# Spreading Pressure and the Commodity Futures Risk Premium*

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**Abstract**

This paper investigates the impact of trading on the commodity futures risk premium. We focus on intra-commodity spreading positions and study the asset pricing implications of spreading pressure (SP), that is, spreading positions scaled by open interest, on the cross-section of commodity futures returns. We document that SP negatively predicts futures excess returns. A battery of empirical tests shows that SP helps separate commodities that trade based on economic fundamentals from commodities that are subject to market frictions introduced via commodity index investments. We propose an SP factor, a long-short portfolio based on SP that is priced in the commodity futures market, even after controlling for well-known factors, and is robust to accounting for omitted variable biases and measurement errors.

**JEL classification:** G12, G13, G23

**Keywords:** commodity financialization, commodity index trades, spreading positions

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# 1 Introduction

According to the Futures Industry Association (FIA) annual survey, the trading volume of global commodity futures increased markedly in recent years, from 2.19 billion contracts in 2009 to 9.01 billion in 2020. The dramatic increase, and the subsequent sharp decrease in commodity prices over the 2008-2009 crisis, has triggered heated debates about whether and how speculators' trading activity impacts commodity price swings. Some studies have found no impact. Rather, they posit that speculators' activities moderate prices, bringing them closer to fundamentals (e.g., Brunetti, Büyükşahin and Harris, 2016). Others argue that the financialization of commodity markets has enabled *uninformed* speculators, particularly with the influx of index traders, to add noise in and hence move commodity prices away from fundamentals and increase volatilities (Basak and Pavlova, 2016; Brogaard, Ringgenberg and Sovich, 2019).

In a recent theoretical paper, Goldstein and Yang (2022) reconcile both sides of this argument. They show that financial traders can bring both noise and information to the market, while the overall effect of financialization can be time-varying. Building upon the latter standpoint, we aim here to investigate the impact of trading activities on the time-varying commodity futures risk premium. In particular, we focus on non-commercial *spread trade* positions, and study their asset pricing implications for the cross-section of commodity futures returns.

Commodity spread trades are intra-commodity investing strategies that involve simultaneously buying and selling the same amount of futures contracts with different maturities within a single commodity. They have gained in popularity among investors in commodity futures markets due to their lower barriers to entry (i.e., no short-selling constraint, lower margin requirement to obtain high leverage). The financialization of the commodity markets from around 2005 has prompted the exponential growth of such strategies (Tang and Xiong, 2012; Singleton, 2014). Speculators take intra-commodity spread positions in order to obtain risk exposures to the change in the shape of commodity futures term structures.[1] Hence, the extent to which speculators enter spread trade positions may reflect the information on the commodity futures term structure and futures returns.

Using commodity traders' weekly positions from the Commodity Futures Trading Commission (CFTC), we compute *spreading pressure* (SP hereafter),−defined as speculators' spreading position scaled by open interest,−and relate them to weekly excess returns obtained from Bloomberg. Based on SP and the returns of 26 commodities from 1992 to 2020,

[1] Intra-commodity spread trading strategies include *calendar spread* and *butterfly spread* positions. The calendar spread entails the risk of both slope and curvature changes of futures curves; the butterfly spread is only related to risk of changes in curvature.

we first document the pricing power of SP in the cross-section of commodity futures returns: SP predicts futures excess returns negatively such that our commodity-level Fama and MacBeth (1973) regression associates a 1%-increase in smoothed SP with a 1.81%-decrease in returns.[2] Turning to a portfolio approach, the SP portfolio,−going short and long the commodities with high and low SP respectively,−can generate a superior risk-return profile compared to other well-known pricing portfolios in the literature, e.g., basis, momentum, or basis-momentum, with excess returns of 15.37% per annum and the Sharpe ratio of 0.61, both net of transaction costs.

In the asset pricing tests, the SP risk factor,−proxied by the return of our SP portfolios,− carries a significant risk premium ranging from 11.47% to 16.85% per annum depending on the model specification, and importantly it is not subsumed by the existing pricing factors in commodity futures returns.[3] As for the cross-sectional fit of the model, the addition of the SP factor to the incumbent model improves $R^2$ significantly, e.g., from 0.59 to 0.75 for the two-factor model of Boons and Prado (2019), and from 0.41 to 0.65 for the three-factor model of Bakshi, Gao and Rossi (2019). We confirm that the SP risk is also distinct from alternative sources of risk, e.g., liquidity, volatility, inventory, or financial intermediary risk. These results suggest that our SP factor captures a dimension of commodity risk that is not spanned by the risk factors the literature has documented so far, and hence it deserves a careful investigation.

Once we uncover the pricing effect of SP on the commodity futures return, we move on to explore the potential drivers of our results. We conduct a series of empirical tests, which indicate that our pricing results are linked to informational frictions that are introduced via commodity index investments. For example, our results are stronger in the post-2005 period, after commodity financialization, especially for the short leg (high SP commodities) of our trading strategy.[4] Similarly for the short leg only, the average position size per trader decreases after 2005 while the number of traders goes up markedly. We find that the short (long) leg of our trading strategy predominantly includes index (non-index) commodities. However, a strategy that shorts only index commodities does not exhibit a similar performance. Moreover, the data from the disaggregated Commitment of Traders (DCOT) report suggest that pricing results come mainly from positions of managed money investors, although we cannot isolate the index positions in those reports. On the other hand, quarterly

[2] We refer to the 52-week average of SP as *smoothed* SP.

[3] In estimating the price of risk, we mainly rely on the Fama and MacBeth (1973) two-pass procedure, but also check for spurious factors by using the three-pass procedure developed recently by Giglio and Xiu (2021).

[4] Buyuksahin et al. (2008) document that there exists a structural change after mid-2004 in the trading of commodity futures across maturities.

index investment reports from the CFTC (over a shorter sample, 2007Q4-2015Q3) indicate a positive relation between changes in spread and index investment positions. Most importantly, we show in a difference in difference setting, that the inception of one of the largest commodity futures exchange-traded fund (ETF), Invesco DB Commodity Index Tracking Fund (DBC), drives the increase in spreading positions for those commodities that the DBC fund tracks.

We interpret our results within the framework of models of commodity financialization (Brunetti and Reiffen, 2014; Sockin and Xiong, 2015; Basak and Pavlova, 2016; Goldstein and Yang, 2022). Models based on symmetric information and uninformed trading (e.g., Brunetti and Reiffen, 2014; Basak and Pavlova, 2016) imply that the entry of uninformed speculators (e.g., index traders) who do not trade based on economic fundamentals results in higher valuations (and lower expected returns) for index commodities. Models based on asymmetric information (Sockin and Xiong, 2015; Goldstein and Yang, 2022), on the other hand, highlight the dual role of financial traders who bring both information (via speculative trades) and noise (via hedge-based trades) to the market. They can potentially distort price signals for commodity users and producers (Brogaard, Ringgenberg and Sovich, 2019). Goldstein and Yang (2022) also show that informational friction is time-varying. Thus, in a market with few financial speculators (e.g., during the early days of commodity financialization), a positive information effect prevails until financial hedgers dominate the market.

Our cross-sectional strategy that invests in low SP commodities and shorts high SP commodities delivers a high trading performance. We argue that the profitability of such a strategy stems from the fact that the long leg of the portfolio is immune to these informational frictions relative to the short leg. It is driven primarily by fundamentals such as global economic growth expectations, and it is highly exposed to shocks in real economic uncertainty. The short leg, on the other hand, is exposed to such informational frictions through financial investors, especially after the influx of index traders. We confirm such an asymmetric exposure to fundamentals between the short and long leg by showing that the short leg return is less sensitive to asset returns (e.g., S&P 500 and MSCI Emerging Markets Index) and various uncertainty measures. The performance of this strategy is superior to alternative strategies suggested in the literature (e.g., momentum, basis-momentum), and only declines during the early days of commodity financialization.

