay between hedgers and speculators, as contended by the risk transfer or hedging pressure hypothesis, while ascribing also a role to the theory of storage. Let t denote the current time, and $t + T_0$ the approximate date when an imminent hazard is expected to materialize, $E_t\left(S_{i,t+T}\right)$ is the future spot price of commodity i, and $F_{i,t}^T$ the futures price for delivery at time T immediately after the hazard date ($T_0 < T$). Building on the view that the difference between the futures price and the spot price can be decomposed as the expected premium and the expected change in the spot price (Fama and French, 1987)

$$F_{i,t}^T - S_{i,t} = E_t\left[Prem_{i,t}^T\right] + E_t\left[S_{i,t+T} - S_{i,t}\right] \tag{1}$$

since $E_t\left[S_{i,t}\right] = S_{i,t}$, the expected premium is therefore conceptualized as the bias of the futures price as a forecast of the future spot price, namely

$$E_t\left[Prem_{i,t}^T\right] = F_{i,t}^T - E_t\left[S_{i,t+T}\right] \tag{2}$$

Let us consider an impending hazard that, if and when it occurs at $t + T_0$, will drastically reduce the commodity supply and/or increase the commodity demand; e.g. severe *heatwaves* in the U.S. summer time can impair the corn pollination and hence, damage the crops, and simultaneously hike the demand for natural gas for air conditioning.[3] The hazard-fear leads economic agents (who tend to assume the worse) to predict a violent spike in the spot price post-hazard, $E_t(S_{t+T})$ increases, and accordingly this influence their commodity futures positions. Consumers may more long positions, while the producers may decrease their short positions in the hope of selling their commodity produce at a very high price spot at $t + T$. Overall, the hazard fear induces an increase in the net long (or decrease in the net short) positions of hedgers. In order to entice speculators to absorb the latter, the commodity futures prices increases by a large amount so that the futures price is set above the expected future spot price, $F_{i,t}^T > E_t(S_{t+T})$. The difference reflects the hazard fear-driven futures premia that short speculators (long hedgers) expect to earn (pay) for trading in futures markets. Assuming the expected future spot price does not change from t to T, we can rewrite Equation (2) at t=T as $0 = F_{i,T}^T - E_t(S_{t+T})$ which subtracted from (2) implies that $\Delta F_{i,t:t+T}^T = F_{i,t+T}^T$-$F_{i,t}^T < 0,$ the subsequent fall in the commodity futures prices as maturity approaches is the CFEAR premium received by speculators for absorbing the decrease (increase) in hedgers' short (long) positions induced by supply-disrupting-hazard fear.

Likewise, the commodity-hazard fear may be associated with an impending event that shifts down the commodity demand and/or shifts up the commodity supply (e.g., a positive shock to unemployment that shrinks the demand for natural gas or a weather event that boosts an agricultural harvest).[4] In this context, the violent drop in the commodity price that is anticipated induces the commercial participants to take less long (more short) positions in futures. Specifically,

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[3] Based on surveys conducted over 26-years, Goetzmann et al. (2017) find that the subjective probability of a severe, single-day stock market crash is much higher than what the historical probability of such rare events suggests. As Till and Eeagleye (2006) argue agricultural commodity markets tend to assume the worse when it comes to real or perceived threats to the food supply.

[4] Weather events typically disrupt the commodity supply but they can occasionally favour the supply instead. For instance, the timing of El Niño determines whether the impact is positive or negative to coffee supply. The warm weather that El Niño brings in June-August aids the arabica coffee harvest as the crop solidifies and warmer weather protects against the spread of the Roya fungus (which thrives in wetter conditions). However, drier El Niño weather in December-February adversely affects the next arabica crop, helping to support coffee prices as the event continues (see Material Risk Insights www.material-risk.com).

producers take more short positions to hedge their output while the consumers of the commodities may decrease their demand for long positions given the possibility of buying their inputs at a low price spot. The hedgers are more net short (or less net long) and they entice speculators to absorb this change in positions (i.e., to be less net short or more net long) by setting the commodity futures price below the expected future spot price. The subsequent fall in the price of the commodity futures contracts is the CFEAR premium captured by long speculators for accommodating the increase in hedgers' short positions prompted by demand-reducing hazard fear.

Thus we conjecture that taking long positions at each portfolio formation time in the extreme quintile Q1 of futures contracts on the commodities exposed to imminent hazards that are overall mostly demand-reducing (or supply-favouring) hazards is profitable; the hazard fear induces a too low futures price, $F_{Q1,t}^{T} < E_t\left(S_{Q1,t+T}\right)$ which is expected to increase over time enabling a premium for long speculators $\Delta F_{Q1,t:t+T}^{T} = F_{Q1,t+T}^{T}$-$F_{Q1,t}^{T} > 0$ (Hypothesis H_{01}). We conjecture that taking simultaneous short positions in the extreme quintile Q5 of futures contracts on the commodities most threatened by imminent supply-reducing (or demand-increasing) hazards is profitable; the hazard fear inflates the current futures price, $F_{Q2,t}^{T} > E_t\left(S_{Q2,t+T}\right)$, which is expected to decrease enabling a premium for short speculators $\Delta F_{Q5,t:t+T}^{T} = F_{Q5,t+T}^{T}$-$F_{Q5,t}^{T} < 0$ (Hypothesis H_{02}).

Bringing the dynamics of inventories into consideration, the inherent asymmetry of inventories may play a role in the CFEAR premium. Specifically, since inventories can (in principle) increase without bound but cannot decrease below zero, they lend themselves as an easier lever to cushion violent commodity price drops (due to hazards that reduce the demand or favour the supply) than violent price jumps (due to hazards that reduce the supply or increase the demand). Thus, it is plausible that speculators require more compensation to take short positions in commodity futures markets exposed to an imminent price-increasing hazard than to take long positions in commodity futures facing price-reducing hazards. In effect, supply-reducing (or demand-increasing) hazards are more worrisome for economic agents as it then more difficult to entice speculators to take short positions due to the difficulty of using inventories as lever; this is similar to a short-selling constraint, namely, speculators can short-sell but are reluctant to do so which opens the possibility of fear (sentiment)-induced mispricicng in commodity futures. Accordingly, we conjecture that the excess return captured by the short quintile of commodity futures (Q5, as defined above) is larger in magnitude than that captured by the long quintile of commodity futures (Q1, as defined above): $|\Delta F^{T}_{Q5,t:t+T}| > \Delta F^{T}_{Q1,t:t+T}$ (Hypothesis H_{03}).

Finally, we also conjecture that exposure to hazard-fear is able to price the time-series and cross-sectional variation of commodity futures beyond known risk factors; namely, the hazard-fear portfolio attains significant risk-adjusted returns or "alpha" (Hypothesis H04) and is a key priced factor (Hypothesis H05). Specifically, our portfolio analysis of the predictive content of hazard fear takes into consideration the possibility that any hazard-fear premium might be fully explained by the traditional hedging pressure theory – the risk of net supply-demand imbalance among hedgers in the futures contracts induced by fundamental macroeconomic shocks – which splits a futures price into an expected risk premium and a forecast of a future spot price as in Equation (2). We measure the risk-adjusted CFEAR premium as the excess returns that remain after controlling for exposure to hedging pressure and other known risks. Specifically, we control also for hedging pressure, basis and momentum risks, all of which relate to the backwardation-contango cycle, and other risks that relate to imbalances in the supply-demand for futures contracts that materialize when the market clearing ability of speculators is impaired such as illiquidity and volatility risks.

3. EMPIRICAL METHODOLOGY AND DATA

In this section, we begin by discussing the construction of the commodity-hazard fear (CFEAR) index, and the Google search data required. Next, we describe the long-short CFEAR portfolio construction methodology, and the commodity futures data required. The observation period for the analysis runs from the first week of January 2004 to the last week of December 2018.

2.1 *Commodity hazard-fear (CFEAR) characteristic*

Following the extant literature that typically uses Google search volume as proxy for investor attention and information demand, the construction of the novel commodity-hazard fear (CFEAR) index in our study is based on internet search volume data obtained from *Google Trends.*[5] Google organizes the searches by their origin (different regions and worldwide). We use the *worldwide* search data in the main empirical sections, and the *US search* data in the robustness tests section.

We opt for the weekly sampling frequency for the Google search data three reasons.[6] First, a relatively high-frequency such as weekly or daily (instead of monthly) is most pertinent to capture the dynamics of investor search behaviour or information demand; e.g. Da et al. (2011, 2015), Smith et al. (2012), Vozlyublennaia (2014), and Ji and Guo (2015) employ weekly search data and Ben-Rephael (2017) and Han et al. (2017b) use daily data. Second, our empirical framework is an out-of-sample portfolio analysis that mimics the real-time decisions of a commodity futures investor; most commodity factor investing studies are based on monthly-rebalanced portfolios (e.g., Basu and Miffre, 2013; Fernandez-Perez et al., 2018; Szymanowska et al., 2014; Boons and Prado, 2019) since the daily rebalancing frequency is rarely used by practitioners for transaction cost considerations. Thus, the weekly frequency offers a reasonably balanced time resolution to study the information content of internet search queries in a realistic portfolio framework. A final reason is that due to Google Trends constraints each downloadable time-series has at most a time span of five years which can be, in principle, circumvented by concatenating sequential blocks of

[5] Google is the most widely used internet search engine worldwide; see https://www.google.com/trends.
[6] The weekly searches data from *Google Trends* cover Monday (hh:mm:ss) 00:00:00 to Sunday 23:59:59.

data; unfortunately, Google Trends also imposes quotas on the number of time series; thus, the blocks of data have to be retrieved on different days which may introduce noise as explained below.

The methodology to build our commodity-hazard fear index is inspired by the Da et al. (2015) approach to construct a Financial and Economic Attitudes Revealed by Search (FEARS) in equity markets. We adapt their methodology to construct a commodity-hazard fear (CFEAR) index for the purpose of testing empirically the presence of a hazard-fear factor in commodity futures markets. The rationale is that an imminent threat to the commodity supply or demand triggers fear about dramatic price swings; we take the CFEAR index as proxy for this hazard-related fear.

Using various sources (Iizumi and Ramankutty, 2015; Mu, 2007; Tomasso and Till, 2006; Till and Eagleeye, 2006; Filimon and Sornette, 2011; Israel and Briones, 2012; United Nations Office for Disaster Risk Reduction, 2018), we compile a primary list of raw (or primary) keywords that reflect commodity market price risks associated with weather disasters (WE), agricultural diseases (DI), geopolitical (GP), and economic (EC) vulnerabilities.[7] Next we refine the raw keywords by examining the "top related searches" provided by *Google Trends*. From the top 10 related searches we retain the keywords that are related to our goal and not redundant.[8,9] Finally, we add to the retained keywords the 'risk' and 'warning' terms, e.g. we consider *tsunami*, *tsunami risk* and

[7] We have considered additional sources such as Material Risk Insights (see www.material-risk.com).
[8] For instance if we search for *hail damage* one of the top related searches is *hail storm* so we can consider both. As regards redundant terms, for instance, top related searches associated with the term *hurricane* are those pertaining to specific hurricanes such as *Katrina hurricane*; the Google searches for the raw term *hurricane* exhibit a peak around the dates when the most catastrophic hurricanes have occurred which suggests that the specific term does not provide any additional information not already captured by the raw term. In other cases the top related searches have nothing to do with the aim of the paper, for instance, for the keyword *flood,* one of the top related searches is *flood lights*.
[9] We use keywords not surrounded by commas since, e.g. using the keywords *tropical storm* in Google Trends one obtains the number of searches that have been conducted including those two words in any order, e.g. it includes searches by *what is the probability of a tropical rain storm*. However, keywords with commas are much more restrictive as, for instance, using "*tropical storm*" in Google Trends one obtains the searches conducted by phrases that contain those two words literally.

tsunami warning. We thus end up with $J = 149$ keywords which are listed in Table 1 by category: 113 weather (WE), 10 crop diseases (DI), 14 geopolitical (GP) and 12 economic (EC) hazards.

Out of the 149 keywords, searches by those in the first three (WE, DI and GP) categories are most likely to reflect concerns about commodity supply-reduction and/or demand-increases, whereas the EC keywords typically relate to demand-reduction. As WE examples, an *extreme cold* spell (or *frosts*) can 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.[10,11] Among the DI hazards, an increase of *crop diseases* would reduce de supply of grain commodities or an outbreak of *La Roya* fungus would reduce the supply of coffee. GE hazards such as the *Russian crisis* or *Ukraine crisis* can threat the natural gas supply or the *Middle East conflict* can damage the provision of oil. As instances of EC hazards, a *recession* or a *crisis* can lead to a reduction of the demand for metal commodities such as copper, silver or platinum which are very linked to industrial performance.

[Insert Table 1 around here]

Let *j* denote a search keyword and *w* a sample week. *Google Trends* obtains the ratio between the volume of queries associated to the keyword *j* during week *w*, denoted $V_{j,w}$, and the entire volume of queries (for any keyword) in the same time period $V_{k,w}$; the subscripts *j* and *k* stand for the *j*th keyword and any keyword, respectively. Subsequently, the ratio $S_{j,w} \equiv V_{j,w}/V_{k,w}$ is then

[10] The data collection by 15 out of the 149 keywords (*avalanche, blizzard, cold, frost, frosts, gust, gusts, heat, heavy rain, hurricanes, rain, snow, storm, wildfire* and *wind*) is carried out within the Weather category of Google Trends since those terms can have other meanings unrelated to commodity supply and demand. For instance, the query *frost* can be related to the meteorological phenomena or to Jack Frost. We do not include livestock diseases since these events can simultaneously shift down the supply (e.g., cattle slaughtering) and demand (e.g., less beef consumption due to a health scare) and hence, the price can swing upwards or downwards. Hence, it is difficult for economic agents to predict the effect of a contagious livestock disease on the future livestock commodity spot price.

[11] The geopolitical keywords include *terrorist attack(s)* as potential supply disrupting threats. As discussed in ETF research "[…] *Even though industry data shows Brent oil production to be at multi-year highs, the price has risen to $110 (€79.5) a barrel. This is because of geopolitical risk in Ukraine, as well as a fall in production in the Middle East and Africa due to political instability and terrorism.*" (Revesz, 2014)

divided by its historical maximum value and multiplied by a factor of 100 to scale it between 0 and 100; this is the Google Search Volume Index (GSVI) provided by *Google Trends* which has the interpretation of a search probability. We collect weekly GSVI data for each of J=149 keywords (denoted $S_{j,w}$ hereafter); thus, $S_{j,w}$ denotes the relative intensity of Google searches or search volume ratio for the keyword $j = 1,..,J$ during the week $w = 1,..,W$, with $0 \leq S_{j,w} \leq 100$.[12] In effect, the $S_{j,w}$ measure can be interpreted as a search probability equal to 0 if the jth keyword is not searched at all on week w, and equal to 100 in the peak search week of the keyword.

Google Trends compiles the GSVI data using random samples (not the entire population) to represent total searches and therefore the search data for a given week w downloaded on two different dates t_1 and t_2 can slightly differ, $\{S_{j,w}\}_{t1} \neq \{S_{j,w}\}_{t2}$. However, this well-known GSVI sample bias is small, as discussed in Carrière-Swallow and Labbé (2013), Da et al. (2011), and McLaren and Shanbhogue (2011) inter alia. Nevertheless, following the latter studies, we alleviate concerns on this issue by downloading GSVI time-series per keyword on six different dates and defining our final Google search volume as the average of them, i.e. $S_{j,w} \equiv \frac{1}{6}\sum_{d=1}^{6}\{S_{j,w}\}_d$. In our study, the six dates are 6th, 7th and 9th February 2019, and 15th, 16th and 17th February 2019.[13]

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.

[Insert Figure 1 here]

We observe that the peaks in Google searches by *hurricane* precede the occurrence of ost notorious hurricanes such as, for instance, Hurricane Sandy on October 2012 or Hurricane Irma on September 2017. A peak in Google searches tends to be followed by an increase in lumber prices

[12] Google removes those terms introduced repeatedly by the same user to prevent artificial manipulation.
[13] 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%.

which subsequently drop. Similar patterns are observed on 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 afterwards gradually adjusted upwards. These graphical examples provides *prima facie* evidence that the search intensity $S_{j,t}$ reflects concerns about impending hazards. Of course, we cannot and do not assert that the users behind these searches are exclusively commodity market participants. In fact, this does not need to do so since what is important for the present research is that imminent hazards are accompanied by an increase in Google searches by keywords related to the hazard and thus, the increase in the Google searches can be taken as signal that an impending hazard is anticipated.

Our goal is to obtain a commodity-specific signal to proxy for economic agents' expectation as to the hazard fear-related price direction. 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 $\Delta S_{j,w} \equiv \log\left(\frac{S_{j,w}}{S_{j,w-1}}\right), j = 1, \ldots, J$. Working with changes mitigates the possibility of a relationship between search data and economic/financial variables that is actually spurious because it is solely driven by the presence of stochastic trends (McLaren and Shangobue, 2011; Baur and Dimpfl, 2016). Unreported Augmented Dickey-Fuller test results confirm that the J search volume changes $\Delta S_{j,w}$, like the commodity futures returns, are stationary whereas the levels are not.

As in Da et al. (2015), we winsorize the time-series of GSVI changes, $\{\Delta S_{j,w}\}_{w=1}^{W}$, at the 5% level (2.5% in each tail); thus, if the Google search change $\Delta S_{j,w}$ associated with *j=drought* on week w exceeds the limit $\pm 1.96\sigma_j^{\Delta S}$ we shrink it closer to the mean by replacing it by $\overline{\Delta S}_{j,w} \pm 1.96\sigma_j^{\Delta S}$ (where $\overline{\Delta S}_{j,w}$ and $\sigma_j^{\Delta S}$ are the mean and standard deviation of $\{\Delta S_{j,w}\}_{w=1}^{W}$. Next, we obtain the deseasonalized Google search change time-series as the residuals of a regression of the winsorized $\Delta S_{j,w}$ on monthly dummy variables. We do so to ensure that our data are not contaminated by noise related to seasonality in the demand for information, e.g., Google searches by weather keywords may systematically increase in the run-up to holiday seasons such as summer or Christmas. Finally, we normalize the series by scaling the winsorized and deseasonalized series by their standard deviation so that all J time-series (associated with keywords $j = 1, \dots, J$) of Google searches have unit standard deviation and are thus more comparable. Let us denote by $\Delta S^*_{j,w}$ the winsorized, deseasonalized and normalized Google search series.