The extant literature on commodity futures factor pricing has proposed a number of risk factors. Yang (2013), Szymanowska et al. (2014) and Bakshi, Gao and Rossi (2019) include a carry factor based on a term structure signal called *basis*. Low-basis commodity futures carry higher carry factor risk premiums compared to their high-basis counterparts. Gorton, Hayashi and Rouwenhorst (2013) and Bakshi, Gao and Rossi (2019) show that the risk premium on a momentum factor is also significant, while Fernandez-Perez et al. (2018) find that commodity futures with a negative skewness have significantly higher returns than positive skewness ones. Boons and Prado (2019) introduce a so-called basis-momentum factor based on the slope and curvature of the futures term structure. Research has also explored other pricing factors, such as value (Asness, Moskowitz and Pedersen, 2013), volatility (Bakshi, Gao and Rossi, 2019), liquidity (Marshall, Nguyen and Visaltanachoti, 2012), and inflation (Hong and Yogo, 2012).

The SP factor we propose here differs from the aforementioned studies in that it is based on the positions of market participants rather than on futures' prices. Regarding traders' position-based risk factors in commodity markets, hedging pressure has been extensively studied in the literature (Bessembinder, 1992; Basu and Miffre, 2013; Dewally, Ederington and Fernando, 2013). Commodity futures with high shorting demand from hedgers tend to have larger risk premiums on a hedging pressure factor than futures with lower shorting demand. In a recent paper, Kang et al. (2020) show the interplay between the hedging pressure and the short-term speculative trading. While hedgers pay for price insurance in line with normal backwardation theory (Keynes, 1923), they receive a liquidity premium for the service they provide for speculators. However, Kang et al. (2020) focus on directional positions of speculators, and do not touch upon spreading positions.

Our paper is closely related to Boons and Prado (2019), in that both studies take up the challenge of pricing a large cross-section of commodity futures with a parsimonious factor model (Daskalaki, Kostakis and Skiadopoulos, 2014). Boons and Prado (2019) is the first paper that documents the negative relation between their speculative strategy, i.e., basis momentum, and speculators' spreading positions. However, they do not further investigate the drivers of SP, and its cross-sectional pricing implications. Importantly, we show that the SP factor we propose complements the pricing ability of the basis momentum factor, and becomes particularly important following commodity financialization.

This paper contributes to the aforementioned literature of commodity futures pricing in several key aspects. First, we document the predictability of SP on commodity futures excess returns. Second, we propose a novel pricing factor that is missing in the existing commodity futures factor models. Third, we establish a link between speculators' spread positions and the commodity futures risk premium. We also contribute to the literature on the role of financial traders and index investors in particular, and financial intermediation in general in the commodity futures markets. Finally, this paper is one of the first studies to explore the economic determinants and information content of SP.

# 2 Data and Summary Statistics

In this section we explain our data collection, introduce the key variables used in our empirical analysis and provide summary statistics.

## 2.1 Commodity Futures Returns

We obtain daily prices for individual commodity futures contracts from Bloomberg. Our sample period is October 6, 1992 through December 29, 2020. Our analysis focuses on twenty-six commodity futures contracts with different maturities covering five major sectors: 1) energy (heating oil, natural gas, RBOB/unleaded gasoline, and WTI crude oil), 2) grains (corn, oats, rough rice, soybean oil, soybean meal, soybeans, and wheat), 3) meats (feeder cattle, lean hogs, live cattle, and frozen pork belly),[5] 4) metals (high-grade copper, palladium, platinum, silver, and gold), and 5) soft (cocoa, coffee, cotton, lumber, orange juice, and sugar).

To match the weekly frequency of the CFTC's trader positions data, we calculate weekly (Tuesday to Tuesday) excess returns on fully collateralized futures positions (e.g., Gorton, Hayashi and Rouwenhorst, 2013; Koijen, Moskowitz, Pedersen and Vrugt, 2018; Bakshi, Gao and Rossi, 2019; Boons and Prado, 2019):

$$R_{j,t+1}^{(n)} = \frac{F_{j,t+1}^{(n)}}{F_{j,t}^{(n)}} - 1, \quad n \geqslant 1, \tag{2.1}$$

where $F_{j,t}^{(n)}$ is the $n$-th nearby futures contract for commodity $j$, i.e., the contract with the $n$-th shortest maturity, at the end of week $t$ among all available contracts. Our return calculations mainly use the prices of front month contracts (i.e., first or second nearby contracts depending on calendar dates) in order to ensure sufficient liquidity.[6]

[Table 1 about here]

Table 1 shows the summary statistics for annualized excess returns of front month contracts of the 26 commodities.[7] The returns exhibit quite a variation across commodities

[5]Frozen pork belly futures were delisted on July 15, 2011.

[6]A first nearby contract is defined as the shortest-maturity contract whose first notice day comes after the end of the week in order to avoid a case where the contract is required to take a physical delivery of underlying commodities (Bakshi, Gao and Rossi, 2019). In such a case, the definition of front months would also depend on the calendar date on which the week ends. More specifically, for weeks that end prior to the seventh calendar day of the month, we would use a first nearby contract; for weeks that end on or after the seventh calendar day, we would use a second nearby contract (Kang, Rouwenhorst and Tang, 2020).

[7]The summary statistics for two subperiods of pre- and post-January 4, 2005 are reported in Online Appendix, Table I-1.

with a mean of 3.22% and a standard deviation of 28.34%. The average Sharpe ratio is 0.12 implying that investing in an individual commodity futures may not have an attractive risk-return profile. Futures returns appear to be serially uncorrelated as the magnitude of first-order autocorrelations, AR(1), is very low for the most of commodities. It is also noteworthy that corn and WTI crude oil are the top 2 open-interest commodities.

## 2.2 Trader Positions

Commodity futures position data by different types of traders come from the Commodity Futures Trading Commission (CFTC). CFTC releases weekly Commitments of Traders (COT) reports that contain the aggregate long and short positions of three types of traders: commercial, non-commercial, and non-reportable. It also reports the spread trade positions for non-commercial investors. Following the literature we label commercials as *hedgers*, non-commercials as *speculators*, and non-reportables as *small speculators*. The data capture traders' weekly positions from Tuesday to Tuesday, and they are published on Friday of the same week. The CFTC has published disaggregated COT (DCOT) data since 2006, from which we can break down trader positions even further, splitting non-commercials into money managers and other reportables.[8]

Following the COT report, we capture the size of traders' positions and their trading behavior based on five measurements: 1) percentage of the total market held by the different trader types, 2) hedging pressure (HP), 3) spreading pressure (SP), 4) net trading (Q) by hedgers and speculators, and 5) the propensity to trade (PT) by speculators with long or short positions only, and speculators with spread positions only (who we label as "*spreaders*"). We first define the sector-level measure of market shares by trader type $i$ at time $t$ as the open interest-weighted average of percentage market shares at the commodity level. These are calculated as total positions (both long and short), divided by open interest, as follows:

$$\%\, market^i_{j,t} = \frac{Long^i_{j,t} + Short^i_{j,t}}{2 \times Open\, Interest_{j,t}}, \tag{2.2}$$

where i={hedgers, speculators, small speculators, spreaders} and for commodity $j$.

[Figure 1 about here]

Figure 1 reports the evolution of relative positions by futures trader type over time for each commodity sector (energy, metals, soft, grains, and meats). Several interesting

[8] Money managers are traders who engage in managing and conducting organized futures trading on behalf of clients. The category includes commodity trading advisers (CTAs), commodity pool operators (CPOs), and unregistered funds identified by the CFTC. Other reportables are non-commercials other than money managers.

patterns emerge. First, it is commonly observed across sectors that both speculators' and spreaders' total positions began gradually increasing in early 2000 with a marked increase in spread positions following commodity financialization around 2005. Second, spreaders are the largest group in the energy sector, exceeding even those of directional speculators. Third, spreader positions in the metals sector show an interesting pattern around the 2008/2009 crisis, increasing markedly before the crisis, and dropping significantly afterward. However, contrary to the notion that traders opt for a spread position when a commodity market is highly uncertain (Boons and Prado, 2019), we do not find a significant increase in spread positions during the crisis for any other sector. Last but not least, we find no significant correlation in trade positions between spreaders and directional speculators.

We define our main variable, spreading pressure ($SP$) of commodity $j$, as total spreader positions divided by open interest:

$$SP_{j,t} = \frac{Spreader_{j,t}}{Open\,Interest_{j,t}}. \tag{2.3}$$

Next, we construct control variables that include hedging pressure, net trading, and trade propensity as follows. We use hedging pressure ($HP$) on commodity $j$ to capture hedging demand, defined as hedgers' net short positions divided by open interest:

$$HP_{j,t} = \frac{Short_{j,t}^{hedger} - Long_{j,t}^{hedger}}{Open\,Interest_{j,t}}, \tag{2.4}$$

and also construct directional speculative pressure (DP) on commodity $j$ to capture speculative demand, defined as directional speculators' net long positions divided by open interest:

$$DP_{j,t} = \frac{Long_{j,t}^{speculator} - Short_{j,t}^{speculator}}{Open\,Interest_{j,t}}. \tag{2.5}$$

We also define net trading ($Q$) as the change in trader type $i$'s net long positions in commodity $j$ divided by its open interest:

$$Q_{j,t}^{i} = \frac{NetLong_{j,t}^{i} - NetLong_{j,t-1}^{i}}{Open\,Interest_{j,t-1}}. \tag{2.6}$$

A limitation of this measure is that speculators' net trading only reflects changes in trade positions for directional speculators (i.e., long-only or short-only), not for spreaders, since their $NetLong$ is always zero. As in Kang, Rouwenhorst and Tang (2020), we also construct the measure of propensity to trade ($PT$), defined as the sum of absolute changes in long and short positions between $t-1$ and $t$, divided by total long and short positions at $t-1$:

$$PT^i_{j,t} = \frac{abs(Long^i_{j,t} - Long^i_{j,t-1}) + abs(Short^i_{j,t} - Short^i_{j,t-1})}{Long^i_{j,t-1} + Short^i_{j,t-1}}. \tag{2.7}$$

[Figure 2 about here]

Figure 2 shows the evolution of SP over time for six selected commodities: three high-SP commodities (natural gas, WTI crude oil, and lean hogs) and three low-SP ones (platinum, palladium, and oats). It also provides a further breakdown of spreader positions since 2006 into money managers and others. It appears to show a structural break around 2005 in level of SP, but only for high-SP commodities. Specifically, the mean of SP for natural gas, WTI crude oil, and lean hogs experience a dramatic jump in value after 2005, but we do not observe the same trend for platinum, palladium, and oats. It is important to note, however, that all three commodities in the high-SP group are also constituents of popular commodity indexes (S&P GSCI Index and Dow Jones-UBS Commodity Index), while their lower-SP counterparts are all non-index commodities.[9] These observations imply that spreading positions may be related to the financialization of commodity markets, or, more accurately, to the presence of rapidly growing index investments in the markets since 2005 (Tang and Xiong, 2012; Singleton, 2014).

[Figure 3 about here]

To look more closely at the behavior of SP within the calendar year, we plot the weekly average of SP for two commodities (palladium and WTI crude oil) in Figure 3. The figure clearly shows there is a maturity effect on the level of SP. We note that SP for palladium reaches the peak when the date gets closer to maturity (the first notice day or last trading day, whichever comes first), while do not see a similar pattern for WTI crude oil. In most of our analysis, we will use a 1-year (52-week) time window to smooth out the effect of seasonality and the maturity of futures contracts to construct our *smoothed* SP measure. Kang, Rouwenhorst and Tang (2020) use the same approach to compute their measure of hedging pressure.

[Table 2 about here]

Table 2 reports the summary statistics of traders' position variables, namely, spreading pressure, hedging pressure, directional speculative pressure, net trading, and propensity to

[9] According to CFTC index investment reports, there is a significant increase in managed money flows to platinum, along with an increase in index investment. Not surprisingly, this coincides with the diminishing role of platinum in the low-SP group (see Online Appendix, Figure I-1).

trade for the 26 commodities. There are a number of important observations. For spreading pressure, the energy sector has the largest value at the commodity level. Regarding hedging pressure, the average is positive for all commodities except natural gas, feeder cattle, and frozen pork belly, and metals (meats) has the highest (lowest) hedging pressure at the sector level. Hedging and directional speculative pressures are related. Metals also have the highest directional speculative pressure at the sector level. The means of absolute net trading changes for hedgers and speculators are 3.38% and 3.04%, respectively. As for propensity to trade, spreaders exhibit a higher propensity to trade than directional speculators.

# 3 SP and Futures Excess Return

In this section we explore the relation between spreading pressure (SP) and the commodity futures excess returns and introduce the SP factor as a long-short portfolio based on the SP signal.

## 3.1 Return Predictability of SP

We investigate whether SP exhibits predictive power for futures excess returns by employing a cross-sectional regression across the 26 commodities. To gain a sense of the relationship, we first simply examine a cross-sectional fit between average returns and average SP (Figure 4). To compare as precisely as possible, we also provide a cross-sectional fit for the two other trader categories, hedgers and (directional) speculators. The results show a stark contrast that excess returns are negatively related with SP whereas the relation is positive for the other two cases, hedging pressure and directional speculative pressure. The positive relation between excess returns and hedging pressure is consistent with the normal backwardation theory, where hedgers hold a net short position, and an increase in short demand will discount futures prices in order to find counterparties. For the same reason, the theory suggests that directional speculators' net long positions is positively related to returns, because speculators are the counterparties of hedgers, which is confirmed in our sample.

[Figure 4 about here]

To examine the predictability of spreading pressure formally, we follow Kang, Rouwenhorst and Tang (2020) to conduct Fama and MacBeth (1973) cross-sectional predictive regressions as follows:

$$R^{(k)}_{j,t+1} = b_0 + b_{\overline{SP}}\overline{SP}_{j,t} + b_{BM}BM_{j,t} + b^h_Q Q^h_{j,t} + b^s_Q Q^s_{j,t} + \epsilon_{j,t+1}, \tag{3.1}$$

where $R^{(k)}_{j,t+k}$ is the return of commodity $j$'s $k$-$th$ nearby contract at week $t+1$, $\overline{SP}_{j,t}$ is the smoothed SP, $BM_{j,t}$ is basis-momentum, $Q^h_{j,t}$ is the change in hedgers' net positions, and $Q^s_{j,t}$ is the change in speculators' net positions. Basis-momentum is documented to predict commodity futures excess returns with stronger predictive power than more well-known trading signals such as carry or momentum (Boons and Prado, 2019).[10] Also, the change in hedgers' (speculators') net positions is shown to predict excess returns positively (negatively) (Kang, Rouwenhorst and Tang, 2020).

[Table 3 about here]

Panel A in Table 3 shows that commodities with higher SP in week $t$ tend to have significantly lower excess returns in week $t+1$ (coefficient = -1.81 and t-statistics = -3.24) (Model 1). The significance of the predictability of spreading pressure remains unchanged even after controlling for other well-known factors, i.e., $BM_{i,t}$, $Q^h_{i,t}$, and/or $Q^s_{i,t}$ (Models 5 to 8).[11] For comparison, we also report the predictive power of SP for the longer-term futures returns in Panel B and Panel C for the second and third front month contracts, respectively. The predictability of SP decreases slightly but it remains statistically significant.

We now turn to a portfolio analysis to examine whether the low SP portfolio performs better than the high SP portfolio. We construct the portfolio with weekly rebalancing by sorting commodities each week based on SP, and go short and long the commodities with the high and low SP, respectively. To remove any seasonality and maturity effects, we use smoothed SP (i.e., the past 52-week average) as a trading signal. Portfolios Low3 (High3) represent the portfolio of the three lowest (highest) spreading pressure commodities; portfolios Mid include the remaining commodities. For comparison, we also construct portfolios based on other well-known trading signals such as basis (carry), momentum and basis-momentum.[12]

[Table 4 about here]

[10]Basis-momentum denotes the difference between momentum signals from front-month and second-month futures strategies:

$$BM_t = \prod_{s=t-52}^{t}\left(1+R^{(1)}_{long,s}\right) - \prod_{s=t-52}^{t}\left(1+R^{(2)}_{long,s}\right)$$

[11]As a robustness test, we vary the number of weeks ahead to longer than one week in order to gauge whether spreading pressure can have long-term predictive power. Table I-2 in the Online Appendix shows that spreading pressure can also predict excess returns significantly and negatively for two, three, and four weeks ahead.