Seeking to focus on the most relevant keywords (hazards) for each commodity, we carry out a data-based selection of the most relevant keywords. Specifically, as in Da et al. (2015) we employ a regression-based filtering process; specifically, we estimate by OLS the sensitivity of the commodity excess returns, $r_{i,t-l}$, to the Google search changes $\Delta S^*_{j,t-l}$ for each of the 149 keywords

$$r_{i,t-l} = \alpha + \beta^{CFEAR}_{i,j,t-l} \cdot \Delta S^*_{j,t-l} + \varepsilon_{t-l}, \quad l = 1, \dots, L \text{ weeks} \tag{4}$$

and retain only the keywords with the largest sensitivity $\beta^{CFEAR}_{i,t-l}$ estimate (according to the Newey-West robust *t*-statistic at the 10% level or better). Suppose that for the *i*th commodity the first J_1 keywords (hazards) are retained as the most relevant, then at the final step we define the trading signal for commodity *i* as the aggregate value of those sensitivities

$$CFEAR_{i,t} \equiv \sum_{j=1}^{J1} \hat{\beta}^{CFEAR}_{i,j,t-l}$$

such that if $CFEAR_{i,t} > 0$ this is telling us that overall (across all types of hazards affecting commodity *i*) the effect on the futures return was positive, namely, akin to a supply-disrupting of demand-increasing hazard effect, and vicevers.[14] Da et al. (2015) carry out a similar regression-based filtering but retaining only the keywords with large and positive *t*-statistic since their goal is

[14] Da et al. (2015) seek to focus only on those keywords associated with a contemporaneous deterioration in the overall equity market and accordingly they filter the "negative" keywords by estimating a similar regression of the equity market excess return on each of the Google search series (per keyword) using past expanding windows of data, $r_t = \alpha + \beta^{\Delta S}_{j,t} \Delta S^*_{j,t} + \epsilon_t$, and retain the keywords with significant $\hat{\beta}^{\Delta S}_{j,t} < 0$.

to focus on the Google searches associated with “negative” beliefs (i.e., pessimism) that, accordingly, commove with *falling* equity prices. The total number of long and short positions is identical in commodity futures (zero net-supply asset), and therefore falling futures prices are unfavorable for commodity futures market participants that are long but favourable instead for those that are short. For this reason, we retain the keywords (hazards) whose searches, as proxy for fear, most strongly affect the futures price in either direction.

In robustness tests, we will repeat the signal construction by side-stepping the winsorization, deseasonalization and normalization of the Google searches series. The motivation against these transformations in our analysis is that since the goal is to exploit surges in hazard-related Google searches as conveying relevant commodity market fear, the winsorization (and final normalization) may filter out important information. Likewise, there may be informative seasonality associated with the Google searches since, say, in the case of corn the fear about extreme weather events ought to be highest in the pre-pollination period when the corn growth is most sensitive.

2.2 *CFEAR factor construction*

Our representative investor forms at each portfolio formation time *t* (week-start) a long-short portfolio of commodities using the hazard fear-based sorting signal $\hat{\beta}_{i,t}^{CFEAR}$. To avoid look-ahead bias and perform the analysis out-of-sample, the investor’s decisions at each time *t* hinge only on past information. For this purpose, we construct the CFEAR index iteratively at each portfolio formation time *t* using the available past data. With the commodity hazard-fear index at hand, and using the same past window of data, we measure the commodity-specific CFEAR signal using equation (4). We use recursive (expanding) windows with initial length of $L = 52$ weeks.[15]

[15] Da et al. (2015) estimate their keyword-selecting regressions $r_t = \alpha + \beta_{j,t}^{\Delta S} \Delta S_{j,t}^{*} + \epsilon_t$ using expanding windows to maximize the statistical power of the outcome. A difficulty with the use of fixed length windows in our context is that the hazards considered may occur twice or once within a year (or even more infrequently) and so a fixed length window of 52 weeks maybe too noisy for the estimation of Equation (2)

The CFEAR signal is appropriately standardized cross-sectionally, namely, $\theta_{i,k,t} \equiv (x_{i,t} - \bar{x}_t)/\sigma_t^x$ where $x_{i,t}$ is the $\beta_{i,t}^{CFEAR}$ measure for the *i*th commodity and $\bar{x}_{k,t}$ ($\sigma_{k,t}^x$) is the cross sectional mean (standard deviation) of $x_{i,t}$ at time *t*. Following the theoretical predictions outlined in the Introduction, a high level of fear as regards an impending hazard that disrupts the commodity supply or increases the demand (i.e., fear of a dramatic increase in the commodity price in the future) will increase the long positions of hedgers overall and hence, the commodity futures prices will set low to entice speculators to take risky short positions. Thus at the first portfolio formation time *t*, we sort the available cross-section of 28 commodities according to the disaster-fear signal $\theta_{i,t}$ and take short positions in the $N/5$ commodities (top quintile, Q5 hereafter) with the most positive signals, $\theta_{i,t} > 0$, that is, in those commodity futures whose price has co-moved most positively (or least negatively) with the CFEAR index over the preceding *L*-week window (i.e., associated with supply reducing or demand increasing hazards). We take long positions in the bottom quintile Q1 that is, on the commodity futures that have co-moved most negatively or least positively with the CFEAR index (most extreme $\theta_{i,t} < 0$). The constituents of the long and short portfolios are equally weighted, and the weights are appropriately scaled so that 100% of the investor mandate is invested, that is, $\sum_i w_{i,t}^L = \sum_j |w_{j,t}^S| = 0.5$ with $w_{i,t}^L = |w_{j,t}^S| = w_t$ for all i, j.

We hold the long and short legs of the CFEAR portfolio for 1 week on a fully-collateralized basis; thus, the weekly portfolio excess return is 1/2 the return of the longs minus 1/2 the return of the shorts. We reconstruct the CFEAR index and form a new portfolio on the subsequent week-start using the new past window (length $L + 1$ weeks) and so on until the end of the sample period.

In order to test whether exposure to extant factors explains the hazard-fear premium, we adopt a "traditional" model in commodity pricing research that includes as factors the excess returns of

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to obtain the commodity-specific CFEAR signal. Considering *L*=520 weeks (10 years) poses the problem that it reduces considerable the sample of portfolio returns. We address this issue in the robustness tests.

the equally-weighted, weekly rebalanced, long-only portfolio of all commodities (AVG), and excess returns of well-known long-short portfolios to capture the premia related to the fundamental backwardation/contango cycle using roll-yield, momentum, and hedging pressure signals.

The *roll-yield* (or basis) characteristic of commodity *i* is defined, following the literature, as

$$Roll_{it} \equiv \ln\left(f_{i,t}^{front}\right) - \ln\left(f_{i,t}^{second}\right) \tag{5}$$

where $f_{i,t}^{front}$ and $f_{i,t}^{second}$ denote, respectively, the logarithmic time *t* price of the front-end and second-end commodity futures contract (e.g., Bakshi et al., 2017; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Szymanowska et al., 2014). A positive (negative) roll-yield signals a negatively (positively)-sloping term structure which is typical of backwardation (contango).

The *momentum* trading signal for commodity *i* is the trend in returns, and is formally computed as the average excess return of its front-end futures contract over a lookback period of *W* weeks

$$Mom_{it} \equiv \frac{1}{W}\sum_{j=0}^{W-1} r_{i,t-j}^{front} \tag{6}$$

which for a reasonably long lookback period has been shown to be able to proxy for the backwardation/contango cycle. The intuition is that following a negative shock to inventories, which exerts upwards pressure on the spot price, a period of high expected futures risk premia will follow as inventories are gradually restored (Gorton et al., 2012). On a given week *t* the commodities in the cross-section with the largest $Mom_{it} > 0$ tend to be the most backwardated.

Finally, the hedging pressure (HP) characteristic for commodity *i* is defined as

$$HP_{S,it} \equiv \left(\frac{1}{W}\right)\sum_{j=0}^{W-1} \frac{Long_{S,it-j} - Short_{S,it-j}}{Long_{S,it-j} + Short_{S,it-j}} \tag{7}$$

where $Short_{S,it}$ and $Long_{S,it}$ are, respectively, the week *t* total short open interest and long open interest of non-commercial traders along the entire curve (i.e. all available maturity contracts).[16] This signal conveys the extent of the net long positions of commodity futures speculators.

We measure the commodity momentum and HP characteristics over a lookback period of $W = 52$ weeks (one year) because prior studies have shown that the signals thus defined are relatively good predictors of commodity futures returns; see e.g., Erb and Harvey (2006), Miffre and Rallis (2007), Asness et al. (2013), Bakshi et a. (2017), Szymanowska et al. (2014) and Boons and Prado (2018), on momentum; and Basu and Miffre (2013) and Kang et al. (2016), on hedging pressure.

We standardize cross-sectionally the above signals (like the CFEAR signal) to construct the corresponding factors; namely, $\theta_{i,k,t} \equiv (x_{i,k,t} - \bar{x}_{k,t})/\sigma^x_{k,t}$ where $x_{i,k,t}, k = 1, \ldots, 3$ denotes the momentum, roll-yield or HP signal. We form the corresponding portfolios at each week start *t* by taking long (short) positions in the most backwardated (contangoed) commodities, that is, those with positive (negative) $\theta_{i,k,t}$; any other element of the portfolio construction is as described above.

We collect end-of-day settlement prices from *Datastream* for the front- and second-nearest contracts on 28 commodities: 17 agricultural (4 cereal grains, 4 oilseeds, 4 meats, 5 miscellaneous other softs), 6 energy, and 5 metals (1 base, 4 precious). Table 2 lists them.

[Insert Table 2 around here]

Given that the weekly Google Trends data reflects all searches from Monday to Sunday, for consistency we measure the weekly commodity excess returns as $r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$ where $P_{i,t}$ is the settlement price at Monday-end of each week *t* in the sample period. Thus the long-short portfolio formed at week-start (Monday) *t* is based on Google search data covering the immediately

[16] The CFTC aggregates all the positions of traders along the entire curve. The results are very similar when we use instead the hedgers' hedging pressure signal $HP_{H,it} \equiv \left(\frac{1}{W}\right)\sum_{j=0}^{W-1}\frac{Short_{H,it-j}-Long_{H,it-j}}{Short_{H,it-j}+Long_{H,it-j}}$.

preceding week and prior weeks $GSVI_{t-j}, j = 1, \dots, L$; we use an expanding lookback period starting from L=52 weeks. We obtain the long/short open interests of large speculators from the *Commitments of Traders* report of the Commodity Futures Trading Commission (CFTC).

We deploy the strategies by taking positions on the first nearest-to-maturity (or front) contracts as these are the most liquid (i.e., those with the largest open interest and trading volume among the contracts of all available maturities). Specifically, excess returns are changes in logarithmic prices of the front-end contract up to one month before maturity when we roll to the second-nearest contract. This standard rolling approach mitigates the confounding impact of erratic prices and volumes as maturity approaches. Table 2 reports summary statistics for the weekly excess returns (annualized) of each commodity – mean, standard deviation, and first-order autocorrelation, AC(1) – together with their primary uses and main hazards.[17] The AC(1) coefficients and unreported *t*-statistics suggest that the weekly commodity excess returns are very weakly autocorrelated.

4. EMPIRICAL RESULTS

We begin by discussing the in-sample predictive ability of the commodity CFEAR signal through panel regressions in Section 3.1 before examining its out-of-sample predictive ability in an economic (portfolio) evaluation framework in Section 3.2. Then we deploy time-series tests to assess whether the CFEAR portfolio delivers abnormal risk-adjusted returns (Section 3.3). Lastly, in Section 3.4 we assess the cross-sectional pricing ability of the CFEAR

3.1 Does the CFEAR signal predict returns?

We estimate panel regressions of the commodity excess returns on week *t*+1 on the commodity CFEAR signal (while controlling for other commodity characteristics) measured on week *t* using various model specifications which can be formalized altogether as

[17] The sources are Baker et al. (2018) and reports from *Materials-Risk.com* and *Commodity.com*.

$$r_{i,t+1} = [u_i] + [u_{t+1}] + \gamma_{CFEAR}\beta_{i,t}^{CFEAR} + \quad \boldsymbol{\delta}_C'\boldsymbol{C}_{i,t} + \varepsilon_{i,t} \tag{8}$$

where square brackets denote a discretionary component. We consider a simple pooled ordinary least squares (POLS) regression model ($u_i \equiv u$, $u_{t+1} \equiv 0$) , a panel fixed effects (FE) model with either commodity FE only ($u_{t+1} \equiv 0$) to control for the passive predictability component related to systematic differences across commodity markets, time FE only ($u_i = 0$) to control for the passive predictability component related to seasonality or business cycle variation common across markets, or two-way FE to control for both. Significance *t*-statistics for POLS and FE are computed using the Newey-West standard errors, time-clustered standard errors and commodity-clustered standard errors. We also consider the panel mean group estimator of Pesaran and Smith (1995; PMG) that allows for full heterogeneity in the predictive slopes $(\gamma_{CFEAR,i},\ \boldsymbol{\delta}_{C,i}')'$ across commodities by averaging estimates from *N* individual time-series regressions and exploiting their dispersion to obtain the significance *t*-statistics. Table 3 reports the estimation results.

[Insert Table 3 around here]

As shown in column (1) of the table, POLS estimation, the predictive slope of the CFEAR characteristic is negative and strongly significant at -12.48 ($t = -3.80$) which translates to a decrease in the subsequent weekly excess returns of -5.59% per year for a one standard deviation increase in the CFEAR signal. Adding the commodity FE has almost no impact on the coefficient estimate, while adding the time FE improves the model fit notably, while the coefficient on lagged CFEAR remains large and significant at $-11.24\,(t = -3.53)$; this contrast between the commodity FE and time FE indirectly leaves a large role for the CFEAR signal to predict differences in returns in the cross-section. Columns (6)-(11) show that the momentum, basis and hedging pressure characteristics have very weak in-sample predictive content over the period 2004-2018. Unsurprisingly, the last columns (12)-(14) show that the strong CFEAR predictive ability for weekly commodity returns is robust to the inclusion of these characteristics.

We further test whether the strong in-sample predictive ability of the CFEAR signal for weekly commodity returns is challenged by the inclusion of the lagged excess return, $r_{i,t}$, as explanatory variable in Equation (6). The results reported on the Table A.1 of the online annex indicate that the lagged return is essentially insignificant and hence, the model fit (as measured by the $adjR^2$) barely changes and the CFEAR signal retains its strong predictive ability for commodity excess returns.[18] This is consistent with the small AC(1) coefficients reported in Table 2.

Overall, these results suggest that the CFEAR characteristic measured at each week-start has in-sample predictive content for the commodity excess returns in the subsequent week. The predictability is robust to the joint consideration of traditional HP, basis and momentum predictors. However, in-sample predictability based on purely statistical criteria (significance *t*-statistics) is not tantamount to out-of-sample (OOS) predictability based on economic criteria (profitability measures). To assess the latter we now evaluate commodity futures portfolios formed at each time *t* using a CFEAR signal (and other traditional signals) based on past information.

3.2 CFEAR portfolio analysis

As just noted, this portfolio analysis is meant to assess the merit of the CFEAR characteristic as an out-of-sample commodity return predictor. Table 4 provides a battery of performance statistics for the CFEAR portfolio (and underlying quintiles), and for an equally weighted (AVG) long-only portfolio of the 28 commodity futures with weekly rebalancing, and traditional portfolios formed similarly using the hedging pressure, basis and momentum signals.

[Insert Table 4 around here]

[18] These findings are unlikely to be contaminated by lagged-dependent-variable bias in dynamic panel fixed effects models for various reasons. One is that *N* is small relative to *T* in the present context (*N*=28 commodities, *T*= 732 weeks) which acts towards reducing this potential bias towards zero. Another is that the same results are obtained for the POLS and PMG approach of Pesaran and Smith (1995) which do not suffer from this problem as tests clearly suggest that the model residuals are not autocorrelated.

We observe a monotonic decrease in the excess returns of the hazard fear-based commodity quintiles from 3.42% (Q1; most negative β_i^{CFEAR} signal) to -10.49% (Q5; most positive β_i^{CFEAR} signal). Accordingly, a long-short portfolio that takes long (short) positions in the commodities with the most negative (positive) β_i^{CFEAR} signal captures a significant premium of 6.96% per annum ($t = 3.00$) whereas the basis, hedging pressure and momentum portfolios capture over the same sample period a much smaller premium of 3.46% ($t = 1.27$), 5.98% ($t = 2.32$), and 1.51% ($t = 0.51$), respectively. Overall, these results suggest that the CFEAR measure has at least as good OOS predictive content for commodity excess returns as traditional characteristics such as basis, hedging pressure and momentum. The CFEAR portfolio excess returns translate into a Sharpe ratio of 0.7152 which represents an attractive reward-per-unit-of-risk versus the Sharpe ratios of traditional portfolios at 0.3387 (basis), 0.5926 (HP) and 0.1296 (Mom). It is also noticeable that the CFEAR strategy stands well in terms of tail/crash risk as borne out, for instance, by a 99% VaR and maximum drawdown of 0.0311 and -0.1465, respectively, while the corresponding tail risk measures for the traditional portfolios lie, respectively, in the ranges [0.0331, 0.0421] and [-0.2872, -0.1828]. Confirming extant wisdom, the long-only (AVG) portfolio strategy is very unattractive with a negative mean return of -3.32%.

Comparing the returns of the long (Q1; most negative CFEAR signal) and short (Q5; most positive CFEAR signal) legs of the hazard fear-based portfolio reveals that the significant CFEAR premium is mainly driven by the underperformance of the short-positions, namely, the commodities with the most positive $\beta_{i,t}^{CFEAR}$ achieve a large (in absolute value) mean return of –10.49% p.a. (t = -2.69). This finding is consistent with the inherent asymmetry of inventories; specifically, since inventories can (in theory) increase without bound but cannot become negative, they are an easier lever to cushion violent commodity price drops (due to hazards that reduce the demand or favour the supply) than violent price jumps (due to hazards that reduce the supply or increase the demand). Thus, it is plausible that speculators require more compensation to take short positions in commodity futures markets exposed to an imminent price-increasing hazard than to take long positions in commodity futures facing price-reducing hazards.

One may ask next whether the returns of the CFEAR long-short portfolio are driven by a few commodities that perpetually enter the long and/or short portfolios. To address this question, Figure 2 shows the frequency of portfolio formation weeks $t = 1,\ldots,T$ that each commodity enters the long and short CFEAR portfolios (Q1 and Q5 quintiles, respectively, according to the standardized $\beta_{i,t}^{CFEAR}$ signal). The results are organized per commodity sector.

[Insert Figure 2 around here]

With the exception of soybean oil, the frequencies are smaller from 100% (most of the frequencies are below 50%) which suggests that the portfolio constituents change over the sample weeks.

Examining the graph per (sub)sector, we observe that the *energy* commodities are more often in the short Q5 portfolio (than in the long Q1 portfolio) which indicates that the hazards they are subject to are mainly supply-reducing or demand increasing; the exception is heating oil which is about 45% of the time in the long Q1 portfolio (and rarely in the short Q5 portfolio) suggesting that over the sample period under study it has been more often than not exposed to hazards that decreased demand (or increased supply) than to hazards the reduced supply (or increased demand). In contrast, the metals are more often in the long Q1 portfolio which is consistent with the fact that they are mainly exposed to EC hazards (e.g., recession) that are typically demand reducing.