[12]The literature shows that Carry ($C_t$) and Momentum ($M_t$) are:

$$C_t = \frac{\ln F^2_t - \ln F^1_t}{T_2 - T_1}, \qquad M_t = \prod_{s=t-52}^{t}\left(1+R^{(1)}_{long,s}\right)$$

Table 4 reports the results of our portfolio analyses. For Panel A, the low SP portfolio indeed performs much better than its high SP counterpart so that a long-short strategy buying the former and shorting the latter (the SP portfolio) yields high, and statistically significant, returns and Sharpe ratios (15.37% and 0.61 respectively, both net of transaction costs). The performance of SP portfolios is superior to other pricing portfolios (Panels B to D): basis-momentum (15.27% and 0.56), basis (-3.48% and -0.12), and momentum (10.16% and 0.32).[13]. The comparison is clearer when we plot cumulative returns generated by each pricing portfolio (Figure 5). We observe that the performance of the SP portfolio is comparable to the best alternative, basis-momentum portfolio, by the end of the sample. Panel B of 5) shows that the success of SP portfolio is especially driven by the more recent sample post the commodity market financialization around 2005. It is also noticeable that the performance of the SP portfolio is particularly weak in the early days of commodity financialization (2001-2005). We will revisit this issue to further explore the time-varying performance of this strategy in the later section.

[Figure 5 about here]

## 3.2 The SP Factor

In this section, we investigate whether spreading pressure is a priced commodity factor by employing time series and cross-sectional tests. We use the return of the SP portfolio constructed in the previous section to proxy for the SP factor. In a similar vein, we construct other pricing factors, such as basis-momentum Boons and Prado (2019), and three factors from Bakshi, Gao and Rossi (2019), a carry, a momentum, and the equal-weighted average excess return on all commodities as a commodity market factor. Before conducting the formal test, we first glance at the correlations among commodity pricing factors.

[Table 5 about here]

Panel A of Table 5 shows that the magnitude of correlations between the SP factor and other well-known factors is not large (with correlation coefficients lower than 0.30). Panel B, presents correlations between the SP factor and average futures returns for each of five commodity sectors (energy, grain, meats, metals, and soft). The correlations are fairly low, suggesting that the SP factor has its own variation, and is not influenced heavily by a particular commodity sector.

[13] The superior performance of SP portfolios is robust to the number of commodities used to construct the portfolios (Online Appendix, Table I-3), alternative measures of SP (Online Appendix, Table I-4), and accounting for sector-fixed effects (Online Appendix, Table I-5)

Next, we employ a time series test by regressing our SP factor on other pricing factors to determine whether it generates a significant alpha. The idea is that, if the spreading pressure factor is not captured by existing factors, we should observe a significant time series alpha (Barillas and Shanken, 2017, 2018):

$$R_{\overline{SP},t} = \alpha + \sum_{i=1}^{K} \beta_i F_{i,t} + \epsilon_t, \tag{3.2}$$

where $K$ is the number of factors, and $F_{i,t}$ is factor $i$ at time $t$. Table 6 shows multivariate regressions of the spreading pressure factor on a set of incumbent commodity factors from a one-factor model (basis (carry) factor) proposed by Szymanowska et al. (2014), a two-factor (basis-momentum and the average commodity market factor) model proposed by Boons and Prado (2019), and a three-factor model (carry, momentum, and the average commodity market factor) proposed by Bakshi, Gao and Rossi (2019). The intercepts of the time series regressions are highly significant, and their economic magnitudes are large for all pricing models. Specifically, abnormal returns on the SP factor-mimicking portfolio are 16.92%, 13.58%, and 15.55% against the benchmark factor from Szymanowska et al. (2014), Boons and Prado (2019), and Bakshi, Gao and Rossi (2019), Panels A to C, respectively.

[Table 6 about here]

Once we ascertain that the SP factor captures a dimension of commodity risk not spanned by the incumbent factors, we move on to run a cross-sectional test to gauge whether the SP factor is priced in the cross-section of commodity futures returns, using as test assets 17 portfolios constructed by univariate-sorting commodity futures, with three each on carry, momentum, basis-momentum, and SP, and five on sector. In doing so, we intend to compare the SP model with the existing commodity factor pricing models of Boons and Prado (2019), and Bakshi, Gao and Rossi (2019), nested in:

$$R_{p,t} = \gamma_0 + \lambda_{\overline{SP},t}\beta_{\overline{SP},t} + \lambda_{BM,t}\beta_{BM,t} + \lambda_{C,t}\beta_{C,t} + \lambda_{M,t}\beta_{M,t} + \lambda_{Avg,t}\beta_{Avg,t} + \epsilon_{p,t} \tag{3.3}$$

where $R_{p,t}$ is the return of portfolio $p$ at week $t$, $\lambda$ is factor risk premia, and we estimate $\beta_t$ as a fixed parameter using the entire sample.

The first two model specifications are $\lambda_{t,BM} = \lambda_{t,C} = \lambda_{t,M} = \lambda_{t,Avg} = 0$ and $\lambda_{t,\overline{SP}} = \lambda_{t,C} = \lambda_{t,M} = \lambda_{t,Avg} = 0$, which means SP/basis-momentum is the only factor in these models (Panel A). To test two-factor models (Panel B), we consider a model with SP and average commodity market factor (the third specification), the Boons and Prado (2019) model with basis-momentum and average commodity market factor (the fourth specification), and a model with spreading pressure and basis-momentum (the fifth specification). The sixth specification is used to test whether spreading pressure remains priced after accounting for the Boons and Prado (2019), which is with $\lambda_{t,C} = \lambda_{t,M} = 0$. The seventh specification is $\lambda_{t,BM} = \lambda_{t,Avg} = 0$, i.e., a three-factor model in Bakshi et al. (2019), with carry, momentum, and average commodity market factor. These two three-factor models are displayed in Panel C. The eighth specification is $\lambda_{t,BM} = 0$, used to test whether spreading pressure remains priced when we augment Bakshi et al. (2019) model (Panel D).

[Table 7 about here]

Table 7 presents the results of our asset pricing tests with the SP factor by employing Fama and MacBeth (1973) two-pass cross-sectional regression (Panels A to D), for which we report the estimates of annualized risk premia along with two versions of t-statistics by Shanken (1992) and Kan, Robotti and Shanken (2013).[14] For the goodness of cross-sectional fit, we provide two types of $R^2$ (OLS and GLS), and a generalized version of the cross-sectional F-test statistics of Shanken (1985) ($CSRT_{SH}$) and their corresponding p-values under the null hypothesis of zero pricing errors. The SP risk premia are estimated as 15.17% and it is statistically significant based on either version of t-statistics (Model 1). The SP factor survives even after the inclusion of other sets of incumbent pricing factors, namely, the commodity market factor or/and the basis-momentum factor (Model 3 and Models 5 and 6), and the carry, momentum, and commodity market factors (Model 8). For the goodness of fit of the pricing model based on GLS $R^2$, the models with SP factor is slightly better than the models with basis-momentum factor in Boons and Prado (2019), whether or not we augment them with the commodity market factor (27.70% vs. 26.24% for the single factor, and 31.31% vs. 29.33% for the two factor models). Notably, the GLS $R^2$ of the three factor model in Bakshi, Gao and Rossi (2019) increases significantly when augmented it with the SP factor (15.57% vs. 42.34% for Models 7 and 8). Interestingly, the combination of the SP and basis-momentum factors, along with commodity market factor, yields the best explanatory power (75.47% of OLS $R^2$ and 49.42% of GLS $R^2$ for Model 6). The $CSRT_{SH}$ statistic indicates that we cannot reject the null of zero pricing errors, implying Model (6) is less likely to be misspecified.

While the two-pass procedure is standard in the literature, the resulting price of risk estimates can be biased due to omitted variables and measurement errors. To account for those biases, we also employ a three-pass procedure developed recently by Giglio and Xiu (2021). Reported in Panel E of Table 7 are, for each of five risk factors, the risk premium

[14] Shanken (1992) standard error corrects for the presence of errors in in the first-stage betas, and the Kan, Robotti and Shanken (2013) standard error additionally corrects for conditional heteroskedasticity and model misspecification.

estimate, the $R^2$ of the projection of the factor onto the estimated latent factors ($R^2_g$), and the p-value of the test that the factor is weak.[15] The risk-premium estimate on SP shrinks to half its size (7.40%), but it remains economically and statistically significant. More importantly, our SP factor does not seem to be heavily contaminated by noise and biases: (i) it is fairly well explained by the recovered latent factors ($R^2_g = 40.21\%$) and (ii) we can reject the null (p-value=0.00) that SP is a weak factor in the cross-section of test assets.

To summarize, both time series and cross-sectional tests suggest that the SP factor reflects a unique dimension of the risk in the commodity futures market, and it can bring in an incremental explanatory power to the incumbent pricing models of commodity futures in the literature.[16] In the following section, we will explore what potentially drives our pricing results.

# 4 Unraveling SP Factor

In this section we explore the SP factor. First, we test how SP factor changes over time. Next, we question whether we can extract any additional information from the term structure of commodity futures. We then exploit the DCOT dataset to analyze different trader categories. Finally, we search for potential drivers of SP factor and its components ruling out alternative explanations.

## 4.1 SP Factor over Time

To gain a better idea on the potential source of the profitability of our SP portfolio, we want to examine its time-series variability. Prior literature documents structural changes in the commodity futures market due to commodity financialization and an influx of index traders around 2004-2005 (e.g., Buyuksahin et al., 2008; Hamilton and Wu, 2014), speculative trades leading to the oil price boom and bust between 2003 and 2008 (Kilian and Murphy, 2014), the positive informational effect of financial traders in the early days of commodity

[15] Following the method proposed by Giglio and Xiu (2021), we estimate 2 latent factors onto which each of commodity risk factors is projected. For robustness, we expand the set of test assets to 34 including spreading returns (Panel E of Online Appendix Table I-7) and to 75 including managed portfolio returns (Panel B of Online Appendix Table I-8)).

[16] We conduct a battery of robustness tests to confirm the pricing result of the SP factor. First, responsive to the critique of (Lewellen, Nagel and Shanken, 2010), we run the asset pricing test at the individual commodity level (Online Appendix, Table I-6). Second, we use the spreading returns used in Szymanowska et al. (2014) as well as the nearby returns (Online Appendix, Table I-7). Third, following Bakshi et al. (2019), we generate additional test assets by interacting the baseline portfolio with the list of conditioning variables (Online Appendix, Table I-8). Fourth, we conduct sub-sample tests for the period post 2005 to account for a structural break in commodity futures risk premia during the era of financialization of commodity markets (Hamilton and Wu, 2014; Tang and Xiong, 2012) (Online Appendix, Tables I-9, I-10 and I-11).

financialization (Goldstein and Yang, 2022), and the rise of electronic trading platforms for commodity futures markets in the last quarter of 2006 (Raman, Robe and Yadav, 2017). We first test how these events affect the return of the SP portfolio overall, and also the returns of its long leg (low SP commodities) and short leg (high SP commodities) separately. In particular, we run the regression of SP (and its long and short legs) on different time dummy variables:

$$R_{p,t} = \alpha + \beta_p I_t + \gamma_i R_{p,t-1} + \varepsilon_t, \tag{4.1}$$

where $R_{p,t}$ includes returns of SP ($R_{\overline{SP},t}$), returns of the long leg ($R_{Long,t}$), and the short leg ($R_{Short,t}$) of SP portfolios. The time dummy used in Model (1) is $I_{t\geq 2005}$, which equals 1 when the time is post-2005. Similarly, the time dummy variables used in Models (2), (3) and (4) are $I_{2001\leq t\leq 2005}$, $I_{2003\leq t\leq 2008}$,$I_{2006Sep\leq t\leq 2006Dec}$, respectively. We include the lag of return $R_{p,t-1}$ as a control variable.

[Table 8 about here]

Table 8 reveals some key observations about the time series properties of SP portfolio returns. While the SP factor return is not significantly higher during the post-2005 period, the superior performance of such a strategy in the recent sample comes from the short leg of the portfolio. In other words, it is significantly more profitable to short high SP commodities in the post-2005 period. This observation confirms the important role that financialization plays to the SP portfolio returns.

Interestingly, the SP factor returns dropped significantly in the earlier days (2001-2005) due to positive (negative) returns for holding (shorting) high SP commodities. Returns to the long leg (low SP) of the portfolio are not affected by either time dummy. We can rationalize this evidence with the Goldstein and Yang (2022) model, which predicts a positive informational effect, that is, signalling via speculation-based trades dominates the noise generated via hedge-based trades. However, this effect only prevails in the short leg of the SP portfolio, since the long leg is immune to the frictions caused by commodity financialization.

[Figure 6 about here]

In order to test this claim, we compute the price delay measure (inefficiency) for the long (low SP) and short (high SP) legs of the SP portfolio around 2005 (between 2001 and 2008). Following Hou and Moskowitz (2005) and (Brogaard, Ringgenberg and Sovich, 2019), we compute the ratio of $R^2$ from a regression of weekly portfolio returns on four lags of portfolio returns of each leg. The pre-2005 series is normalized to 1, and the post-2005 series is relative to the pre-2005 period. Figure 6 shows that the information inefficiency of the short leg of the

SP portfolio increased substantially post-2005. We observe no such increase in the long leg of the SP portfolio. The third specification in Table 8 shows that the so-called "bubble view" or "Masters Hypothesis" is not behind the SP portfolio's profitability (Masters, 2008; Cheng and Xiong, 2014). In other words, the speculative activity in the commodity futures market that led to the oil price boom and bust (2003 and 2008) does not explain the returns to the SP factor, or to either legs of the portfolio. Finally, Raman, Robe and Yadav (2017) argue that an important dimension of commodity financialization is the rise of electronic futures markets in the last quarter of 2006. When we include an electronification dummy in the final specification, we see that the return on the short leg of the SP factor portfolio is significantly lower in this period due to the lower returns, suggesting that the electronification of the commodity market has facilitated the entry of index traders.

## 4.2 Commodity Futures Term Structure

A number of researchers have explored the slope and curvature of the futures term structure based on observable economic fundamentals. They show that its shape can depend on the behavior of different types of market participants. Karstanje et al. (2017) link the slope of futures curves to hedging pressure, housing (construction growth), and inventories, and find that curvature is positively related to interest rates and business inventories (new order growth), and negatively related to industrial production. Focusing on the oil futures market, Heidorn et al. (2015) find that only fundamental investors (producers, merchants, processors, and users) influence the level of the futures term structure, and financial traders (swap dealers and money managers) affect the slope and curvature.

More recently, Van Huellen (2020) relates the shape of term structures to index investment, and shows that index pressure can drive futures curves to become upward-sloping and concave, while hedging pressure induces downward-sloping and convex curves. However, when index traders' long positions exceed hedgers' short positions, the term structure of commodity futures can exhibit wave-like shapes. In a similar vein, we explore the relationship between SP and commodity futures curves in this section.

Following the literature, we define the slope and curvature of commodity futures curves as basis and the difference between basis, as follows:

$$slope_{j,t} = \frac{\ln F^3_{j,t} - \ln F^1_{j,t}}{T^3_{j,t} - T^1_{j,t}}, \tag{4.2}$$

$$curvature_{j,t} = \frac{\ln F^3_{j,t} - \ln F^2_{j,t}}{T^3_{j,t} - T^2_{j,t}} - \frac{\ln F^2_{j,t} - \ln F^1_{j,t}}{T^2_{j,t} - T^1_{j,t}}, \tag{4.3}$$

where $F_{j,t}^n$ is the price of the $n$-th nearby contract with time-to-maturity $T^n$ for a commodity $j$ at week $t$. Positive (negative) slopes denote the futures curve is upward (downward), and positive (negative) curvatures indicate a convex (concave) futures curve.

Speculators tend to enter spread positions to bet on the change in futures term structure. For example, calendar spread is a bet on the slope, while butterfly spread is more of a bet on the curvature. As such, it is conceivable that SP contains information such as speculators' expectations about relative changes in futures prices for contracts of differing maturities. Likewise, hedging pressure reflects hedgers' demands for price insurance.