To investigate the extent to which the $\beta_{i,t}^{CFEAR}$ signal acts as commodity futures return predictor in a manner that is independent of the traditional roll-yield, hedging pressure and momentum signals, Table 3, Panel B, reports the pairwise correlations among the excess returns of all portfolios. The commodity CFEAR portfolio is very mildly associated with traditional portfolios with correlations ranging from -0.03 to 0.29. These results suggest that the predictive content of the CFEAR signal only mildly overlaps with that conveyed by traditional signals.

[Insert Figure 3 around here]

Figure 3 plots the future value of $1 invested in the CFEAR portfolio, in traditional long-short commodity portfolios, and in the long-only AVG portfolio. Confirming the findings in Table 4, the graph suggests that the CFEAR factor is an attractive investment.

3.3 Time-series pricing tests

The analysis in the preceding section reveals that the CFEAR strategy captures attractive mean excess returns in commodity markets. We now test whether the CFEAR premium can be rationalized as compensation for exposure to plausible risk factors. We consider the benchmark

$$r_{CFEAR,t} = \alpha_P + \beta_{AVG} AVG_t + \beta_{TS} TS_t + \beta_{HP} HP_t + \beta_{Mom} Mom_t + v_{P,t}, \; t = 1, \ldots, T \qquad (9)$$

where the regressors are the excess returns of the AVG portfolio as proxy for overall commodity risk, and the excess returns of the term-structure, hedging pressure and momentum portfolios as proxies for backwardation/contango risk following the literature (Bakshi et al., 2017; Basu and Miffre, 2013, among others). We test for the significance of the intercept (or alpha) that represents the excess returns of the commodity-FEAR 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 specification as employed by Fernandez-Perez et al. (2018) and Bianchi et al. (2018) inter alia, and simple versions with one factor at a time. Table 5 reports the results.

[Insert Table 5 around here]

Confirming our prior findings from the portfolio correlation analysis in Table 4 (Panel B), the betas of HP and Mom are positive, whereas the beta of TS is negative. The alpha of the CFEAR portfolio is economically sizeable and statistically significant in all the models averaging 6.69% per annum ($t > 3$), slightly down from 6.96% in average excess returns. Therefore, risk exposure does not tell the whole story since while the CFEAR portfolio has significant exposure to backwardation-contango related risks, it still provides substantial risk-adjusted returns (alpha). Since this time-series regression results suggest that the CFEAR factor is clearly not subsumed by traditional risk factors, it may improve the cross-sectional pricing ability when added to a model that includes the benchmark factors. We examine this conjecture in the next section.

3.4 Cross-sectional pricing tests

In this cross-sectional asset pricing analysis we employ, for consistency, the same benchmarks as in the preceding time-series tests. Specifically, the two questions we seek to address empirically are: i) Is exposure to the CFEAR factor priced?, iii) Does the CFEAR factor improve the explanatory power (and reduce the average pricing error) of an extant commodity pricing model?

As previous commodity pricing studies we employ two sets of test assets. The first is a set of portfolios defined as the quintiles resulting from sorting the individual commodity futures according to the roll-yield, momentum, hedging pressure, and CFEAR signals, and the six sub-sector portfolios ($N = 5 \times 4 + 6 = 26$ portfolios).[19] As Daskalaki et al. (2014) inter alia point out, a bias may emerge as regards the significance of the prices of risk from the fact that the test assets are portfolios sorted by the same criterion used to construct the risk factors. To lessen this concern we add portfolios based on (sub)sectoral criteria, and to fully to alleviate the concern, the second set of test assets are the 28 individual commodities whose cross-section of returns is harder to price and represents a hurdle for a new factor (Daskalaki et al., 2014; Boons and Prado, 2019).

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

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i \cdot \boldsymbol{F}_t + \varepsilon_{i,t}, t = 1, \ldots, T \tag{9}$$

[19] The *metals* sector is used as portfolio instead of considering base metal and precious metal subsectors because our cross-section only contains only one base metal, copper, within the former. Moreover, the classification is not clearcut; copper is sometimes listed as a precious metal because it is used in currency and jewelry, but it is not a precious metal as it is plentiful and readily oxidizes in moist air.

where $\boldsymbol{F}_s = (r_{CFEAR,t}, r_{AVG,t}, r_{mom,t}, r_{TS,t}, r_{HP,t})'$ is the week t excess return of different portfolios, and $\varepsilon_{i,t}$ is an error term. As in Kan, Robotti and Shanken (2013) and Boons and Prado (2019), at step two we estimate a single CS regression of the average excess returns on the full-sample betas

$$\bar{r}_i = \lambda_0 + \boldsymbol{\lambda}\widehat{\boldsymbol{\beta}}_i + \epsilon_i, i = 1,2, \dots, N \quad (10)$$

where $\boldsymbol{\lambda} = (\lambda_{CFEAR}, \lambda_{AVG}, \lambda_{mom}, \lambda_{TS}, \lambda_{HP})'$ are the prices of risk. Table 5 reports the OLS estimates $\{\hat{\lambda}_0, \ \hat{\boldsymbol{\lambda}}\}$, and test their significance using *t*-statistics based on Shanken (1992) standard errors (t_S, to correct for error-in-variables in $\widehat{\boldsymbol{\beta}}$) and Kan, Robotti and Shanken (2013) standard errors (t_{KRS}, to additionally correct for conditional heteroscedasticity and model misspecification). We also report the explanatory power, adjusted $R^2(\%)$, and mean absolute pricing error, $MAPE(\%) = \frac{100}{N}\sum_{i=1}^{N}|\hat{\varepsilon}_i|$, of Equation (10) to assess the merit of adding the CFEAR factor.[20]

For the 28 individual commodities as test assets, an unbalanced panel, we adopt the traditional Fama and MacBeth (1973) approach. Since the betas of individual commodities are notably time-varying, as in Boons and Prado (2019) we obtain first the conditional commodity-level betas by estimating Equation (8) over a one-year rolling window of weekly returns up to week *t*-1. At step two, with the betas $\widehat{\boldsymbol{\beta}}_{i,t-1}$ at hand, we estimate week-by-week *cross-sectional* OLS regressions

$$r_{i,t} = \lambda_t^0 + \boldsymbol{\lambda}_t\widehat{\boldsymbol{\beta}}_{i,t-1} + \epsilon_{i,t}, i = 1,2, \dots, N \quad (11)$$

where $\boldsymbol{\lambda}_t$ are the sequential (weekly) prices of risk. We report the average prices of risk from step two alongside *t*-statistics computed with both the Fama-MacBeth (1973) standard error formulae, t_{FM}, and the Shanken (1992) corrected version, t_{FMS}. As in Boons and Prado (2019), to ensure comparability with the portfolio-level tests, the adjusted R^2(%) and MAPE(%) are from regressions of the average excess returns of the individual commodities on the full-sample betas.[21]

[20] Like Boons and Prado (2019) we use this approach for the portfolio-level tests so as to compute the Kan, Robotti and Shanken (2013) *t*-statistics. The results of the portfolio level-tests are similar when we deploy the Fama-MacBeth approach based on Shanken *t*-statistics as shown in Table A.2 of the online Annex.

[21] A further reason for obtaining the R^2 from a single averaged-return regression is that the average R^2 from the weekly regressions can be high even when the ex ante (average) risk premium is zero, as the ex post risk premia could be large but positive in some weeks and large but negative in others (Kan et al., 2013).

[Insert Table 6 around here]

As shown in Panel A for the 26 commodity portfolios, the parsimonious single-factor Model 1 with the CFEAR factor only reveals that the hazard fear-risk is significantly positively priced at 8.13% per annum. The cross-sectional fit of this model (adjusted R^2 of 48.49% and MAPE of 0.049%) is superior to that of parsimonious Models 2 to 5 with each of the traditional factors in turn as suggested by an adjusted R^2 in the range 0.25% (AVG factor) to 37.61% (HP factor) and similarly by MAPE. When the traditional AVG, momentum, basis and HP factors are considered together with the CFEAR factor (Model 7), the price of hazard-fear risk remains statistically and economically unchanged at 8.28% p.a. In fact, the cross-sectional fit of Model 7 as borne out by an adj.-R^2 of 72.32% and a weekly MAPE of 0.032% is notably better than that of the traditional four-factor Model 6 with counterpart measures of 45.90% (adj.-R^2) and 0.049% (MAPE). These findings are reaffirmed in Panel B for the 28 individual commodities, despite representing a more challenging hurdle for any new factor; specifically, the price of the CFEAR risk factor is a significant 7.6% p.a. in the model that includes also the four traditional factors.[22]

5. WHAT ECONOMIC FORCES DRIVE THE CFEAR EFFECT?

Having established that the CFEAR signal has in-sample and out-of-sample predictive ability for commodity excess returns that is independent of traditional signals (basis, hedging pressure and momentum) and that the CFEAR factor is a key determinant of cross-sectional variation in commodity excess returns, we seek to understand the underlying economic forces.

4.1 Is the CFEAR premium a skewness premium in disguise?

The theoretical motivation to formulate this question is that the commodity futures contracts in the short quintile Q5 are those with the most positive $\beta_{i,t}^{CFEAR}$ characteristic in Equation (6); hence, these

[22] The findings of the commodity-level tests as regards the pricing ability of the CFEAR factor are not challenged when we estimate rolling 5-year betas at step one of the Fama-MacBeth approach.

are the commodities most strongly associated with hazards that dramatically reduce the supply or increase the demand and hence, experience upward price swings that materialize as large positive skewness. Vice versa the commodity futures contracts in Q1 (most negative $\beta_{i,t}^{CFEAR}$ characteristic) are those most strongly associated with hazards that harshly reduce the demand (or increase the supply) and hence, exhibit violent downward price movements and large negative skewness. Hence, the negative (positive) returns of the Q5 (Q1) quintiles might simply reflect the investors' dislike for negatively skewed assets, that is, the CFEAR premia may be fully rationalized as exposure to the commodity skewness risk factor documented by Fernandez-Perez et al. (2018).

To address this question, as in Fernandez-Perez et al. (2018), we construct the skewness risk factor using as signal the realized skewness of each commodity based on daily returns in the prior year. First, in time-series regressions we address the question of whether the CFEAR portfolio returns can be explained as 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 7 reports the results.[23]

[Insert Table 7 around here]

The time-series regression of CFEAR portfolio returns on the skewness risk factor (Model i in Panel A of Table 7) confirm the above rationale in suggesting that the CFEAR portfolio has a significantly positive skewness beta of 0.1325 ($t = 2.59$) but a significant alpha of 6.37% p.a. remains. More importantly, the CFEAR portfolio alpha at 6.68% in the traditional four-factor Model ii, drops insignificantly to 6.34% ($t = 2.95$) when the skewness risk factor is added.

We turn now to the cross-sectional regressions employing the same set of 26 portfolios as test assets for comparison. Panel B of Table 7 reports the results. The cross-sectional adjusted R^2 of

[23] Online Annex Table A.3 shows that the skewness portfolio captures a premia of 4.44% p.a. over the sample period. Consistent with the above theoretical motivation, the excess returns of the skewness portfolio and the CFEAR portfolio are significantly positively correlated at 14%.

Model 1 in Table 6 that includes only the CFEAR factor at 48.49% is similar to that of the model that includes only the skewness factor at 45.32% (Model 1 in Table 7). We observe that exposure to skewness risk captures a significant positive price of risk in Model 1 at 0.1439 ($t_{KRS} = 2.17$). When we add the CFEAR factor in Model 2 the economic and statistical significance of the skewness factor lessens to 0.1059 ($t_{KRS} = 1.64$) while the cross-sectional fit improves notably (the adjusted R^2 increases from 45.32% in Model 1 to 65.55% in Model 2) and the MAPE falls from 0.047 to 0.037. Overall, the CFEAR factor retains its strong cross-sectional pricing ability in models that include the skewness risk factor (Model 2 and Model 4). The cross-sectional regression results using the individual commodities do not challenge these findings and are reported in the Online Table A.4 to preserve space. These results reinforce the insights from the time-series tests in suggesting that the CFEAR factor relates to but is not subsumed by skewness risk.

4.2 Basis-Momentum, illiquidity and volatility risk

In a recent study by Boons and Prado (2019) a signal related to the slope and curvature of the commodity futures curve, referred to as basis-momentum, it shown to be an excellent predictor of commodity excess returns. Their evidence suggests that the basis-momentum factor is priced in the cross-section of commodities and commodity portfolios. Theoretically, this novel 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 such as in episodes when overall commodity market volatility or illiquidity is higher. Since the commodity hazards we are concerned with may create fear-induced imbalances in supply and demand of commodity futures, we test whether the CFEAR premium relates to exposure to basis-momentum risk.

As in Boons and Prado (2019) we define the basis-momentum signal as the difference between the average past returns (momentum) in a first- and second-nearby futures contract

$$BM_{it} \equiv \frac{1}{W}\sum_{j=0}^{W-1} r_{i,t-j}^{front} - \frac{1}{W}\sum_{j=0}^{W-1} r_{i,t-j}^{second} \tag{12}$$

using a one-year lookback period ($W = 52$ weeks).

[Insert Table 8 around here]

The basis-momentum portfolio captures a premium of 5.19% p.a. that exceeds the momentum and basis premia, in line with the findings in Boons and Prado (2019), despite differences in our sample periods (c.f. Table 4 and Online Annex Table A.3). The basis-momentum factor is positively correlated with the momentum and basis portfolio at 0.36 and 0.24, respectively, also in line with the findings in Boons and Prado (2019). Panel A of Table 8 suggests that the CFEAR excess returns reflect compensation for exposure to the basis-momentum factor as borne out by a significantly positive BM beta in Model i and Model iii. However, the alpha of the CFEAR strategy in the traditional four-factor Model ii at 6.68% p.a. ($t = 3.14$) decreases very little and remains significant at 6.23% p.a. ($t = 2.80$) after controlling for the BM factor.

The cross-sectional regressions in Panel B of Table 8 reveal first, in line with the findings in Boons and Prado (2019) that that exposure to basis-momentum is priced. Augmenting the traditional four-factor model with the BM factor improves the pricing model notably from 45.90% (adj.-R2) and 0.049% (MAPE) to 74.07% and 0.034%, respectively (c.f. Table 6 and Table 8). However, the significant pricing ability of the CFEAR factor is not challenged. Overall, we thus conclude that CFEAR predictability is not fully captured by the basis-momentum effect.

Next we test whether the CFEAR risk is directly related to illiquidity risk. We consider two illiquidity risk factors. One is a tradeable risk factor constructed, following Marshall et al. (2012) and Szymanowska et al. (2014), as the excess returns of a long-short portfolio based on the Amivest liquidity measure obtained at each portfolio formation time as the dollar daily-volume over absolute daily excess return during the prior 2 months $LR_{it} = \frac{1}{D}\sum_{d=1}^{D}\frac{\$Volume_{id}}{|r_{id}|}$ where D is the number of days. We employ the inverse $1/LR_{it}$ as illiquidity signal and take long positions in Q1 (most illiquid commodities) and short positions in Q5 (less illiquid commodities) using the portfolio approach described above in Section 3. The second illiquidity risk factor is the first-difference in the TED spread, the spread between the 3-month certificate of deposit and the T-bill rate, as proxy for innovations to funding illiquidity as in Boons and Prado (2019), Koijen et al. (2017) and Nagel (2016) inter alia. Table 9 reports the results.

[Insert Table 9 around here]

The time-series results in Panel A suggest that the CFEAR portfolio is significantly negative exposed to illiquidity shocks. Specifically, the negative beta of the Amivest-based illiquidity risk factor suggests that that the commodities in Q5 (those with the most positive CFEAR) are relatively illiquid. This may suggest that when there are imminent hazards that are likely to reduce the supply or increase the demand (which might be difficult to mitigate with inventories since the inventory cannot be negative) those commodities most affected become less liquid. This might be because the exchanges increase the margins as a way to avoid a large upward swing in the commodity price. However, the constant coefficient of Models i and iv of Table 9 which has an alpha interpretation as all the risk factors are tradeable, and that of Models ii and v remain economically large and significant at 7% p.a. ($t > 3$). Overall, these findings suggest that the CFEAR portfolio is exposed to illiquidity risk but it also captures a premium unrelated to this.

The cross-sectional tests in Panel B suggest that illiquidity risk is negatively priced. These pricing findings concur with those in Boons and Prado (2019) even though the 26 commodity portfolios we employ as test assets somewhat differ from theirs. 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 the illiquidity risk decreases notably in magnitude and is statistically insignificant. This suggests that the CFEAR factor is priced partly because it exposes investors to illiquidity risk shocks.

Last but not least, we examine the extent to which the CFEAR premia captures imbalances in the supply-demand of futures contracts that increase with commodity market volatility. For this purpose, we compute at each portfolio formation time (week-start) two distinct measures of commodity market volatility using past 22-daily excess return data. As in Boons and Prado (2019), we compute an aggregate market volatility measure, $AggrVar,$ as the variance of the excess returns of the AVG portfolio (equally-weighted portfolio of all 28 commodities), and an average market volatility measure, $AveVar,$ as the average of the variances of the excess returns of each of the 28 commodities. We first-difference both measures (annualized) to proxy for innovations in commodity market volatility. Table 10 reports the time-series and cross-sectional tests.

[Insert Table 10 around here]

The time-series regressions suggest that CFEAR portfolio is negatively exposed to commodity market volatility risk but a significant alpha remains, and the cross-section regressions suggest that the price of volatility risk is substantial but is reduced notably and becomes insignificant when we control for the CFEAR factor. The similarity of findings for the volatility risk and illiquidity risk analyses is not surprising given that volatility acts as proxy for state variables driven the market liquidity, namely, the ability of speculators to clear the market (Boons and Prado, 2019).

To shed light on the negative exposure of the CFEAR portfolio returns, following Boons and Prado (2019), we estimate predictive time-series regressions to ascertain how past illiquidity or past volatility affects the CFEAR portfolio returns. The model specification employed is

$$r_{i,t+1:t+k}^{CFEAR} = a_0 + a_1 z_t + \varepsilon_{i,t+1:t+k} \tag{13}$$

where *t* denotes each portfolio formation time (week-start in our analysis), $r_{i,t+1:t+k}^{CFEAR}$ are the CFEAR portfolio weekly returns compounded over k={1, 4, 24, 52} weeks, and the predictor denotes either the (standardized) TED spread, aggregate commodity market variance or average commodity market variance $z_t = \{\text{TED}, \text{AggVar}, \text{AvgVar}\}$. Table 11 reports the estimated coefficients and significant *t*-statistics based on Newey-West h.a.c. robust standard errors.

[Insert Table 11 around here]

The results suggest that the predictive coefficient a_1 is significant and positive in all three cases. Thus, commodity market volatility and funding illiquidity predict the CFEAR returns with a positive sign. An explanation for why the CFEAR returns increase in lagged volatility or illiquidity (i.e., positive a_1 in Equation (6)) but the CFEAR returns are contemporaneously negatively exposed to volatility and illiquidity shocks (i.e., negative betas in the contemporaneous time-series pricing regressions) can be found in the Fama and French (1987) definition of the expected future spot price as the current futures price plus a risk premium, $E_t(S_{t+T}) = F_t^T + Prem_t$. Specifically, since the CFEAR premium is increasing in lagged volatility or illiquidity, holding $E_t(S_{t+T})$ constant, a volatility/illiquidity shock will lower the futures price contemporaneously.