We investigate whether SP contains information about traders' expectations about the shape of the commodity futures curve. To this end, we conduct a predictive pooled regression of the one-week-ahead slope and curvature of the futures term structure on current SP with time and commodity fixed effects:

$$\{Slope_{j,t+1}, Curvature_{j,t+1}\} = \alpha_{t+1} + \mu_j + \beta_{SP} SP_{j,t} + \beta_{HP} HP_{j,t} + \beta_T T_{j,t}^1 + \varepsilon_{j,t+1}. \quad (4.4)$$

As control variables, we use hedging pressure ($HP$) and time to maturity of the first nearby contract ($T^1$), which are also related to the shape of the commodity futures term structure. In addition, our analysis is based on data from four states with different futures curve shapes.

[Table 9 about here]

Table 9 reports the regression results.[17] We first note that the most likely state in the data is an upward-sloping concave curve (44.75% of the time, increases from 40.51% to 47.70% in the post-2005 sub-sample). The last row of the table shows that SP predicts a steeper curve, regardless of the state. The only state for which it cannot significantly predict the curve's slope is when the futures curve is downward and concave (when hedging pressure is likely to dominate). On the other hand, the effect of SP on the curvature of the term structure depends on current state of curvature which is disguised when averaged across states.

[Figure 7 about here]

In Figure 7 we plot the average slope (Panel A) and average curvature (Panel B) for the commodities in the long and short leg of the SP portfolio over time, where vertical lines indicate three sub-sample periods, 1993-2000, 2001-2004 and 2005-2020. We first note while the average slope of the commodities in the long leg (low SP) of the SP portfolio hovers around zero throughout the sample, the average slope of the commodities in the short leg (high SP) of the SP portfolio is generally positive, except in the early days of commodity

[17] In Online Appendix Table I-12, we repeat the analysis in the pre-2005 and post-2005 sub-samples.

financialization, with a marked increase in slope in the post-2005 sample. This indicates a non-zero risk premium in the term structure of commodity futures associated with SP.[18] Panel B of Figure 7 shows that the short (long) leg is also associated with a concave (convex) futures curve in line with the prediction that index (hedging) pressure drives the shape of the commodity futures term structure (Brunetti and Reiffen, 2014; Van Huellen, 2020).

## 4.3 SP Factor by Trader Category

Our previous empirical tests are all based on weekly COT data from the CFTC that begin from the earliest available date, October 6, 1992. The CFTC also publishes the disaggregated COT (DCOT) report, with more detailed trader categories beginning from June 13, 2006. Although the DCOT sample period is relatively short, we can still obtain further insights into SP by analyzing the spread positions held by more detailed trader types.

DCOT data break down trader positions into two subcategories: 1) producers/merchants/processors/users, and 2) swap dealers for commercials, as well as two additional subcategories of 1) money managers and 2) other reportables for non-commercials. The non-reportables from the DCOT report remain the same as those in the COT report, which contains data on spread positions held by swap dealers, money managers, and other reportables. The spread positions held by commercials in the COT report are equal to the sum of those held by money managers and other reportables. So we construct an alternative proxy for the SP factor by using DCOT data, and investigating the determinants of commodity futures risk premia on SP from total speculators. As an intermediary in the commodity futures market defined by the CFTC, swap dealers' SP is of interest to us. We aim to analyze whether information carried by swap dealers' SP differs from that of non-commercials.

Similarly to the construction of our original SP factor, we construct a SP factor from the managed money category (other reportables or swap dealers) by buying three commodities with the lowest SP and shorting three commodities with the highest SP.[19] We then conduct cross-sectional tests for seven asset pricing factor models by using seventeen portfolios as test assets, nested in:

$$\begin{aligned} R_{p,t} =& \gamma_0 + \lambda_{\overline{SP}} \beta_{\overline{SP},t} + \lambda_{\overline{SP}}^{ManagedMoney} \beta_{\overline{SP}\_ManagedMoney,t} \\ &+ \lambda_{\overline{SP}}^{OtherReportable} \beta_{\overline{SP}\_OtherReportable,t} + \lambda_{\overline{SP}}^{SwapDealer} \beta_{\overline{SP}\_SwapDealers,t} + \epsilon_{p,t}, \end{aligned} \tag{4.5}$$

where $R_{p,t}$ is the return of portfolio $p$. Test portfolios are constructed by sorting on carry (3),

[18] We thank our discussant Christopher Jones for this suggestion.

[19] Detailed results of long-short strategies on SP by trader category are reported in Online Appendix Table I-13.

momentum (3), basis-momentum (3), spreading pressure (3), and sector (5). The specifications of Models (1) to (4) are single-factor models that use SP from the overall commercial, managed money, other reportables, or swap dealer categories as pricing factors, respectively. Model (5) is the two-factor model with SP from the managed money and other reportables categories. We include Model (5) to investigate which non-commercial traders' activities contribute most heavily to the risk premia of the SP from overall non-commercials. The Model (6) two-factor model, with SP from overall speculators and swap dealers, tests whether SP from intermediaries carries different types of information with respect to speculators' SP.

[Table 10 about here]

Table 10 shows that SP from overall non-commercials, managed money, other reportables, and swap dealers are all priced by using a single-factor model (Models (1)-(4)). To further differentiate between money mangers and others, we estimate bivariate models controlling for the SP from swap dealers. Models (6) shows that both the magnitude and statistical significance of the SP risk premia increase for money mangers with the highest $R^2$. This suggests that the risk premia of SP are mainly caused by SP from managed money. It also shows that SP from swap dealers does not carry any additional useful information for commodity futures excess returns beyond that of money mangers or other reportables.

## 4.4 Drivers of SP Factor

**Asset returns.** An important prediction of the commodity financialization models is the increased integration of commodity returns with other asset classes, especially equity markets (e.g., Cheng and Xiong, 2014; Basak and Pavlova, 2016). We next test the link between SP factors, including both legs of the portfolio, and the returns to other asset classes. We focus on U.S. market returns (S&P 500), MSCI Emerging Markets Asia index returns, as well as U.S. Dollar Index Futures Contracts returns and JP Morgan Treasury Bond Index returns. Following the literature (Tang and Xiong, 2012; Henderson, Pearson and Wang, 2015), we also control for the growth rate of the Baltic Dry Index, the change in the ten-year break-even inflation rate (start from January 5, 1999), and the lagged return variables. In particular, we regress the SP factor (as well as its long and short legs separately) on asset returns, time dummies, including 2001-2005 and Covid (2020) periods, and control variables:

$$R_{p,t} = \alpha + \beta^a_m R^a_{m,t} + \beta_\tau \times \mathbb{I}_\tau + \gamma_n C_{n,t} + \varepsilon_t, \tag{4.6}$$

where $R_{p,t}$ is the return of SP portfolio and its corresponding long and short legs ($R_{\overline{SP},t}$, $R_{Long,t}$ and $R_{Short,t}$), $R^a_{k,t}$ is normalized returns of indices, $\mathbb{I}_\tau$ is the time dummy ($\mathbb{I}_{2001\leq t\leq 2005}$

and $\mathbb{I}_{t=2020}$), $C_{n,t}$ is a set of control variables.

In Table 11, we note that the only variable that explains the SP factor (and both of its legs) is MSCI Emerging Markets Asia index returns. They exhibit a stronger effect on the long leg of the SP portfolio, suggesting that economic fundamentals, such as global economic growth expectations, particularly in Asia, play an important role in explaining SP portfolio returns. Both S&P 500 and the USD index returns correlate with individual components of the SP portfolio, but the effect cancels itself out in the long-short strategy without an overall effect on the SP factor.

[Table 11 about here]

**Economic Uncertainty.** There is also an extant literature on the impact of uncertainty shocks on economic activity and business cycles (Bloom, 2009; Ludvigson, Ma and Ng, 2021), and growing interest in the implications for commodity markets (Watugala, 2019). Cheng, Kirilenko and Xiong (2015) investigate how changes in the CBOE Volatility Index (VIX), an implied volatility measure based on S&P 500 index options, affected the trading activity of commodity market participants around the global financial crisis. Ludvigson, Ma and Ng (2021) highlight the importance of distinguishing financial or macroeconomic uncertainty from real economic uncertainty. The latter is related to shocks to production, and constructed with seventy-three real activity variables. Negative shocks to production increase real economic uncertainty, which indicates a bad economic state. Arguably, this is a better measure of uncertainty for commodity markets.