4.3 Uncertainty and sentiment

We now turn to the question of whether the CFEAR premia is influenced by investor uncertainty and sentiment. Specifically, using uncertainty and sentiment as our criteria for this purpose we classify the sample weeks as those of high versus low uncertainty (and bearish versus bullish sentiment) and re-evaluate the performance of the long-short CFEAR portfolio per regime. Next we address the research question via a regression analysis to conduct statistical tests.

We first consider financial uncertainty as proxied by the CBOE implied volatility index (VIX) also known as the "investor fear gauge" that measures the expected price fluctuations of the S&P 500 options over the next 30 days. Although this is an equity-related proxy, widely used as sentiment signal, the equity market is still the most liquid and hence, proxies from this market are typically adopted as representative of general financial market sentiment (Gao and Süss, 2015). [24]

[24] 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 in 2007 for oil, 2010 for gold and 2011 for silver and energy) and there are no commodity market-wide implied volatility indices available to date. For instance, the Crude Oil ETF Volatility Index ("Oil VIX", Ticker - OVX) measures the market's expectation of 30-day volatility of crude oil prices by applying the VIX methodology to United States Oil Fund, LP (Ticker - USO) options spanning a wide range of strike prices.

Additionally, we employ the financial uncertainty index constructed by Jurado, Ludvigson and Ng (2015) for the 1-month-ahead horizon that exploits the information from 148 financial variables – these include valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different ratings and grades, yields on Treasuries and yield spreads, and a broad cross-section of industry, size, book-market, and momentum portfolio equity returns.[25]

In order to focus on uncertainty that is more tightly linked to the macroeconomy, we employ the macroeconomic uncertainty index constructed by Jurado, Ludvigson and Ng (2015) for the 1-month-ahead horizon. This index subsumes the information content of 132 macroeconomic variables in different categories such as real output and income (e.g., Industrial Production Index), labour market (e.g. unemployment), housing, consumption, orders, and inventories, money and credit (e.g., M1, M2), interest and exchange rates (e.g., Treasury Bill), and prices (e.g., CPI, PPI).

Fourth, we consider uncertainty about the commodity market inventory. For this purpose, we proxy for each commodity the current inventory level by the roll-yield, as it is usual practice since the inventory data available is noisy or unavailable (Gorton et al., 2012). The aggregate commodity inventory uncertainty measure at each portfolio formation time (week start) is the average of the N variances of the daily roll-yields of each commodity in the preceding month.

Finally, we proxy for commodity price uncertainty by measuring the average commodity market (realized) variance at each portfolio formation time as the equal-weight combination of the sum of squared daily excess returns of individual commodities in the preceding month.

[25] We obtain the data from Professor Sydney C. Ludvigson's website which we gratefully acknowledge. In the Jurado et al. (2015) diffusion index forecasting framework, uncertainty is based on multiple indicators (collapsed into a small set of common factors), and is measured as the conditional 12-month ahead forecast error variance. We map their monthly uncertainty indices into weekly ones by simple interpolation.

Using the mean of each uncertainty measure as cutoff, we classify the weekly CFEAR portfolio returns into those occurring in high versus low uncertainty weeks. Table 12 reports the CFEAR premia, alpha (in the context of the traditional four-factor model) and Sharpe ratio with Newey-West h.a.c. robust *t*-statistics to test $H_0: r_{CFEAR}^{high} = r_{CFEAR}^{low}$ vs $H_0: r_{CFEAR}^{high} > r_{CFEAR}^{low}$ where r_{CFEAR}^{high} denotes the CFEAR return or risk-adjusted return in the high uncertainty period.

[Insert Table 12 around here]

The results reveal that the CFEAR premium is much higher in the high VIX (bearish sentiment) period than in the low VIX (bullish sentiment) in magnitude ant the differential is strongly significant at the 1% level or better. Specifically, the CFEAR premium is 15.59% per annum ($t = 3.81$) in high VIX periods versus an insignificant 2.30% ($t = 0.82$) in low VIX periods. The same observation can be made as regards the CFEAR alpha of 0.1527 (high VIX) versus 0.0209 (low VIX), and Sharpe ratio of 1.5081 (high VIX) versus 0.2470 (low VIX).

Likewise, we observe that the CFEAR premium (and alpha) is larger in high-uncertainty weeks as suggested by the the Jurado et al. (2015) financial uncertainty and macroeconomic uncertainty indices, the commodity price uncertainty, and the commodity inventory. But the corresponding high-vs-low CFEAR premium (and alpha) differentials are not reliably different from zero. The contrasting result between the VIX as uncertainty indicator and the above measures (namely, the more pronounced risk-adjusted CFEAR premium in high versus low VIX periods, both economically and statistically) suggests that investor-sentiment plays a key role.

The rationale is that the "investor fear gauge" VIX is commonly perceived as capturing time-varying risk aversion but is also a widely-perceived as a reliable market-based measure of investor sentiment (see e.g. Da et al., 2014; Gao and Süss, 2016). In fact, 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). While highly correlated with the VIX at 83%, as shown in Panel B of the Table 12, the financial uncertainty index of Jurado et al. (2015)

is less likely to reflect sentiment since none of the many financial variables it aggregates is regarded as a sentiment proxy in the literature. Overall, these results suggest that the premium demanded by commodity futures speculators for absorbing the hazard-fear induced changes in net positions of hedgers is more pronounced in periods of adverse (pessimistic) sentiment in financial markets. Thus, we assert that sentiment induced-mispricing also drives the CFEAR premium.

A natural question is whether a long-short commodity portfolio based on overall financial market sentiment as proxied by the VIX is as effective as the CFEAR portfolio to capture the hazard-fear premium. To assess this, we re-deploy Equation (4) replacing the CFEAR index by the log changes in the VIX. Unreported results, to preserve space, suggest that the resulting premia is small at 2.99% p.a. (t=0.90) and the correlation of the CFEAR portfolio returns and VIX-based commodity portfolio returns is very low at 0.03. This confirms that, although the CFEAR premium demanded by speculators increases in bearish (pessimistic) investor sentiment periods, the CFEAR signal captures specific commodity-hazard fear that the VIX is unable to capture. The CFEAR premium is influenced by overall financial market sentiment but not subsumed by it.

6. EXTENSIONS AND ROBUSTNESS CHECKS

In additional tests we begin by accounting for transaction costs, then we cycle through several aspects of the CFEAR signal construction method and long-short portfolio construction method.

5.1. Turnover and transaction costs

To get a sense of how trading intensive each strategy is, we measure the portfolio *turnover* (TO) defined as the time average of all the trades incurred

$$TO_j = \frac{1}{T-1} \sum_{t=1}^{T-1} \sum_{i=1}^{N} \left(\left| w_{j,i,t+1} - w_{j,i,t^+} \right| \right) \tag{14}$$

$t = 1, \ldots, T$ denotes each of the (weekly) portfolio formation periods in the sample, $w_{j,i,t+1}$ is the ith commodity allocation weight dictated at week t by the jth strategy, $w_{j,i,t^+} \equiv w_{j,i,t} \times e^{r_{i,t+1}}$ is the actual portfolio weight right *before* the next rebalancing at $t + 1$, $r_{i,t+1}$ is the weekly return of the ith commodity from week-start t to week-start $t + 1$. Thus the TO measure also captures the mechanical evolution of the allocation weights due to within-week price dynamics (*e.g.*, $w_{j,i,t}$ increases to w_{j,i,t^+} when $r_{i,t+1} > 0$). The TO measure ranges from 0 with the buy and hold strategy to 2 when all the portfolio constituents change. Figure 4, Panel A graphs the TOs.

[Insert Figure 4 around here]

The results from Figure 4 suggest that the trading intensity of the commodity CFEAR portfolio with a TO of 0.10 is notably less than that of the basis (TO $= 0.38$), momentum (0.27), Skewness (0.21), and basis-momentum (0.37) portfolios, similar to that of the illiquidity portfolio (0.10) but slightly more trading intensive than the HP portfolio (0.06).

We also calculate the net return of each long-short portfolio as

$$r_{P,t+1} = \sum_{i=1}^{N} w_{i,t} r_{i,t+1} - TC \sum_{i=1}^{N} \left| w_{i,t} - w_{i,t-1^+} \right| \tag{15}$$

using proportional trading costs of 8.6 bps (Marshall et al., 2012). Figure 4, Panel B, shows the Sharpe ratios before and after TC for the CFEAR long-short portfolio, and all other long-short commodity portfolios considered in the paper. It is noticeable that transaction costs subsume only a small part of the returns of the CFEAR strategy and accordingly, it still affords a very attractive performance both in relatively terms (vis-à-vis traditional strategies) and in absolute terms.

5.2. CFEAR index measurement

We now consider alternative ways to construct the CFEAR trading signal and then reappraise the magnitude of the CFEAR premia and its ability as risk factor to explain the cross-sectional variation of the same 26 commodity portfolios considered earlier. First, we sidestep the construction of the CFEAR index, Equation (4), and defined the CFEAR characteristic for each commodity as the median of the slope coefficients obtained regressing its past excess returns on the GSVI changes by each of the 149 keywords as explained in Section 2.1.

Second, we consider US Google searches (by the IP address of the user). Third, we sidestep the winsorization of the Google search changes $\Delta S_{j,w}$ at step one to accommodate the possibility that large changes in the search volume from one week to the next reflect information as opposed to noise. Fourth, we sidestep instead the deseasonalization of the $\Delta S_{j,w}$ series. Finally, we construct four alternative CFEAR indices by excluding each of the four keyword classes (WE, DI, GP and EC) in turn. Table 13 summarizes in Panel A the excess returns of the long-short CFEAR portfolio and Panel B reports the price of the CFEAR risk factor as obtained in a cross-sectional regression that includes the traditional AVG, hedging pressure, basis and momentum factors for the same 26 commodity portfolios as employed above, and the cross-sectional adjusted $R^2(\%)$.

[Insert Table 13 around here]

Column (1) of Panels A and B suggest that the alternative approach that sidesteps the construction of the CFEAR factor and defines the trading signal as the median slope across the 149 keyword-related regressions does not challenge the key findings. As shown in cols. (2) and (3), the CFEAR premia is a bit stronger when using world searches than when considering only the US searches, as one might expect, since hazard-fear is not necessarily confined to the US. The winsorization of the Google searches somewhat increases the CFEAR premia, as shown in col. (4), confirming that it filters out the noise induced by the construction of the Google search series. Skipping the deseasonalization of the Google search volume changes increases the CFEAR premium suggesting that there is periodicity in some of the hazards (e.g., certain weather events are more likely to occur in one season than another) which is informative. Finally, the CFEAR premia obtained when we exclude the DI, GP and EC keywords, in turn, remains significant throughout as shown in cols. (5) to (8). When we exclude the WE keywords,, the CFEAR premium shrinks but the CFEAR factor retains its cross-sectional pricing ability. Nevertheless, it is difficult for us to say whether the decrease in the CFEAR premia when we exclude the WE keywords is driven by the stronger role played by the weather hazards or instead the result is an artifact of the much larger number of WE keywords (76% of the total) in the sample.[26]

5.3. CFEAR portfolio construction

We now consider alternative portfolio formation methods. First, the ranking period is a fixed-length window of 10 years ($L = 520$ weeks). Second, we focus on the extreme quintiles (Q1 and Q5 with $N/5$ commodities in each) as in the main analysis, but instead of equally-weighting the constituents, we weigh them by $|\theta_{i,k,t}|$ so that the size of the positions depends on the strength of the standardized signal. Next we consider various approaches that include in the long-short portfolios all N commodities (i.e., $N/2$ commodities in the long portfolio and the remaining $N/2$ in the short portfolio) with various weighting schemes. The binary weighting scheme gives the same weight $+1/N$ to each of the constituents of the long portfolio and $-1/N$ to the constituents of the short portfolio. The *standardized rankings* approach weighs each of the constituents by their standardized ranking. The *standardized signals* approach weighs each of the constituents by $|\theta_{i,k,t}|$. The *winsorized-and-standardized* signals approach is similar but we winsorize the signals cross-sectionally $\{x_{i,k,t}\}$ $i = 1, \dots, N$ prior to standardizing them to mitigate the distorting effect of outliers in the portfolio allocations.[27] Again in all of these cases, we appropriately scale the commodity weights to ensure $\sum_i \tilde{\theta}_{i,t}^L = \sum_i \left|\tilde{\theta}_{i,t}^S\right| = 0.5$. Finally, we restrict the cross-section of commodities to the 80% commodities with the largest weekly open interest (number of outstanding

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[26] We regress the CFEAR index on the hedging pressure, basis and momentum returns and define the filtered CFEAR index as the residuals seeking better to isolate the search behavior purely associated with fear (sentiment) as opposed to that driven by the fundamental backwardation-contango cycle. The unreported results to preserve space reveal a significant mean CFEAR excess return of 6.43% p.a. ($t = 2.41$) which is able significantly to price the cross-section of commodity portfolios ($\lambda_{CFEAR} = 0.0903$ ($t = 2.87$).

[27] Following DeMiguel et al. (2019), at each portfolio formation time we shrink the observations for the *k*th characteristic $\{x_{i,k,t}\}$ $i = 1, \dots, N$above the upper threshold $Q_{3,k} + 3 \cdot R_k$ to this threshold value, and those below the lower threshold $Q_{1,k} - 3 \cdot R_k$ to this threshold value; $Q_{1,k}$ and $Q_{3,k}$ are the first and third quartiles of the distribution $\{x_{i,k,t}\}$ $i = 1, \dots, N$ and R_k is the interquartile range

contracts) at each portfolio formation time. This is further to make sure (alongside working with the front contracts) that the excess returns of the CFEAR portfolio do not reflect compensation for illiquidity. Table 14 reports the results.

[Insert Table 14 around here]

The main findings survive the alternative portfolio construction methods. The CFEAR premium is economically sizeable at 7.63% (versus 6.96% for an expanding lookback period starting from 52 weeks; c.f. Table 4) when the lookback period of $L = 52 \cdot 10$ weeks is considered. This is aligned with our discussion in Section 2.2, noting that for the commodity-specific CFEAR signal to be reliable may require a long ranking period in order to provide reliable signals as most of the hazards occur infrequently (twice or once within a given year or less infrequently). However, the CFEAR premium is more mildly significant which relates to the fact that the sample of returns is notably shorter, by 10 years, from December 2008 to December 2018.

Finally, we construct the CFEAR portfolio using the traditional approach of rebalancing at each month end (instead of weekly rebalancing) and holding the corresponding long-short positions for one month. We use the same approach for the AVG, momentum, basis and hedging pressure portfolios. The results are shown in Table 14.

[Insert Table 14 around here]

The results confirm that the momentum and basis strategies may have lost some of their "flavor" in the 2004-2018 period (see e.g., Barroso and Santa-Clara, 2015). The CFEAR premia remains economically sizeable and statistically significant at 6.42% ($t = 2.78$) translating into a Sharpe ratio of 0.7209 versus a hedging pressure premium of 5.16% ($t = 1.99$) and Sharpe ratio of 0.5592. Accordingly, we assert that our findings are not an artifact of the weekly portfolio frequency.

7. Conclusions

This paper introduces a commodity hazard-fear signal related to commodity price expectations driven by fear about impending hazards that shift the commodity supply or demand. We find that commodity hazard-fear as proxied by the volume of Google searches by 149 weather, disease, geopolitical and economic hazard-related keywords has in-sample predictive ability for commodity excess returns. We address the out-of-sample predictability question through a portfolio framework with asset pricing implications. Hazard-fear is a good predictor of commodity excess returns and exposure to the CFEAR factor is priced and is a key determinant of cross-sectional variation in individual commodity returns and commodity portfolio returns.

The CFEAR excess returns reflect some compensation for exposure to various risk factors such as commodity skewness, basis-momentum and illiquidity, but this is not the whole story. The CFEAR premium is significantly more pronounced in bearish (pessimistic) investor sentiment periods suggesting that the premium also reflects sentiment-induced mispricing. The findings are robust to transaction costs, CFEAR signal measurement and portfolio construction methods.

References

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013) Value and Momentum Everywhere. *Journal of Finance* 68, 929–985.

Baker, H.K., Filbeck, G., and Harris, J. H. (2018) *Eds.* Commodities: Markets, Performance and Strategies, Oxford University Press.

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

Barroso, P., and Santa-Clara, P. (2015). Momentum has its moments. Journal of Financial Economics 116, 111-120.

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

Ben-Rephael, A., Da, Z., and Israelsen, R. D. (2017) It Depends on Where You Search: Institutional Investor Attention and Underreaction to News. *Review of Financial Studies* 30, 3009–3047.

Bloom, N. (2014). Fluctuations in Uncertainty. *Journal of Economic Perspectives* 28, 153-176.

Brennan, M. (1958). The supply of storage. *American Economic Review* 48, 50-72.

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

Carrière-Swallow, Y., and Labbé, F. (2013) Nowcasting with Google Trends in an Emerging Market. *Journal of Forecasting* 32, 289–298.

Chen, I.-H., Kirilenko, A., and Xiong, W. (2015) Convective flows in commodity futures markets. *Review of Finance* 19, 1733-1781.

Cootner, P. H. (1960) Returns to Speculators: Telser versus Keynes on JSTOR. *Journal of Political Economy* 68, 396–404.

Da, Z., Engelberg, J., and Gao, P. (2011) In Search of Attention. *Journal of Finance* 66, 1461–1499.

Da, Z., Engelberg, J., and Gao, P. (2015) The Sum of All FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies* 28, 1–32.

D'Amuri, F., and Marcucci, J. (2017). The predictive power of Google searches in forecasting US unemployment. *International Journal of Forecasting* 33, 801-816.

Dergiades, T., Milas, C., and Panagiotidis, T. (2015) Tweets, Google trends, and sovereign spreads in the GIIPS. *Oxford Economic Papers* 67, 406–432.

Dimpfl, T., and Jank, S. (2016) Can Internet Search Queries Help to Predict Stock Market Volatility? *European Financial Management* 22, 171–192.

Di Tomasso, J. and Till, H. (2000). Active "Commodities Based" Investing, *Journal of Alternative Investments* 1, 70-80.

Dzielinski, M. (2018) Asymmetric Attentiona and Volatility Asymmetry. *Journal of Empirical Finance* 45, 59-67.

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

Fama, E. F., and MacBeth, J. D. (1973) Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81, 607–636.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., and Miffre, J. (2018) The Skewness of Commodity Futures Returns. *Journal of Banking and Finance* 86, 143-158.

Filimon, E., and Sornette, D. (2011) Weather to Buy or Sell. Extreme Weather Impact on Corn Futures Market. *Master Thesis. ETH Zurich*.

Goetzman, W., Kim, D., and Shiller, R.J. (2017). Affect, media and earthquakes: Determinants of crash beliefs from investor surveys, Yale University Working Paper.

Gorton, G., and Rouwenhorst, G. (2006) Facts and Fantasies about Commodity Futures. *Financial Analysts Journal* 62, 47–68.

Gorton, G., Hayashi, F., and Rouwenhorst, G. (2012) The fundamentals of commodity futures returns. Review of Finance 17, 35-105.

Han, L., Lv, Q., and Yin, L. (2017a) Can investor attention predict oil prices? *Energy Economics* 66, 547–558.

Han, L., Li, Z., and Yin, L. (2017b) The effects of investor attention on commodity futures markets. *Journal of Futures Markets* 37(10), 1031–1049.

Hicks, J. (1939). Value and capital: and inquiry into some fundamental principles of economic theory, Clarendon Preess, Oxford, UK.

Hirshleifer, D. (1988). Residual risk, trading costs and commodity futures risk premia. Review of Financial Studies 1, 173-193.

Hong, H., and Yogo, M. (2012) What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics* 105(3), 473–490.

Hougan, M. (2007). Morningstar enters commodities space. ETF research September 2007.

Iizumi, T., and Ramankutty, N. (2015) How do weather and climate influence cropping area and intensity? *Global Food Security* 4, 46–50.

Israel, D. C., and Briones, R. M. (2013) Impacts of Natural Disasters on Agriculture, Food Security, and Natural Resources and Environment in the Philippines. *Economic Research Institute for ASEAN and East Asia* , 1–53.

Ji, Q., and Guo, J.-F. (2015) Market interdependence among commodity prices based on information transmission on the Internet. *Physica A: Statistical Mechanics and its Applications* 426, 35–44.

Kaldor, N. (1939) Speculation and Economic Stability. *Review of Economic Studies* 7(1), 1–27.

Keynes, J. M. (1930) *A Treatise on Money, Vol. 2: The Applied Theory of Money*. Macmillan.

Lemieux, J., and Peterson, R. A. (2011) Purchase deadline as a moderator of the effects of price uncertainty on search duration. *Journal of Economic Psychology* 32, 33–44.

McLaren, N. and Shanbhogue, R. (2011) Using Internet Search Data as Economic Indicators, Bank of England Quarterly Bulletin Q1, SSRN WP http://ssrn.com/abstract=1865276.

Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N. (2012) Commodity Liquidity Measurement and Transaction Costs. *Review of Financial Studies* 25, 599–638.

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

Mondria, J., Wu, T., and Zhang, Y. (2010) The determinants of international investment and attention allocation: Using internet search query data. *Journal of International Economics* 82, 85–95.

Niesert, R.F., Oorschot, J.A., Veldhuisen, C.P., Brons, K. and Lange, R.J. (2019). Can Google search data help predict macroeconomic series? *International Journal of Forecasting*, forthcoming.

Revesz, R. (2014). Hedging against geopolitical risk. ETF Research April 2014.

Smith, G. P. (2012) Google Internet search activity and volatility prediction in the market for foreign currency. *Finance Research Letters* 9(2), 103–110.

Szymanowska, M., De Roon, F., Nijman, T., and Van Den Goorbergh, R. (2014) An Anatomy of

Commodity Futures Risk Premia. *The Journal of Finance* 69(1), 453–482.

Till, H., and Eeagleeye, J. (2006). “Commodities – Active Strategies for Enhanced Return”, in R. Greer (ed) The Handbook of Inflation Hedging Investments, NY: McGraw-Hill, pp. 127-157.

Till, H. (2000). Passive strategies in the commodities futures market. Derivatives Quarterly, Fall.

Tomasso, J. Di, and Till, H. (2000) Active “Commodities–Based” Investing. *The Journal of Alternative Investments* 3, 70–80.

Vlastakis, N., and Markellos, R. N. (2012) Information demand and stock market volatility. *Journal of Banking & Finance* 36, 1808–1821.

Vosen, S., and Schmidt, T. (2011). Forecasting private consumption: Survey-based indicators vs. Google trends. *Journal of Forecasting* 30, 565-278.

Vozlyublennaia, N. (2014) Investor attention, index performance, and return predictability. *Journal of Banking & Finance* 41, 17–35.

Working, H. (1949). The theory of price of storage. *American Economic Review* 39, 1254-1262.

Yang, F. (2013). Investment shocks and the commodity basis spread. *Journal of Financial Economics* 110, 164-184.

Table 1. Google search keywords

This table lists all the search terms (J=149) used to construct the CFEAR index grouped according to the category of hazard or vulnerability that they represent. 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. Commodities sample

This table lists the 28 futures contracts, main exchanges where they are traded, first and last observation date, annualized mean of excess returns (front contract), standard deviation, and first-order autocorrelation with significant *t*-statistic, primary uses (feed animals FA, feed people FP, feedstock for fuel production FF, industrial oil or lubricant OL, industrial uses IU, jewelry JW, power generation PG), and main hazards (weather WE, diseases DI, geopolitical GP, and economic EC) they are subject to. The panel is unbalanced and the longest time period covered is Jan 2004 (week1) to Dec 2018 (week 4).

Commodity	Sub-sector	Exchanges	First obs	Last obs	Excess return			Primary uses							Hazards				
			YYYYMMDD	YYYYMMDD	Mean	StDev	AR1 (*t* stat)	FA	FP	FF	OL	IU	JW	PG	WE	DI	GE	GP	EC
I. Agricultural sector (N=17)																			
Corn	Cereal grains	CBOT	20040105	20181231	-0.0671	0.2912	-0.0021 (-0.04)	√	√	√					√	√			√
Oats	Cereal grains	CBOT	20040105	20181231	0.0120	0.3475	-0.0339 (-1.05)	√	√						√	√			√
Rough rice	Cereal grains	CBOT	20040105	20181231	-0.0819	0.2488	0.0101 (0.23)		√	√					√	√			√
Wheat CBT	Cereal grains	CBOT	20040105	20181231	-0.1227	0.3152	0.0129 (0.34)	√	√						√	√		√	√
Cotton no.2	Oilseeds	NYMEX/ICE	20040105	20181231	-0.0220	0.2872	0.0085 (0.23)		√		√				√	√			√
Soybeans	Oilseeds	CBOT	20040105	20181231	0.0525	0.2486	0.0256 (0.66)	√	√		√				√	√			√
Soybean meal	Oilseeds	CBOT	20040105	20181231	0.1092	0.2872	0.0462 (1.14)	√	√		√				√	√			√
Soybean oil	Oilseeds	CBOT	20040105	20181231	-0.0467	0.2460	-0.0176 (-0.46)	√	√		√				√	√			√
Feeder cattle	Meats	CME	20040105	20181231	0.0270	0.1659	-0.0479 (-1.30)		√						√	√			√
Lean hogs	Meats	CME	20040105	20150706	-0.0662	0.2377	0.0650 (1.27)		√						√	√			√
Live cattle	Meats	CME	20040105	20181231	-0.0075	0.1602	-0.0618 (-2.05)		√						√	√			√
Frozen pork bellies	Meats	CME	20040105	20110705	-0.0228	0.2979	-0.0570 (-0.93)		√						√	√			√
Cocoa	Misc. other softs	NYMEX/ICE	20040105	20181231	0.0253	0.2948	-0.0237 (-0.68)		√						√	√		√	
Coffee C	Misc. other softs	NYMEX/ICE	20040105	20181231	-0.0551	0.3115	0.0115 (0.27)		√						√	√			
Frozen Orange juice	Misc. other softs	ICE/NYMEX	20040105	20181231	0.0176	0.3414	0.0344 (0.93)		√						√	√			
Sugar no.11	Misc. other softs	NYMEX/ICE	20040105	20181231	-0.0417	0.3141	-0.0351 (-0.87)		√	√					√	√			
Lumber	Misc. other softs	CME	20040105	20181231	-0.1229	0.3087	0.0074 (0.21)					√			√	√	√		√
II. Energy sector (N=6)																			
Light crude oil	Energy	NYMEX	20040105	20181231	-0.0753	0.3400	-0.0200 (-0.41)			√					√			√	√
Electricity JPM	Energy	NYMEX	20040105	20150727	-0.1454	0.4428	0.0619 (0.97)							√				√	√
Gasoline RBOB	Energy	NYMEX	20051010	20181231	-0.0305	0.3227	0.0404 (0.72)							√				√	√
Heating oil	Energy	NYMEX	20040105	20181231	-0.0125	0.3095	0.0227 (0.50)							√	√			√	√
Natural gas	Energy	NYMEX	20040105	20181231	-0.3633	0.4224	-0.0102 (-0.26)							√	√			√	√
NY unleaded gas	Energy	NYMEX	20040105	20070102	0.1768	0.3686	-0.0146 (-0.21)							√				√	√
III. Metals (N=5)																			
Copper (High Grade)	Base metals	COMEX	20040105	20181231	0.0682	0.2720	0.0188 (0.32)					√							√
Gold 100oz (CMX)	Precious metals	COMEX	20040105	20181231	0.0560	0.1785	-0.0090 (-0.24)						√		√			√	√
Palladium	Precious metals	NYMEX	20040105	20181231	0.0988	0.3148	0.0220 (0.52)					√	√					√	√
Platinum	Precious metals	NYMEX	20040105	20181231	-0.0114	0.2302	0.0167 (0.48)					√	√						√
Silver 5000 oz	Precious metals	COMEX	20040105	20181231	0.0421	0.3196	0.0117 (0.27)					√	√						√

Table 3. Panel regressions: Predictive ability of CFEAR characteristic

The table presents the estimation results of panel regressions of the weekly excess returns of the 28 commodities on one-week lagged commodity characteristics, Equation (6). The models reported in columns (1) to (5) only include the β^{CFEAR} measure. The models in cols. (6)-(8) only include the roll-yield, momentum and HP(S) measures, respectively. The models in columns (9) and (10) include all four commodity characteristics. POLS is a pooled regression with an unreported intercept, FE are fixed effects models and PMG is the panel mean group estimator of Pesaran and Smith (1995). t-statistics for the POLS/FE estimator are calculated using Newey-West h.a.c standard errors (in parenthesis), standard errors clustered in the time dimension (curly brackets), and commodity dimension (angle brackets). t-statistics for the PMG estimator and based on the standard deviation of the individual time-series coefficients.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	POLS		FE		PMG		FE			PMG		FE	PMG
CFEAR	-12.4841	-12.5989	-11.2446	-10.4937	-22.1841							-10.9702	-26.1549
	(-3.80)	(-3.02)	(-3.53)	(-2.45)	(-3.54)							(-2.52)	(-3.09)
	{-2.52}	{-1.87}	{-2.66}	{-1.77}								{-1.86}	
	<-3.66>	<-4.41>	<-2.95>	<-3.19>								<-3.28>	
Roll-yield						-0.0145			-0.0200			-0.0120	0.0070
						(-1.14)			(-0.55)			(-0.92)	(0.15)
						{-0.90}						{-0.73}	
						<-1.24>						<-0.95>	
Mom							-0.0788			-0.0949		-0.0836	-0.2255
							(-1.18)			(-2.02)		(-1.15)	(-2.73)
							{-0.82}					{-0.81}	
							<-1.59>					<-1.57>	
HP(S)								0.0000			-0.0051	0.0007	0.0005
								(-0.02)			(-1.51)	(0.41)	(0.11)
								{-0.02}				{0.39}	
								<-0.02>				<0.65>	
Comm FE	No	Yes	No	Yes		Yes	Yes	Yes				Yes	
Time FE	No	No	Yes	Yes		Yes	Yes	Yes				Yes	
Adj-R^2 (%)	0.09	0.28	21.17	21.36	0.29	21.34	21.34	21.33	0.36	0.09	0.12	21.38	0.96

Table 4. CFEAR factor and benchmark commodity factors

The table reports the performance of the long-short CFEAR portfolio, the equally-weighted long-only portfolio of all 28 commodities (AVG), and the traditional long-short roll yield, hedging pressure, and momentum portfolios. Q1 (Q5) is the quintile of commodities with the most negative (positive) β^{CFEAR} characteristic. Newey-West robust h.a.c. t-statistics are shown in parenthesis. Panel B reports the pairwise correlations with significance p-values in curly brackets. The sample period is January 2004 (week 1) to December 2018 (week 4).

	CFEAR						AVG	Mom	Term structure	Hedging pressure
	Long (Q1)	Q2	Q3	Q4	Short (Q5)	Q1-Q5				
Panel A: Summary statistics										
Mean	0.0342	-0.0047	-0.0367	-0.0644	-0.1049	0.0696	-0.0332	0.0151	0.0346	0.0598
	(0.78)	(-0.09)	(-0.76)	(-1.42)	(-2.11)	(3.00)	(-0.86)	(0.51)	(1.27)	(2.32)
StDev	0.1710	0.1728	0.1670	0.1641	0.1870	0.0972	0.1336	0.1168	0.1021	0.1009
Downside volatility (0%)	0.0562	0.0582	0.0574	0.0519	0.0615	0.0284	0.0461	0.0363	0.0323	0.0294
Skewness	-0.2840	-0.3671	-0.4806	-0.0799	-0.0910	0.0550	-0.4596	-0.1676	-0.1454	0.0318
Excess Kurtosis	1.3942	1.0673	2.0951	0.8222	1.4493	0.5264	1.7672	0.7764	0.5940	0.6147
JB normality test p-value	0.0010	0.0010	0.0010	0.0010	0.0010	0.0166	0.0010	0.0010	0.0044	0.0070
AR(1)	0.0153	0.0564	0.0698	0.0527	-0.0220	-0.0607	0.0501	-0.0379	0.0152	-0.0511
99% VaR (Cornish-Fisher)	0.0665	0.0671	0.0721	0.0598	0.0728	0.0311	0.0562	0.0421	0.0356	0.0331
% of positive months	52%	52%	50%	48%	47%	56%	50%	50%	54%	54%
Maximum drawdown	-0.3831	-0.5348	-0.6181	-0.6623	-0.8131	-0.1465	-0.5392	-0.2872	-0.1905	-0.1828
Sharpe ratio	0.1999	-0.0273	-0.2200	-0.3924	-0.5611	0.7152	-0.2486	0.1296	0.3387	0.5926
Sortino ratio	0.6082	-0.0809	-0.6397	-1.2403	-1.7066	2.4509	-0.7197	0.4173	1.0720	2.0331
Omega ratio	1.0749	0.9902	0.9227	0.8677	0.8113	1.2914	0.9130	1.0472	1.1297	1.2342
CER (power utility)	-0.0402	-0.0813	-0.1090	-0.1330	-0.1952	0.0459	-0.0790	-0.0192	0.0084	0.0343
Panel B: Correlation structure										
AVG						-0.03				
						{0.48}				
Momentum						0.29	0.02			
						{0.00}	{0.66}			
Term Structure						-0.03	0.05	0.36		
						{0.40}	{0.20}	{0.00}		
Hedging pressure						0.12	0.09	0.33	0.27	
						{0.00}	{0.01}	{0.00}	{0.00}	

Table 5. Time-series tests: alpha of long-short CFEAR portfolio

The table reports estimation results for time-series regressions to test whether the CFEAR portfolio provides alpha in the context of a four-factor benchmark model that includes the AVG, momentum, term structure (or basis) and hedging pressure factors (Fernandez-Perez et al., 0218; Bianchi et al., 2018) and individual factor models. Alongside the alpha, we report the betas (risk exposures) with Newey West h.a.c. *t*-statistics in parenthesis, and adjusted-R^2. The sample period is January 2004 (week1) to December 2018 (week 4).

	annualized alpha	AVG	Momentum	Term structure	HP	Adj-R^2 (%)
Model 1	0.0689	-0.0191				-0.07
	(3.01)	(-0.58)				
Model 2	0.0659		0.2437			8.44
	(2.94)		(5.97)			
Model 3	0.0706			-0.0296		-0.04
	(3.05)			(-0.61)		
Model 4	0.0625				0.1180	1.36
	(2.70)				(2.66)	
Model 5	0.0668	-0.0214	0.2778	-0.1577	0.0557	10.57
	(3.14)	(-0.75)	(6.56)	(-3.02)	(1.24)	

Table 6. 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. (2018) inter alia that includes the average commodity factor (AVG), momentum factor (Mom), term structure or basis factor, and hedging pressure (HP) factor. The test assets are the 26 portfolios (quintiles resulting from sorting the individual commodity futures by the momentum, roll-yield, hedging pressure, 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) corrected (for errors-in-variables) *t*-statistics in parentheses, and Kan, Robotti and Shanken (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 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 adjusted R^2 and mean absolute prediction error (MAPE) reported in both Panels A and B are from a cross-sectional regression of average returns on full-sample betas, to ensure comparability of the models' fit in both panels. The period is January 2004 to December 2018.

	Constant	CFEAR	AVG	Mom	Term structure	HP	Adj.-R^2 (%)	MAPE (%)
			Panel A: Commodity portfolios (N=26 test assets)					
Model 1	-0.0006	0.0813					48.49	0.049
	(-0.85)	(2.53)						
	{-0.78}	{2.61}						
Model 2	-0.0004		-0.0115				0.25	0.068
	(-0.44)		(-0.19)					
	{-0.44}		{-0.16}					
Model 3	-0.0007			0.0731			31.96	0.056
	(-0.96)			(2.08)				
	(-0.73)			{2.28}				
Model 4	-0.0007				0.0531		17.20	0.056
	(-1.02)				(1.65)			
	{-0.80}				{1.68}			
Model 5	-0.0008					0.0709	37.61	0.050
	(-1.17)					(2.20)		
	{-0.87}					{2.16}		
Model 6	0.0001		-0.0353	0.0548	0.0230	0.0643	45.90	0.049
	(0.06)		(-0.58)	(1.60)	(0.77)	(2.08)		
	{0.06}		{-0.53}	{1.67}	{0.80}	{2.01}		
Model 7	-0.0010	0.0828	0.0204	0.0276	0.0387	0.0561	72.32	0.032
	(-1.13)	(2.80)	(0.35)	(0.86)	(1.32)	(1.82)		
	{-1.13}	{2.80}	{0.34}	{0.88}	{1.37}	{1.81}		

Table 6. ***(cont.)***

	Constant	CFEAR	AVG	Mom	Term structure	HP	Adj.-R^2 (%)	MAPE (%)
Panel B: Individual commodities (N=28 test assets)								
Model 1	-0.0007	0.0491					37.75	0.120
	<1.06>	<1.76>						
	(-1.04)	(1.73)						
Model 2	-0.0004		-0.0223				-2.32	0.144
	<0.58>		<0.51>					
	(-0.58)		(-0.51)					
Model 3	-0.0006			0.0220			66.92	0.087
	<0.85>			<0.61>				
	(-0.85)			(0.61)				
Model 4	-0.0009				0.0075		11.79	0.119
	<1.30>				<0.20>			
	(-1.30)				(0.20)			
Model 5	-0.0008					0.0466	43.16	0.114
	<1.10>					<1.59>		
	(-1.09)					(1.57)		
Model 6	0.0003		-0.0578	0.0347	0.0020	0.0587	79.77	0.065
	<0.34>		<1.23>	<0.94>	<0.05>	<2.00>		
	(0.32)		(-1.17)	(0.90)	(0.05)	(1.90)		
Model 7	0.0002	0.0756	-0.0543	0.0139	0.0095	0.0450	80.49	0.059
	<0.20>	<2.76>	<1.14>	<0.37>	<0.25>	<1.51>		
	(0.18)	(2.57)	(-1.06)	(0.35)	(0.23)	(1.41)		

Table 7. CFEAR risk versus skewness risk

The table reports in Panel A estimation results of time-series regressions to test whether the CFEAR portfolio provides alpha in the context of Models i and ii that include the skewness factor of Fernandez-Perez et al. (2018). The traditional four-factor Model ii is reported for comparison. Alongside the alpha, we report the betas (risk exposures) with Newey West h.a.c. *t*-statistics in parenthesis. Panel B reports cross-sectional pricing tests for the same 26 commodity portfolios as in Tables 6-7 for comparison. We report the (annualized) prices of risk from cross-sectional regressions of average excess returns on full-sample betas and Shanken (1992) *t*-statistics corrected for error-in-variables in parentheses, and Kan, Robotti and Shanken (2013) *t*-statistics additionally corrected for model misspecification and heteroskedasticity in curly brackets. The sample period is January 2004 (week1) to December 2018 (week 4).