We therefore aim to examine whether commodities in the long and short legs, as well as the SP factor, are sensitive to uncertainty shocks.[20] In order to test the exposure to uncertainty shocks, we regress the SP factor (and its long and short legs) on changes in different uncertainty measures ($\Delta Uncertainty_{i,t}$). We use the VIX, macro economic, financial, and real economic uncertainty (Ludvigson, Ma and Ng, 2021), time dummies and the controls mentioned above:

$$R_{p,t} = \alpha + \beta_i^u \Delta Uncertainty_{i,t} + \beta_\tau \times \mathbb{I}_\tau + \gamma_n C_{n,t} + \varepsilon_t. \tag{4.7}$$

where $R_{p,t}$ is the return of SP portfolio and its corresponding long and short legs ($R_{\overline{SP},t}$, $R_{Long,t}$ and $R_{Short,t}$), $\mathbb{I}_\tau$ is the time dummy ($\mathbb{I}_{2001\leq t\leq 2005}$ and $\mathbb{I}_{t=2020}$), $C_{n,t}$ is a set of control variables.

Table 12 shows that both the VIX and financial uncertainty shocks reduce the returns of both legs of the strategy. Hence, there is no effect on the SP factor, as it is only significantly

[20]These data come from Sydney C. Ludvigson's website.

and negatively related to changes in real economic uncertainty. Specifically, the return from the long leg with low SP commodities is significantly exposed to real economic uncertainty shocks (coefficient = -28.13 and t-statistics = -1.91). But the short leg (high SP commodities) return is immune to such shocks. This could also be considered evidence for market segmentation in the commodity futures market, where the return dynamics of each leg of the strategy are driven by different trading motives (Goldstein, Li and Yang, 2014). The long leg is more sensitive to fundamental and real economic uncertainty shocks that are relevant for hedgers, while the short leg suffers from the informational frictions from commodity financialization. In the next section, we further explore the latter claim and demonstrate the link between spreading pressure and index investment activity.

[Table 12 about here]

## 4.5 SP and Index Investment

We observe that most commodities in the long portfolio are not part of a major index such as the S&P GSCI Index or the Bloomberg Commodity Index, DJ-UBSCI (at least for most of the sample), while we only short index commodities.[21] This suggests at least some link between spread positions and commodity index investment.

**CFTC data.** To confirm this, we collect data from CFTC quarterly index investment reports (available only over a shorter period, 2007Q4-2015Q3), which contains the total long and short position held by index investors at commodity level. Then we conduct pooled regressions for two models, nested in

$$\Delta SpreadPosition_{j,t} = \alpha_t + \mu_j + \beta_{IndexPosition} \Delta IndexPosition_{j,t} + \epsilon_{j,t}, \tag{4.8}$$

where $IndexPosition_{j,t}$ includes $\{LongIndexPosition_{j,t}, NetIndexPosition_{j,t}\}$, $\alpha_t$ and $\mu_j$ are used to control time and commodity fixed effects, respectively. $LongIndexPosition_{j,t}$ is the total long position held by index investors, and $NetIndexPosition_{j,t}$ is the net long position held by index investors. $SpreadPosition_{j,t}$ is spread positions from non-commercials, money managers, other reportables, or swap dealers. $\Delta Position_{j,t}$ is the change of position, $Position_{j,t}/Position_{j,t-1} - 1$.

Table 13 indicates a positive relation between changes in spread positions and index investment positions, which is driven mainly by the spread positions of managed money investors. Our cross-sectional strategy investing in some non-index commodities (low SP)

[21] We present commodity turnovers for the long and short legs of the SP stragety in Online Appendix, Figure I-2.

and shorting some index commodities (high SP) delivers positive returns and high Sharpe ratios. However, note that our SP strategy is not a mere manifestation of index effects. Cumulative excess returns generated by the SP portfolio are higher than those obtained by simply going long all non-index commodities and short all their index counterparts (Figure I-3).

[Table 13 about here]

**SP Decomposition.** In order to understand whether the entry of index traders affect our SP factor, we further decompose SP into the number of spreaders and the average position size per spreader. In Figure 8 we present the number of spreaders (top figure) and their average position size (bottom figure) in the long/short legs of SP portfolios over the entire sample. Spreaders' average position size at time $t$ for commodity $i$ is defined as $\frac{SpreadingPosition_t/OI_t}{Num.of Spreaders}$. Spreaders' average position size in the long (short) leg of SP portfolios is the equal-weighted average of spreaders' average position size for three commodities in the corresponding leg. We note that while the average trade size is similar across both legs of spreading pressure portfolio, we observe that the number of traders in the short leg (high spreading pressure) is consistently higher compared to long leg (low spreading pressure). This suggests that the difference in returns of both long and short legs of the SP portfolio is partly driven by the influx of new index traders. More importantly, in line with commodity financialization, we see that the influx of new index investors (in the short leg commodities) start in early 2000, remain relatively stable in the period between 2001-2005, and consistently increase in the post-2005 period, with some decline in the recent Covid period. This evidence together with Figure 6 is consistent with Goldstein and Yang (2022)'s model that predicts early entry of financial speculators followed by the substantial influx of hedge-based index traders. The latter group of financial hedgers would hold spreading positions in those commodities that provide diversification benefits despite negative expected returns. Our SP factor reflects both the compensation for taking fundamental risks (long leg) and the negative risk premium associated with index investments (short leg).

[Figure 8 about here]

**DBC Fund Inception.** To establish a causal link between index investment and spreading positions we investigate how the launch of commodity futures exchange-traded fund (ETF) affects the spreading pressure of its traded commodities. We take Invesco DB Commodity Index Tracking Fund (DBC), one of the largest commodity futures exchange-traded fund (ETF), as an example. The inception date of DBC ETF is February 3, 2006. Until

October 2009, it tracks Deutsche Bank Liquid Commodity Index with six commodities, including WTI Crude Oil, Heating Oil, Gold, Corn and Wheat in our sample, and Aluminum that is not included in our sample.[22] In Figure 9, the average spread pressure of commodities traded by DBC funds is similar to other commodities before the launch of DBC ETF. However, after DBC ETF's inception date, the average spread pressure on DBC commodities is substantially higher than the SP on off-DBC commodities. We also conduct a difference-in-difference test to study whether the spreading pressure of a commodity increases once the commodity is traded through ETFs:

$$SP_{j,t} = \alpha + \beta_1 Treat_{j,t} + \beta_2 Post_{j,t} + \beta_3 Treat_{j,t} \times Post_{j,t} + \epsilon_{j,t}, \tag{4.9}$$

where $Treat_{j,t}$ indicates whether commodities are traded by DBC fund (treatment group) and $Post_{j,t}$ indicates whether the date is after the inception date of DBC fund (post-treatment). Using the data three-year before and after the DBC fund's inception date, the coefficient on interaction term, $\beta_3$ is equal to 0.05, with commodity-clustered t-statistics of 2.94. Thus, the average differential change in spreading pressure from pre-treatment sample to post-treatment sample of DBC commodities is 5% significantly higher than the non-DBC commodities.

[Figure 9 about here]

## 4.6 Something Else in Disguise?

In the previous section, we show how commodities in the long and short legs of the spreading pressure strategy differ in terms of index participation and exposure to economic fundamentals via frictions introduced through financial investors. But are they also different in terms of exposure to risk factors such as volatility, liquidity, inventory, or financial intermediary risk? For example, we may expect index commodities to be more liquid thanks to liquidity provisions by index traders (Tang and Xiong, 2012; Brunetti and Reiffen, 2014). That relation is actually more complex because of the dual roles of financial investors (Cheng and Xiong, 2014). Or index participation could potentially increase commodity volatility (Tang and Xiong, 2012; Basak and Pavlova, 2016).[23] We could argue that the priced spreading pressure factor compensates for other commodity market risks such as inventory (Gorton, Hayashi and Rouwenhorst, 2013) or financial intermediary risk (He, Kelly and Manela, 2017).