Panel A: Time-series tests

	alpha	AVG	Mom	TS	HP	Skewness	Adj-R^2
Model i	0.0637					0.1325	1.69
	(2.69)					(2.59)	
Model ii	0.0668	-0.0214	0.2778	-0.1577	0.0557		10.57
	(3.14)	(-0.75)	(6.56)	(-3.02)	(1.24)		
Model iii	0.0634	-0.0219	0.2820	-0.1748	0.0240	0.1295	12.04
	(2.95)	(-0.74)	(6.47)	(-3.40)	(0.51)	(2.71)	

Panel B: Cross-sectional tests

	Constant	CFEAR	AVG	Mom	TS	HP	Skewness	Adj.-R^2 *(%)*	MAPE (%)
	Test assets: Commodity portfolios (N=26)								
Model 1	-0.0007						0.1439	45.32	0.047
	(-1.07)						(2.33)		
	{-0.73}						{2.17}		
Model 2	-0.0007	0.0712					0.1059	65.55	0.037
	(-0.98)	(2.22)					(1.66)		
	{-0.82}	{2.26}					{1.64}		
Model 3	-0.0004		-0.0122	0.0477	0.0221	0.0498	0.1011	51.55	0.047
	(-0.40)		(-0.20)	(1.42)	(0.73)	(1.73)	(1.50)		
	{-0.44}		{-0.19}	{1.43}	{0.72}	{1.76}	{1.22}		
Model 4	-0.0011	0.0820	0.0228	0.0272	0.0380	0.0537	0.0439	72.48	0.032
	(-1.15)	(2.78)	(0.38)	(0.85)	(1.31)	(1.87)	(0.62)		
	{-1.18}	{2.84}	{0.39}	{0.87}	{1.30}	{1.90}	{0.56}		

Table 8. CFEAR risk versus basis-momentum risk

The table reports in Panel A estimation results of time-series regressions to test whether the CFEAR portfolio provides excess returns after controlling for exposure to the basis-momentum (BM) risk factor of Boons and Prado (2019). The traditional four-factor model with the AVG, momentum, term structure or basis and hedging pressure risk factors is also reported for comparison. We report the alpha and betas (risk exposures) with Newey West h.a.c. *t*-statistics in parenthesis. Panel B reports cross-sectional pricing tests for the same 26 commodity portfolios as in Tables 6-7 for comparison. We report the (annualized) prices of risk from cross-sectional regressions of average excess returns on full-sample betas and Shanken (1992) *t*-statistics corrected for error-in-variables in parentheses, and Kan, Robotti and Shanken (2013) *t*-statistics additionally corrected for model misspecification and heteroskedasticity in curly brackets. The sample period is January 2004 (week1) to December 2018 (week 4).

Panel A: Time-series tests

	alpha	AVG	Mom	TS	HP	BM	Adj.-R^2 (%)
Model i	0.0608					0.1687	2.68
	(2.49)					(3.14)	
Model ii	0.0668	-0.0214	0.2778	-0.1577	0.0557		10.57
	(3.14)	(-0.75)	(6.56)	(-3.02)	(1.24)		
Model iii	0.0623	-0.0185	0.2508	-0.1702	0.0629	0.0961	11.22
	(2.80)	(-0.63)	(5.71)	(-3.33)	(1.40)	(1.73)	

Panel B: Cross-sectional tests

	Constant	CFEAR	AVG	Mom	TS	HP	BM	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0005						0.1413	48.20	0.050
	(-0.72)						(2.41)		
	{-0.63}						{2.51}		
Model 2	-0.0005	0.0624					0.0911	57.18	0.046
	(-0.76)	(2.10)					(1.59)		
	{-0.69}	{2.08}					{1.64}		
Model 3	-0.0011		0.0253	0.0259	0.0429	0.0656	0.2100	74.07	0.034
	(-1.08)		(0.39)	(0.81)	(1.50)	(2.10)	(2.39)		
	{-1.11}		{0.37}	{0.83}	{1.53}	{2.00}	{1.95}		
Model 4	-0.0015	0.0663	0.0458	0.0158	0.0478	0.0597	0.1542	83.92	0.028
	(-1.53)	(2.40)	(0.74)	(0.50)	(1.68)	(1.94)	(1.74)		
	{-1.59}	{2.59}	{0.74}	{0.53}	{1.77}	{1.89}	{1.50}		

Table 9. CFEAR risk versus iliquidity risk

The table reports in Panel A the estimation results for time-series regressions of the returns of the CFEAR portfolio on the returns of a long-short commodity portfolio based on the (inverse of) the Amivest liquidity measure as proxy for a tradable iliquidity risk factor, and the first difference of the TED spread as proxy for innovations to funding iliquidity (non-tradeable risk factor); we also include the four traditional factors. Alongside the annualized constant (with an alpha interpretation in models i, iii and iv), we report the betas (risk exposures) with Newey West h.a.c. *t*-statistics in parentheses. Panel B reports cross-sectional pricing tests using as test assets the same commodity portfolios as in Tables 6-8, for comparison. We report the (annualized) prices of risk from cross-sectional regressions of average excess returns on full-sample betas and Kan, Robotti and Shanken (2013) *t*-statistics corrected for error-in-variables, model misspecification and heteroskedasticity in curly brackets. The Shanken (1992) *t*-statistics corrected for error-in-variables, produce qualitatively similar inferences and are not reported for space constraints. The sample period is January 2004 (week1) to December 2018 (week 4).

Panel A: Time-series tests

	Constant	AVG	Mom	TS	HP	Iliquidity	Δ_{TED}	Adj-R^2 (%)
Model i	0.0692					-0.1991		3.75
	(3.08)					(-3.70)		
Model ii	0.0696						-0.0051	0.14
	(3.02)						(-2.28)	
Model iii	0.0668	-0.0214	0.2778	-0.1577	0.0557			10.57
	(3.14)	(-0.75)	(6.56)	(-3.02)	(1.24)			
Model iv	0.0663	-0.0166	0.2532	-0.1367	0.0557	-0.1337		12.11
	(3.16)	(-0.60)	(5.76)	(-2.71)	(1.27)	(-2.68)		
Model v	0.0667	-0.0271	0.2776	-0.1572	0.0543		-0.0051	10.72
	(3.15)	(-0.91)	(6.55)	(-3.02)	(1.21)		(-1.92)	

Panel B: Cross-sectional tests

	Constant	CFEAR	AVG	Mom	TS	HP	Iliquidity	Δ_{TED}	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0005						-0.0824		27.47	0.060
	{-0.63}						{-1.68}			
Model 2	-0.0021							-0.0708	22.62	0.062
	{-2.08}							{-1.62}		
Model 3	-0.0006	0.0752					-0.0369		49.81	0.049
	{-0.67}	{2.63}					{-0.76}			
Model 4	-0.0016	0.0854						-0.0500	58.82	0.045
	{-2.11}	{2.79}						{-1.15}		
Model 5	0.0000		-0.0342	0.0286	0.0428	0.0687	-0.0949		69.23	0.039
	{0.02}		{-0.54}	{0.94}	{1.61}	{2.07}	{-1.88}			
Model 6	-0.0003		-0.0174	0.0413	0.0283	0.0609		-0.0765	61.04	0.044
	{-0.29}		{-0.27}	{1.29}	{0.94}	{1.87}		{-2.19}		
Model 7	-0.0008	0.0670	0.0066	0.0171	0.0479	0.0612	-0.0677		81.15	0.030
	{-0.90}	{2.61}	{0.11}	{0.58}	{1.85}	{1.93}	{-1.38}			
Model 8	-0.0010	0.0804	0.0215	0.0244	0.0391	0.0555		-0.0460	76.70	0.031
	{-1.11}	{2.83}	{0.36}	{0.79}	{1.36}	{1.77}		{-1.39}		

Table 10. CFEAR risk versus volatility risk

The table reports in Panel A the estimation results of time-series regressions of the returns of the CFEAR portfolio on two non-tradeable volatility risk factors: aggregate volatility risk factor and average volatility risk factor which are obtained, respectively, as the innovations (first-difference) in the aggregate commodity market variance and average commodity market variance; we also include the four traditional factors. We report the annualized constant (with an "alpha" interpretation in Model iii only), and the betas (risk exposures) with Newey West h.a.c. *t*-statistics in parenthesis. Panel B reports cross-sectional pricing tests using as test assets the same 26 commodity portfolios as in Tables 6-9 for comparison. We report the (annualized) prices of risk from cross-sectional regressions of average excess returns on full-sample betas and Kan, Robotti and Shanken (2013) *t*-statistics corrected for error-in-variables, model misspecification and heteroskedasticity in curly brackets. The Shanken (1992) *t*-statistics corrected for error-in-variables, produce qualitatively similar inferences and are not reported for space constraints. The sample period is January 2004 (week1) to December 2018 (week 4).

Panel A: Time-series tests

	Constant	AVG	Mom	TS	HP	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)
Model i	0.0695					-0.1174		0.15
	(3.02)					(-1.27)		
Model ii	0.0695						-0.0538	0.30
	(3.02)						(-2.05)	
Model iii	0.0668	-0.0214	0.2778	-0.1577	0.0557			10.57
	(3.14)	(-0.75)	(6.56)	(-3.02)	(1.24)			
Model iv	0.0668	-0.0238	0.2761	-0.1583	0.0541	-0.0718		10.55
	(3.15)	(-0.82)	(6.62)	(-3.03)	(1.21)	(-0.96)		
Model v	0.0668	-0.0233	0.2760	-0.1556	0.0519		-0.0287	10.57
	(3.15)	(-0.80)	(6.58)	(-3.04)	(1.16)		(-1.03)	

Panel B: Cross-sectional tests

	Constant	CFEAR	AVG	Mom	TS	HP	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0018						-0.0038		36.17	0.053
	{-1.79}						{-1.68}			
Model 2	-0.0016							-0.0105	51.25	0.048
	{-1.48}							{-2.42}		
Model 3	-0.0014	0.0787					-0.0025		61.55	0.040
	{-1.57}	{2.58}					{-1.22}			
Model 4	-0.0012	0.0640						-0.0067	59.40	0.044
	{-1.27}	{2.14}						{-1.48}		
Model 5	-0.0003		-0.0174	0.0555	0.0216	0.0606	-0.0016		47.38	0.049
	{-0.21}		{-0.20}	{1.69}	{0.74}	{1.87}	{-0.39}			
Model 6	-0.0014		0.0423	0.0412	0.0369	0.0689		-0.0105	60.83	0.040
	{-1.14}		{0.53}	{1.30}	{1.23}	{2.06}		{-1.74}		
Model 7	-0.0009	0.0825	0.0166	0.0269	0.0393	0.0569	0.0003		72.42	0.032
	{-0.85}	{2.83}	{0.24}	{0.87}	{1.40}	{1.84}	{0.11}			
Model 8	-0.0017	0.0762	0.0551	0.0244	0.0439	0.0600		-0.0061	76.37	0.032
	{-1.39}	{2.65}	{0.76}	{0.80}	{1.57}	{1.89}		{-1.03}		

Table 11. Predictive ability of volatility and illiquidity for CFEAR returns

The table reports estimation results of time-series regression of the CFEAR portfolio returns compounded over 1, 4, 12 and 52 weeks, $r^{CFEAR}_{i,t+1:t+k}$, on predictive variable at t either the (standardized) aggregate commodity market variance, average commodity market variance or TED spread, $z_t = \{\mathrm{AggVar}, \mathrm{AvgVar}, \mathrm{TED}\}$. The table reports the OLS coefficients and t-statistics based on Newey-West h.a.c. robust standard errors. The sample period is January 2004 (week1) to December 2018 (week 4).

Dependent variable: CFEAR(t+1:t+k)					
horizon (in weeks)	Constant	TED [t]	Aggr. Market Variance [t]	Average Market Variance [t]	adj.-R^2 (%)
k=1	0.0014	0.0007			0.10
	(3.06)	(1.55)			
	0.0014		0.0009		0.30
	(3.08)		(2.22)		
	0.0014			0.0010	0.41
	(3.07)			(2.33)	
k=4	0.0056	0.0030			1.29
	(3.47)	(2.19)			
	0.0056		0.0039		2.32
	(3.49)		(3.56)		
	0.0056			0.0039	2.22
	(3.47)			(3.03)	
k=12	0.0168	0.0073			3.05
	(4.77)	(2.28)			
	0.0168		0.0084		4.08
	(4.79)		(2.82)		
	0.0168			0.0058	1.86
	(4.72)			(1.71)	
k=52	0.0684	0.0217			7.33
	(9.14)	(5.14)			
	0.0684		0.0188		5.49
	(9.05)		(4.51)		
	0.0683			0.0181	5.06
	(9.03)			(3.56)	

Table 12. Subsample analysis of CFEAR premia in periods of high/low uncertainty

This table reports in Panel A the CFEAR premia and alpha using the traditional AVG, term structure, momentum and HP factors in col (3) and the latter augmented with the basis-momentum illiquidity (ΔTED) and volatility ($\Delta AggrVar$) factors in col (5)) with significance t-ratios in parenthesis. The t-statistics in cols (2), (4) and (6) are for $H_0: r_{CFEAR}^{high} = r_{CFEAR}^{low}$ vs $H_0: r_{CFEAR}^{high} \neq r_{CFEAR}^{low}$ where $r_{CFEAR}^{high}(r_{CFEAR}^{low})$ denotes the CFEAR return or risk-adjusted return in the high (low) uncertainty period. The last column reports the Sharpe ratio of the CFEAR portfolio in each regime. The criteria for classifying the sample weeks into sub-periods is either the VIX, financial uncertainty or macroeconomic uncertainty indices for 1-month horizon of Jurado, Ludvigson and Ng (2015), commodity price uncertainty and inventory uncertainty as proxied by the averaged N variances of the daily excess return and daily roll-yield of all commodities, respectively, in the preceding month. Panel B reports the correlations among uncertainty proxies. Bold shaded denotes strongly significant at the 5% or 1 % level. Newey-West s.e. are used for all test statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CFEAR premia	*t*-stat Ho: diff=0	CFEAR alpha	*t*-stat Ho: diff=0	CFEAR alpha	*t*-stat Ho: diff=0	Sharpe ratio
Panel A: Sub-sample analysis by uncertainty level							
VIX uncertainty							
I. High	0.1559	2.6183	0.1527	2.7822	0.1367	2.4541	1.5081
	(3.81)		(4.06)		(3.51)		
II. Low	0.0230		0.0209		0.0194		0.2470
	(0.82)		(0.80)		(0.72)		
Financial uncertainty index of Jurado et al. (2015)							
I. High	0.1035	1.1120	0.1081	1.4794	0.0881	0.9831	1.0327
	(2.76)		(3.15)		(2.44)		
II. Low	0.0506		0.0440		0.0445		0.5295
	(1.74)		(1.66)		(1.63)		
Macroeconomic uncertainty index of Jurado et al. (2015)							
I. High	0.1050	1.0352	0.0905	0.7180	0.0718	0.3452	0.9942
	(2.41)		(2.15)		(1.58)		
II. Low	0.0524		0.0555		0.0542		0.5640
	(1.98)		(2.30)		(2.23)		
Commodity price uncertainty (variance)							
I. High	0.1235	1.6172	0.1262	1.9858	0.1128	1.6993	1.1212
	(2.79)		(3.19)		(2.68)		
II. Low	0.0378		0.0323		0.0294		0.4264
	(1.40)		(1.31)		(1.17)		
Inventories uncertainty (variance)							
I. High	0.1483	2.0267	0.1287	1.5947	0.1320	1.8037	1.3607
	(3.11)		(2.71)		(2.59)		
II. Low	0.0367		0.0408		0.0292		0.4008
	(1.42)		(1.69)		(1.24)		

Table 12. *(cont.)*

Panel B: Correlations	VIX	Fin. Unc. index	Macro. Unc. index (Jurado et al. 2015)	Comm. Price Unc.
Fin. Unc. index	0.84			
	{0.00}			
Macro. Unc. index	0.72	0.79		
(Jurado et al. 2015)	{0.00}	{0.00}		
Comm. Price Unc.	0.77	0.73	0.79	
(Jurado et al. 2015)	{0.00}	{0.00}	{0.00}	
Inventory Unc.	-0.03	-0.09	-0.08	-0.01
	{0.43}	{0.01}	{0.03}	{0.84}

Table 13. Robustness tests: alternative CFEAR index construction methods

The table summarizes the performance of the long-short CFEAR portfolio based on a commodity-hazard fear index that is constructed using the approach described in Section 2.1 sidestepping the construction of the CFEAR index in col. (1), using US Google searches (2), without winsorization (3), and without de-seasonalization (4). Finally, in cols (5) to (8) we exclude each category of keywords, in turn from the CFEAR index. Panel B reports the annualized price of the CFEAR risk in the model with the AVG, hedging pressure, basis and momentum factors for the 26 commodity portfolios (Model 7 in Table 6) with Shanken (1992) *t*-statistics in parentheses, and Kan, Robotti and Shanken (2013) *t*-statistics in curly brackets.

	Alternative CFEAR factors							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Median beta of keywords	US searches	Without wins.	Without de-seas.	Excl. EC keywords	Excl. GP keywords	Excl. DI keywords	Excl. WE keywords
Panel A: Summary statistics (CFEAR portfolio)								
Mean	0.0571	0.0422	0.0595	0.0780	0.0565	0.0737	0.0670	0.0381
	(2.24)	(1.80)	(2.45)	(2.88)	(2.51)	(3.09)	(2.69)	(1.38)
StDev	0.0972	0.0865	0.0980	0.1043	0.0941	0.0978	0.1006	0.0993
Downside volatility (0%)	0.0293	0.0247	0.0296	0.0317	0.0277	0.0281	0.0291	0.0294
Skewness	-0.0603	0.0324	-0.0921	-0.1114	0.0378	0.1274	0.1122	-0.0362
Excess Kurtosis	0.4395	0.0839	0.4172	0.6241	0.5975	0.7721	0.5111	0.3244
JB normality test *p*-value	0.0417	0.5000	0.0416	0.0044	0.0082	0.0010	0.0132	0.1696
99% VaR (Cornish-Fisher	0.0322	0.0270	0.0327	0.0354	0.0307	0.0312	0.0316	0.0327
% of positive months	56%	52%	55%	57%	55%	56%	54%	50%
Maximum drawdown	-0.2188	-0.1685	-0.1635	-0.1469	-0.1592	-0.1298	-0.1660	-0.2002
Sharpe ratio	0.5875	0.4878	0.6075	0.7482	0.6006	0.7533	0.6653	0.3838
Panel B: Cross-sectional asset pricing tests (*N*=26 commodity portfolios)								
λ_{CFEAR}	0.0992	0.0918	0.0920	0.0894	0.0894	0.0903	0.0886	0.1086
	(2.88)	(2.83)	(2.87)	(2.90)	(2.90)	(2.87)	(2.80)	(2.40)
	{2.68}	{2.61}	{2.80}	{2.89}	{2.89}	{2.76}	{2.65}	{2.33}
adj-R^2 (%)	67.16	67.64	73.92	70.65	70.65	68.07	70.99	71.91

Table 14. Robustness tests: alternative CFEAR portfolio construction methods

The table summarizes in Panel A the alternative CFEAR factor obtained through different portfolio formation methods. In column (1) the ranking period is a rolling window of 10 years, in col. (2) the Q1 and Q5 quintile constituents are weighed by the strength of the standardized signals. In cols. (3)-(6) all the commodities are included in the long-short portfolios, either equally-weighted (col. 4), weighted by the standardized rankings (col. 5), weighted by the standardized signals (col. 6), or weighted by the winsorized and standardized signals (col. 6). In col. (7) we consider at each portfolio formation time only the 80% of the commodities with the largest trading volume on the prior week. Panel B reports the price of the CFEAR risk factor in the model with the AVG, momentum, term structure and hedging pressure factor for the 26 commodity portfolios (Model 7 in Table 6) with Shanken (1992) *t*-statistics in parentheses, and Kan, Robotti and Shanken (2013) *t*-statistics in curly brackets.

	Alternative CFEAR factors						
	(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	0.0763	0.0684	0.0437	0.0528	0.0530	0.0530	0.0915
	(1.69)	(2.85)	(2.75)	(2.88)	(2.72)	(2.72)	(3.70)
StDev	0.1030	0.1006	0.0585	0.0713	0.0784	0.0785	0.1016
Downside volatility (0%)	0.0313	0.0300	0.0185	0.0212	0.0233	0.0233	0.0291
Skewness	-0.1468	0.0245	-0.1528	-0.0191	-0.0354	-0.0355	0.1058
Excess Kurtosis	0.4001	0.4397	0.4627	0.3821	0.3496	0.3464	0.9006
JB normality test *p*-value	0.2164	0.0487	0.0137	0.0961	0.1306	0.1351	0.0010
99% VaR (Cornish-Fisher)	0.0345	0.0323	0.0198	0.0230	0.0255	0.0255	0.0328
% of positive months	57%	55%	55%	55%	55%	55%	55%
Maximum drawdown	-0.1321	-0.1559	-0.0950	-0.1169	-0.1105	-0.1105	-0.1417
Sharpe ratio	0.7408	0.6800	0.7457	0.7407	0.6758	0.6754	0.9008
Sortino ratio	2.4340	2.2800	2.3562	2.4918	2.2752	2.2754	3.1462
Omega ratio	1.3032	1.2770	1.3083	1.3019	1.2697	1.2695	1.3776
CER (power utility)	0.0497	0.0431	0.0350	0.0400	0.0376	0.0375	0.0656
Panel B: Cross-sectional asset pricing tests (*N*=26 commodity portfolios)							
λ_{CFEAR}	0.0459	0.0883	0.0463	0.0609	0.0693	0.0693	0.0957
	(0.83)	(2.81)	(2.55)	(2.87)	(2.88)	(2.88)	(2.79)
	{0.89}	{2.83}	{2.35}	{2.69}	{2.76}	{2.75}	{2.79}
adj-R^2 (%)	68.11	72.27	61.31	68.13	70.10	70.07	71.74

Table 15. Robustness tests: CFEAR factor and benchmark commodity factors with monthly rebalancing

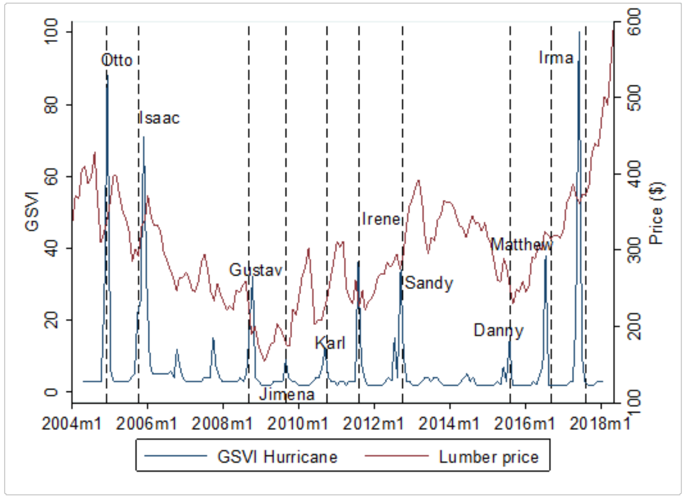
The table reports results for the CFEAR portfolio and benchmarks re-constructed using the conventional end-of-month portfolio formation point (instead of the weekly rebalancing). Q1 (Q5) is the quintile of commodities with the most negative (positive) β^{CFEAR} characteristic. Newey-West robust h.a.c. t-statistics are shown in parenthesis. Panel B reports the pairwise correlations with significance p-values in curly brackets. The sample period is January 2004 (week 1) to December 2018 (week 4).

	CFEAR						AVG	Mom	Term structure	Hedging pressure
	Long (Q1)	Q2	Q3	Q4	Short (Q5)	Q1-Q5				
Panel A: Summary statistics										
Mean	0.0294	-0.0052	-0.0193	-0.0760	-0.0989	0.0642	-0.0330	0.0068	0.0516	0.0516
	(0.63)	(-0.08)	(-0.37)	(-1.64)	(-1.68)	(2.78)	(-0.72)	(0.24)	(1.62)	(1.99)
StDev	0.1721	0.1981	0.1769	0.1770	0.1814	0.0890	0.1471	0.1108	0.1030	0.0923
Downside volatility (0%)	0.1240	0.1700	0.1293	0.1217	0.1305	0.0489	0.1170	0.0677	0.0587	0.0516
Skewness	-0.5401	-1.2012	-0.2950	-0.3251	-0.4383	0.3068	-0.8037	0.2467	0.3772	0.1402
Excess Kurtosis	1.4056	3.1821	1.8981	0.8594	1.7247	0.2179	3.1259	0.7557	1.5263	0.3367
JB normality test p-value	0.0021	0.0010	0.0011	0.0239	0.0013	0.1700	0.0010	0.0488	0.0027	0.4535
99% VaR (Cornish-Fisher)	0.1438	0.1955	0.1525	0.1456	0.1643	0.0490	0.1474	0.0729	0.0656	0.0568
% of positive months	54%	55%	50%	44%	43%	58%	50%	50%	55%	55%
Maximum drawdown	-0.3643	-0.5182	-0.5496	-0.6981	-0.8180	-0.1553	-0.5394	-0.2533	-0.1977	-0.2070
Sharpe ratio	0.1710	-0.0262	-0.1089	-0.4296	-0.5452	0.7209	-0.2244	0.0618	0.5015	0.5592
Sortino ratio	0.2374	-0.0306	-0.1491	-0.6249	-0.7580	1.3136	-0.2822	0.1011	0.8797	0.9996
Omega ratio	1.1360	0.9795	0.9182	0.7264	0.6593	1.7251	0.8357	1.0480	1.4558	1.5001
CER (power utility)	-0.0504	-0.1263	-0.1041	-0.1642	-0.1958	0.0444	-0.0943	-0.0235	0.0257	0.0304
Panel B: Correlation structure										
AVG						0.04				
						{0.65}				
Momentum						0.31	0.21			
						{0.00}	{0.01}			
Term Structure						0.01	0.14	0.26		
						{0.86}	{0.08}	{0.00}		
Hedging pressure						0.32	0.11	0.41	0.17	
						{0.00}	{0.16}	{0.00}	{0.03}	

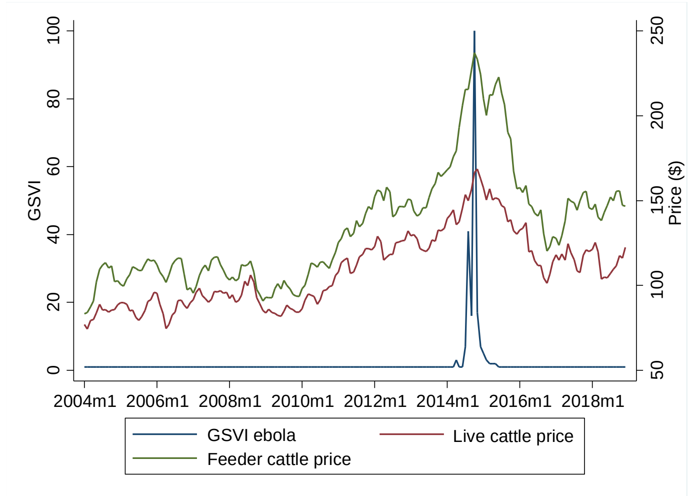
Figure 1. Google searches and commodity prices.

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.

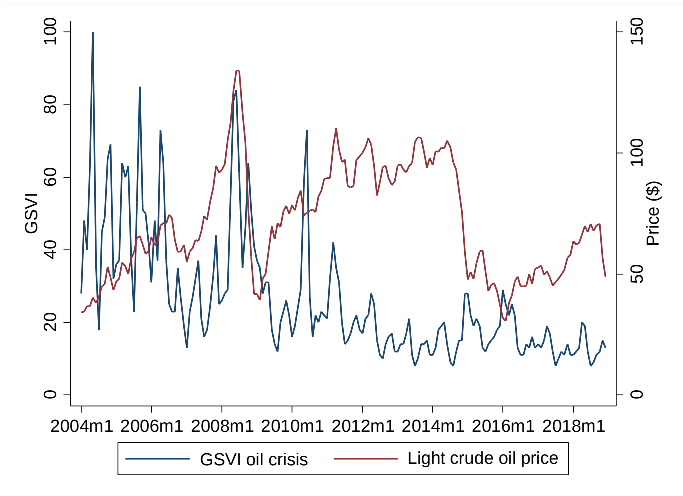
Panel A: *hurricane* (WE) searches vs lumber price



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



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



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

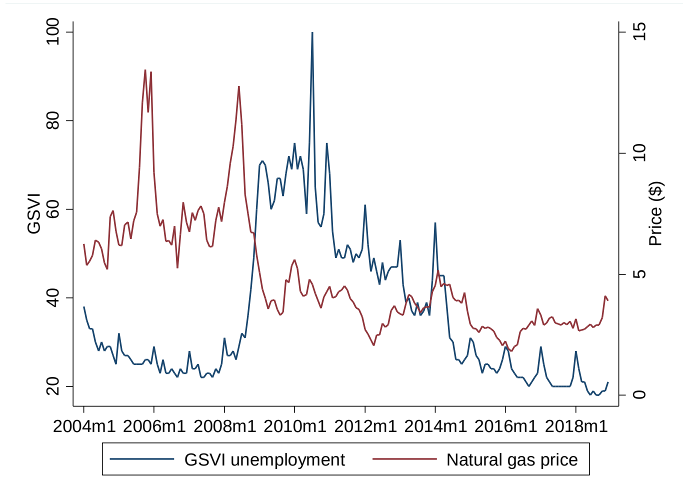


Figure 2. Frequency of commodities in long and short CFEAR-based commodity portfolios

This graph plots the percentage of portfolio formation weeks in the sample period from January 2004 (week 1) to May 2018 (week 4) when each of the 28 commodities enters the long CFEAR portfolio (quintile Q1) and short CFEAR portfolio (quintile Q5). The graph is organized per sector.

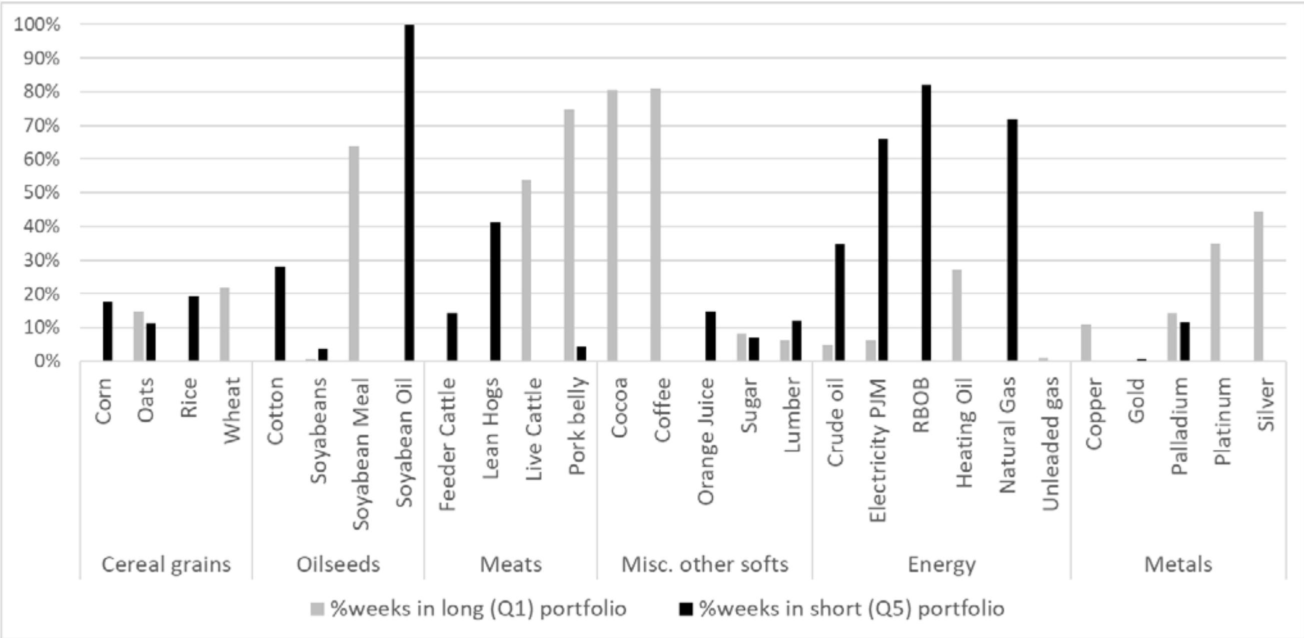


Figure 3. Future value of $1 invested in commodity portfolios.

The graph shows the evolution of $1 invested in the long-only portfolio that equally-weights with weekly rebalancing all commodities (AVG), and the long-short term structure (TS), momentum (Mom), hedging pressure (HP) and CFEAR portfolios.

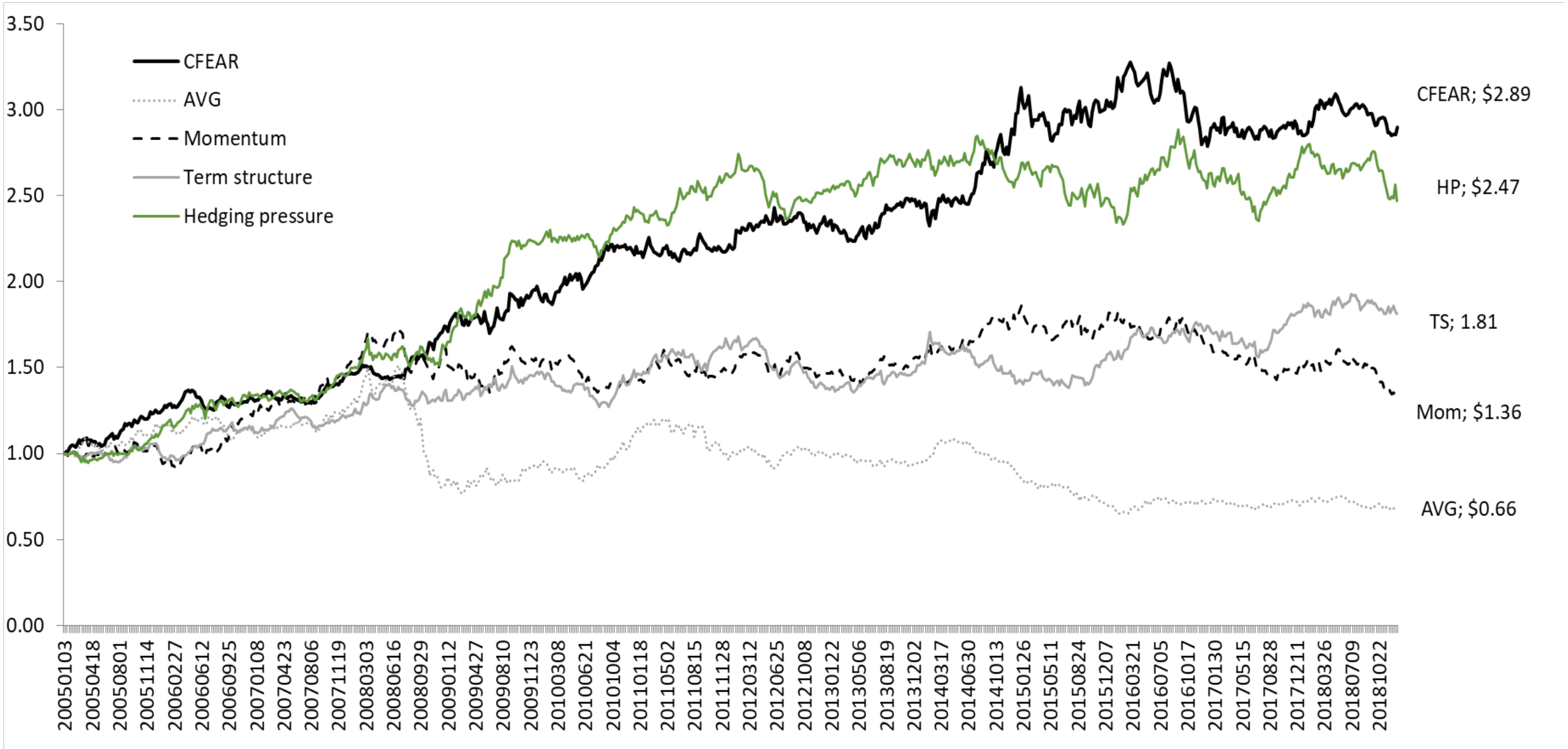
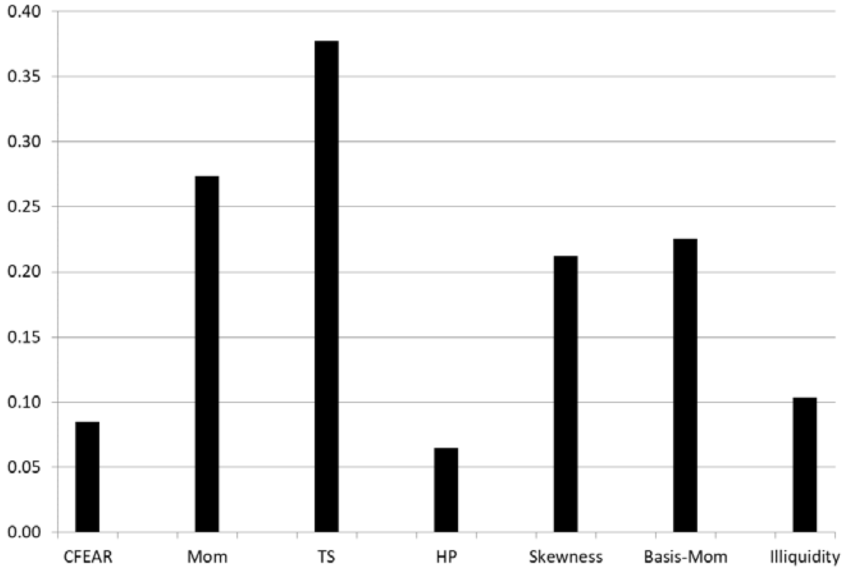


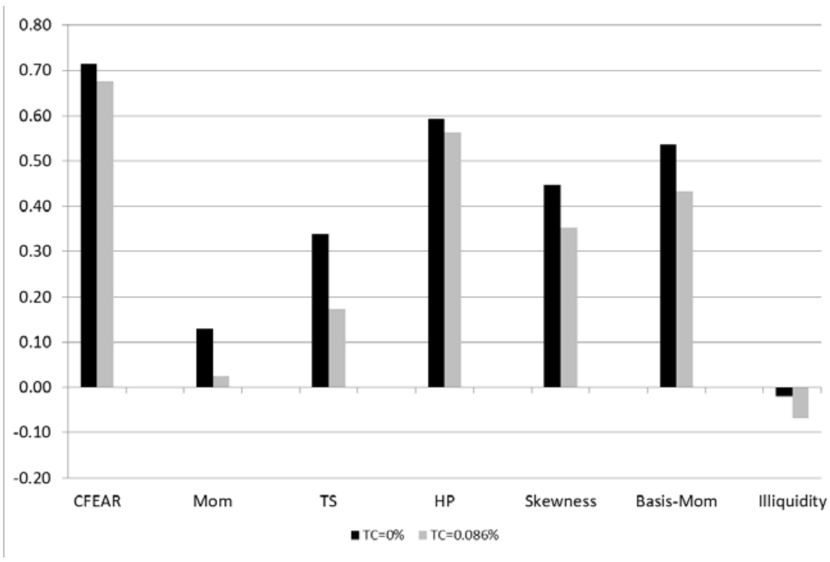
Figure 4. Turnover and transaction costs of commodity portfolios

Panel A plots the turnover of each of the long-short commodity portfolios formed according to the CFEAR, momentum, roll-yield, hedging pressure (speculators), skewness, basis-mom or illiquidity signals. Panel B plots the Sharpe ratios of each of the portfolios before and after transaction costs.

Panel A: Turnover



Panel B: Sharpe ratios



ONLINE ANNEX

Hazard Fear, Information Search Behavior, and Commodity Futures Risk Premia

ADRIAN FERNANDEZ-PEREZ, ANA-MARIA FUERTES, MARCOS GONZALEZ-FERNANDEZ, JOELLE MIFFRE

May 13, 2019

Table A.1 Panel regressions: Predictive ability of CFEAR characteristic

The table presents the estimation results of panel regressions of the weekly excess returns of the 28 commodities on one-week lagged commodity characteristics, Equation (6), and the lagged returns. The models reported in columns (1) to (5) add the β^{CFEAR} measure. The models in cols. (6)-(8) add the roll-yield, momentum and HP(S) measures, respectively. The models in columns (9) and (10) add all four commodity characteristics. POLS is a pooled regression with an unreported intercept, FE are fixed effects models and PMG is the panel mean group estimator of Pesaran and Smith (1995). t-statistics for the POLS/FE estimator are calculated using Newey-West h.a.c standard errors (in parenthesis), standard errors clustered in the time dimension (curly brackets), and commodity dimension (angle brackets). t-statistics for the PMG estimator and based on the standard deviation of the individual time-series coefficients.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	POLS	FE			PMG	FE			PMG			FE	PMG
CFEAR	-12.35 (-3.80) {-2.49} <3.66>	-12.49 (-3.02) {-1.86} <4.41>	-11.21 (-3.52) {-2.65} <2.96>	-10.49 (-2.45) {-1.77} <3.21>	-21.88 (-3.55)							-10.96 (-2.53) {-1.86} <3.28>	-26.36 (-3.05)
Roll-yield						-0.0148 (-1.18) {-0.93} <1.21>			-0.0253 (-0.71)			-0.0123 (-0.95) {-0.76} <0.94>	0.0013 (0.03)
Mom							-0.0815 (-1.22) {-0.84} <1.52>			-0.1116 (-2.49)		-0.0872 (-1.20) {-0.83} <1.59>	-0.2443 (-2.46)
HP(S)								0.0000 (-0.02) {-0.02} <0.02>			-0.0049 (-1.52)	0.0007 (0.44) {0.41} <0.69>	0.0015 (0.29)
Return(t)	0.0128 (1.29) {0.79} <2.17>	0.0109 (1.10) {0.67} <1.80>	0.0032 (0.33) {0.26} <0.42>	0.0008 (0.08) {0.06} <0.10>	0.0088 (1.56)	0.0024 (0.25) {0.20} <0.28>	0.0025 (0.25) {0.20} <0.30>	0.0011 (0.11) {0.08} <0.13>	0.0095 (1.58)	0.0120 (2.02)	0.0097 (1.67)	0.0035 (0.35) {0.28} <0.39>	0.0089 (1.35)
Comm FE	No	Yes	No	Yes		Yes	Yes	Yes				Yes	
Time FE	No	No	Yes	Yes		Yes	Yes	Yes				Yes	
Adj-R^2 (%)	0.11	0.29	21.17	21.36	0.38	21.34	21.34	21.33	0.47	0.20	0.22	21.38	1.07

Table A.2 Portfolio pricing tests using sequential 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. (2018) inter alia that includes the average commodity factor (AVG), momentum factor (Mom), term structure factor, and hedging pressure (HP) factor. The test assets are the 26 portfolios (quintiles resulting from sorting the individual commodity futures by the momentum, roll-yield, hedging pressure, and CFEAR signals, and the six sub-sector portfolios). We report the (annualized) average prices of risk obtained in sequential (weekly) cross-sectional regressions on full-sample betas with *t*-statistics based on Fama-MacBeth (1973) standard errors in curly brackets and Shanken (1992) corrected version in parentheses. The adj-R^2 and the mean absolute prediction error (MAPE) are from a cross-sectional regression of average returns on full-sample betas. The period is January 2004 to December 2018.

	Constant	CFEAR	AVG	Mom	TS	HP	Adj-R^2 *(%)*	MAPE (%)
			Commodity portfolios (N=26 test assets)					
Model 1	-0.0008	0.0571					43.65	0.0507
	<1.13>	<2.08>						
	(-1.11)	(2.03)						
Model 2	-0.0008		-0.0047				-3.52	0.069
	<0.92>		<0.10>					
	(-0.92)		(-0.10)					
Model 3	-0.0007			0.0336			30.80	0.055
	<1.07>			<1.06>				
	(-1.07)			(1.05)				
Model 4	-0.0008				0.0272		14.50	0.056
	<1.21>				<0.92>			
	(-1.20)				(0.92)			
Model 5	-0.0009					0.0439	33.13	0.050
	<1.30>					<1.57>		
	(-1.28)					(1.55)		
Model 6	-0.0004		-0.0229	0.0376	0.0202	0.0507	32.81	0.049
	<0.46>		<0.43>	<1.18>	<0.72>	<1.80>		
	(-0.45)		(-0.42)	(1.15)	(0.70)	(1.75)		
Model 7	-0.0007	0.0610	-0.0059	0.0260	0.0384	0.0495	63.08	0.033
	<0.80>	<2.29>	<0.11>	<0.84>	<1.40>	<1.77>		
	(-0.76)	(2.18)	(-0.10)	(0.80)	(1.33)	(1.68)		

Table A.3 Alternative commodity risk factors

The table reports the performance of the long-short skewness, basis-mom and illiquidity risk portfolios. Newey-West robust h.a.c. *t*-statistics are shown in parenthesis. Panel B reports the pairwise correlations with significance *p*-values in curly brackets between the long-short CFEAR portfolio and the long-short skewness, basis-momentum and iliquidity portfolios. The sample period is January 2004 (week 1) to December 2018 (week 4).

	Skewness risk	Basis-Mom risk	Iliquidity risk
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
AR(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	0.14	0.17	-0.20
	{0.00}	{0.00}	{0.00}

Table A.4 Cross-sectional pricing tests for 28 commodities with additional risk factors.

The table presents cross-sectional pricing regressions for the N=28 commodities as test assets to assess the pricing ability of the CFEAR factor controlling for the skewness risk factor of Fernandez-Perez et al. (2018) in Panel A, the basis-momentum risk of Boons and Prado (2019) in Panel B, a tradeable illiquidity risk factor and non-tradeable iliquidity risk factor (TED spread) in Panel C, and two non-tradeable volatility risk factors (innovations in aggregate commodity market variance and average commodity market variance). The table reports the (annualized) prices of risk from sequential cross-sectional regressions of weekly commodity excess returns on sequential betas with Fama-MacBeth *t*-statistics based on Shanken (1992) standard errors in parenthesis. The period is January 2004 (week 1) to December 2018 (week 4).

	Constant	CFEAR	AVG	Mom	TS	HP	Skewness	Adj.-R^2 (%)	MAPE (%)
Panel A: Skewness risk factor									
Model 1	-0.0006						0.0878	14.28	0.116
	(-0.85)						(2.60)		
Model 2	-0.0006	0.0582					0.0900	45.07	0.114
	(-0.76)	(1.92)					(2.50)		
Model 3	0.0006		-0.0735	0.0170	-0.0072	0.0506	0.0735	78.45	0.066
	(0.64)		(-1.39)	(0.42)	(-0.17)	(1.61)	(2.01)		
Model 4	0.0005	0.0641	-0.0731	-0.0058	0.0022	0.0361	0.0747	79.65	0.061
	(0.59)	(2.13)	(-1.36)	(-0.14)	(0.05)	(1.14)	(2.02)		
	Constant	CFEAR	AVG	Mom	TS	HP	BM	Adj.-R^2 (%)	MAPE (%)
Panel B: Basis-Momentum risk factor									
Model 1	-0.0004						0.0308	1.12	0.135
	(-0.55)						(0.97)		
Model 2	-0.0004	0.0502					0.0508	33.35	0.1226
	(-0.58)	(1.71)					(1.51)		
Model 3	-0.0001		-0.0398	0.0136	-0.0131	0.0596	0.0315	75.50	0.070
	(-0.10)		(-0.78)	(0.33)	(-0.31)	(1.90)	(0.91)		
Model 4	-0.0002	0.0638	-0.0379	0.0007	-0.0015	0.0518	0.0405	74.96	0.068
	(-0.18)	(2.14)	(-0.73)	(0.02)	(-0.04)	(1.63)	(1.15)		

Table A.4 (*Cont.*)

Panel C: Iliquidity risk factors

	Constant	CFEAR	AVG	Mom	TS	HP	Iliquidity	Δ_{TED}	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0006						-0.0307		1.32	0.138
	<-0.92>						<-1.04>			
Model 2	-0.0005							0.0090	-3.82	0.143
	<-0.69>							<0.78>		
Model 3	-0.0006	0.0635					-0.0176		31.27	0.124
	<-0.94>	<2.26>					<-0.59>			
Model 4	-0.0004	0.0459						0.0056	34.14	0.120
	<-0.64>	<1.67>						<0.49>		
Model 5	0.0000		-0.0427	0.0231	0.0216	0.0567	-0.0198		71.77	0.077
	<-0.04>		<-0.92>	<0.61>	<0.56>	<1.95>	<-0.69>			
Model 6	0.0005		-0.0701	0.0446	0.0053	0.0620		0.0166	79.41	0.064
	<0.64>		<-1.45>	<1.21>	<0.14>	<2.14>		<1.52>		
Model 7	-0.0001	0.0819	-0.0409	0.0054	0.0258	0.0443	-0.0100		73.76	0.073
	<-0.13>	<2.95>	<-0.86>	<0.14>	<0.67>	<1.51>	<-0.34>			
Model 8	0.0005	0.0712	-0.0719	0.0147	0.0129	0.0506		0.0095	81.32	0.058
	<0.65>	<2.59>	<-1.49>	<0.39>	<0.33>	<1.72>		<0.87>		

Panel D: Volatility risk factors

	Constant	CFEAR	AVG	Mom	TS	HP	ΔAggrVar	ΔAvgVar	Adj.-R^2 (%)	MAPE (%)
Model 1	-0.0007						0.0001		18.27	0.128
	(-0.94)						(0.29)			
Model 2	-0.0008							-0.0010	9.64	0.138
	(-1.12)							(-0.81)		
Model 3	-0.0005	0.0524					0.0004		45.57	0.113
	(-0.71)	(1.79)					(0.88)			
Model 4	-0.0007	0.0572						0.0004	45.12	0.1168
	(-0.97)	(2.00)						(0.31)		
Model 5	0.0002		-0.0550	0.0372	0.0092	0.0592	0.0004		79.39	0.0642
	(0.24)		(-1.10)	(0.93)	(0.22)	(1.91)	(0.82)			
Model 6	0.0001		-0.0481	0.0349	-0.0030	0.0544		-0.0009	80.05	0.06
	(0.07)		(-0.98)	(0.89)	(-0.07)	(1.77)		(-0.66)		
Model 7	0.0003	0.0709	-0.0603	0.0150	0.0200	0.0477	0.0004		80.08	0.059
	(0.32)	(2.36)	(-1.16)	(0.36)	(0.48)	(1.50)	(0.81)			
Model 8	0.0000	0.0739	-0.0454	0.0147	0.0071	0.0426		-0.0001	79.17	0.06
	(-0.02)	(2.54)	(-0.89)	(0.36)	(0.17)	(1.36)		(-0.04)		

Table A.5 Cross-sectional pricing tests with an enlarged set of 31 test portfolios.

The table presents cross-sectional pricing tests using the four-factor model of Fernandez-Perez et al. (2018) and Bianchi et al. (2018) adding the skewness risk (Panel A), the basis-mom risk (Panel B) and the illiquidity risk (Panel C) portfolios. The test assets are N=31 portfolios; the former 26 portfolios (quintiles sorted on momentum, roll-yield, hedging pressure, and CFEAR), the 6 sectoral portfolios, and the additional 5 portfolios (quintiles sorted on skewness risk in Panel A, basis-momentum in Panel B, and illiquidity in Panel C). We report the (annualized) prices of risk from a cross-sectional regression of average portfolio excess returns on full-sample betas with Shanken (1992) t-statistics in parentheses corrected for errors-in-variables, and Kan, Robotti and Shanken (2013 t-statistics in curly brackets additionally corrected for model misspecification and heteroscedasticity. The period is January 2004 to December 2018.

	Constant	CFEAR	AVG	Mom	TS	HP	Altern. comm. risk	Adj-R^2 (%)	MAPE (%)
Panel A: Skewness risk									
Model i	-0.0007						0.0824	35.33	0.050
	(-1.03)						(2.43)		
	{-0.72}						{2.19}		
Model ii	-0.0006	0.0733					0.0673	60.12	0.0411
	(-0.93)	(2.29)					(2.01)		
	{-0.78}	{2.35}					{2.00}		
Model iii	-0.0002		-0.0214	0.0525	0.0234	0.0509	0.0574	49.16	0.047
	(-0.23)		(-0.36)	(1.54)	(0.78)	(1.70)	(1.96)		
	{-0.25}		{-0.33}	{1.61}	{0.77}	{1.66}	{1.84}		
Model iv	-0.0011	0.0814	0.0256	0.0278	0.0394	0.0486	0.0477	68.94	0.034
	(-1.25)	(2.76)	(0.44)	(0.86)	(1.35)	(1.62)	(1.64)		
	{-1.23}	{2.79}	{0.43}	{0.88}	{1.35}	{1.61}	{1.58}		
Panel B: Basis-Mom risk									
Model i	-0.0006						0.0858	39.59	0.056
	(-0.81)						(2.64)		
	{-0.60}						{2.69}		
Model ii	-0.0005	0.0707					0.0614	57.09	0.047
	(-0.80)	(2.30)					(2.11)		
	{-0.74}	{2.29}					{2.05}		
Model iii	-0.0003		-0.0193	0.0419	0.0269	0.0646	0.0739	58.26	0.045
	(-0.28)		(-0.32)	(1.27)	(0.89)	(2.05)	(2.58)		
	{-0.31}		{-0.28}	{1.34}	{0.93}	{2.01}	{2.41}		
Model iv	-0.0011	0.0776	0.0268	0.0219	0.0410	0.0564	0.0627	75.39	0.032
	(-1.27)	(2.67)	(0.46)	(0.69)	(1.38)	(1.80)	(2.24)		
	{-1.33}	{2.71}	{0.45}	{0.72}	{1.45}	{1.81}	{2.11}		
Panel C: Illiquidity risk									
Model i	-0.0006						-0.0391	12.28	0.060
	(-0.84)						(-1.25)		
	{-0.66}						{-1.05}		
Model ii	-0.0006	0.0781					-0.0144	44.78	0.047
	(-0.84)	(2.52)					(-0.48)		
	{-0.68}	{2.87}					{-0.42}		
Model iii	-0.0002		-0.0210	0.0427	0.0359	0.0620	-0.0368	49.26	0.044
	(-0.23)		(-0.34)	(1.32)	(1.25)	(2.00)	(-1.23)		
	{-0.26}		{-0.34}	{1.43}	{1.31}	{1.93}	{-1.02}		
Model iv	-0.0012	0.0771	0.0291	0.0235	0.0457	0.0538	-0.0233	70.30	0.032
	(-1.31)	(2.76)	(0.49)	(0.74)	(1.60)	(1.74)	(-0.80)		
	{-1.36}	{2.98}	{0.49}	{0.80}	{1.74}	{1.72}	{-0.69}		