[22] See Fact Sheet via https://www.invesco.com/us/financial-products/etfs/product-detail?audienceType=Investor&ticker=DBC for more details.

[23] Figure I-4 shows no significant difference in volatility. The short leg of the spreading pressure portfolio appears slightly more volatile than the long leg. In contrast, we observe a great deal of difference in liquidity between the two portfolio legs, i.e., the long leg is much more illiquid than the short leg.

To test the role of these alternative risk channels, we repeat our cross-sectional asset pricing test by constructing volatility, liquidity, inventory, and financial intermediary risk factors:

$$\begin{aligned} R_{p,t} =& \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{var}^{mkt}\beta_{var,t}^{mkt} + \lambda_{var}^{avg}\beta_{var,t}^{avg} + \lambda_{liquidity}^{AMI}\beta_{liquidity,t}^{AMI} \\ &+ \lambda_{ICR}^{HKM}\beta_{ICR,t}^{HKM} + \lambda_{INV}^{GHR}\beta_{INV,t}^{GHR} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{p,t}, \end{aligned} \tag{4.10}$$

where $R_{p,t}$ is the return of portfolio $p$. We use seventeen portfolios as test assets, constructed by sorting on carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and sector (5). Volatility factors are the innovations in aggregate and average commodity market variances ($\Delta var_{mkt,t}$ and $\Delta var_{avg,t}$), and the liquidity measure is innovations in the aggregate Amihud measure ($\Delta liquidity_{AMI}$). We construct aggregate commodity market variance ($var_{mkt,t}$) as the sum of daily squared returns of equal-weighted commodity portfolio in week $t$. Average commodity market variance ($var_{avg,t}$) is the equally-weighted average of the sum of the daily squared return of all commodities in week $t$. We compute commodity $i$'s Amihud measure as the annual average of daily $\frac{|R_{n,d}|}{Vol_{n,d}}$ by using dollar volume $Vol_{n,d}$ for both front- and second-month contracts ($n = 1, 2$) at day $d$. The aggregate Amihud measure is the mean of the median of front- and second-month Amihud illiquidity over all commodities (Boons and Prado, 2019). Following Gorton, Hayashi and Rouwenhorst (2013), we collect inventory data from the National Agricultural Statistics Service of the U.S. Department of Agriculture (NASS-USDA), the Energy Information Administration (EIA), etc. We then calculate the normalized inventory level for each commodity at time $t$ as the ratio of the inventory level at time $t$ to its past twelve-month moving average from $t-1$ to $t-12$. We construct the inventory risk factor as the return of the long-short portfolio constructed by going long three commodities with the lowest normalized inventory levels, and short three commodities with the highest normalized inventory levels. Following He, Kelly and Manela (2017), we also construct the intermediary capital risk factor on a weekly basis, computed as the AR(1) innovations to the intermediary capital ratio (i.e., shocks to the equity capital ratio of the primary dealer counterparties of the New York Federal Reserve), scaled by the lagged intermediary capital ratio.[24]

[Table 14 about here]

The results of accounting for the alternative risk factors are in Table 14. It shows that, while volatility and liquidity factors are priced in a two-factor model with a market average factor, this is not the case for inventory or financial intermediary risk factors. More importantly, none of these factors survive when we augment the model with our SP factor.

[24]These data come from Zhiguo He's website.

These results suggest that the signal extracted from spread positions is not driven solely by volatility, liquidity, inventory, or intermediary risk factors.

# 5 Conclusion

In this paper, we find that speculators' intra-commodity spread trades carry important information about commodity futures risk premia. Spreading pressure, defined as spread trade positions scaled by open interest, negatively predicts commodity futures returns, which contrasts to the positive predictability of trader positions by hedgers and (long or short only) speculators. Moreover, a long-short portfolio strategy based on spreading pressure (spreading pressure factor) is priced in the cross-section of commodity futures returns, explaining about 75% of return variability in the cross-section when combined with the basis-momentum.

The series of empirical results hint that the potential source of spreading pressure portfolios is link to informational frictions introduced by commodity index trades, especially since the financialization of commodity markets: Our spreading pressure factor is constructed by purchasing commodities with low spreading pressure, typically non-index commodities, and shorting those with high spreading pressure (index commodities). The profitability of the long leg of this strategy stems from the fact that commodities in the long portfolio do not suffer from frictions introduced by financial traders, e.g., noise generated by hedge-based index traders. Their returns are driven by economic fundamentals such as growth in emerging (Asia) markets, and reflect a compensation for exposure to real economic uncertainty shocks. Shorting commodities with high spreading pressure is profitable as it can be seen as selling insurance to financial hedgers except for during earlier years of commodity financialization, when financial speculators brought commodity futures prices closer to fundamentals. Given our findings, we would recommend a more detailed reporting of spreading positions across a larger cross-section of commodity futures. This key source of risk in the modern commodity futures market is ultimately too big to be dismissed.

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Table 1: **Summary Statistics of Commodity Futures Returns**

This table presents the summary statistics of commodity futures returns for which we report annualized mean (Mean), standard deviation (SD), Sharpe ratios (Sharpe) and first-order autocorrelation (AR(1)) of futures front-month returns, as well as average open interest (OI) for each of the twenty-six commodities used in our sample. The sample period is from October 6, 1992 to December 29, 2020. The front-month excess return of a commodity in month $t+1$ is defined as $R^{(1)}_{long,j,t+1} = \frac{F^{(1)}_{j,t+1}}{F^{(1)}_{j,t}} - 1$, where $F^{(1)}_{j,t}$ is the price of the front-month futures contract for commodity $j$ at time $t$. The sample period is October 6, 1992 through December 29, 2020.

| Sector | Commodity | Mean | SD | Sharpe | AR(1) | OI |
|---|---|---|---|---|---|---|
| Energy | Heating Oil | 5.11 | 31.77 | 0.16 | 0.01 | 242,679 |
| | Natural Gas | -13.06 | 45.10 | -0.29 | 0.00 | 698,410 |
| | WTI Crude Oil | 7.10 | 40.08 | 0.18 | 0.02 | 1,114,096 |
| | Unleaded/RBOB Gasoline | 12.23 | 35.34 | 0.35 | 0.04 | 207,508 |
| Grains | Corn | -3.87 | 25.39 | -0.15 | -0.01 | 1,146,663 |
| | Oats | 4.17 | 30.84 | 0.14 | -0.04 | 20,646 |
| | Rough Rice | -5.08 | 24.76 | -0.21 | 0.03 | 9,207 |
| | Soybean Oil | 0.57 | 22.66 | 0.03 | 0.01 | 247,686 |
| | Soybean Meal | 11.73 | 24.95 | 0.47 | -0.02 | 214,290 |
| | Soybeans | 6.28 | 22.04 | 0.29 | 0.00 | 528,170 |
| | Wheat | -5.16 | 27.86 | -0.19 | -0.01 | 330,264 |
| Meats | Feeder Cattle | 2.14 | 15.78 | 0.14 | -0.08 | 28,591 |
| | Lean Hogs | -2.59 | 27.29 | -0.09 | 0.06 | 138,434 |
| | Live Cattle | 1.92 | 15.90 | 0.12 | -0.06 | 207,167 |
| | Frozen Pork Belly | 10.76 | 35.61 | 0.30 | 0.09 | 5,196 |
| Metal | High Grade Copper | 7.56 | 23.63 | 0.32 | 0.05 | 121,054 |
| | Palladium | 16.96 | 34.01 | 0.50 | 0.01 | 15,887 |
| | Platinum | 7.11 | 22.38 | 0.32 | -0.04 | 33,213 |
| | Silver | 8.25 | 28.79 | 0.29 | -0.02 | 125,492 |
| | Gold | 4.73 | 16.12 | 0.29 | -0.02 | 331,193 |
| Soft | Cocoa | 0.92 | 28.47 | 0.03 | 0.01 | 146,764 |
| | Coffee | 0.84 | 36.53 | 0.02 | -0.03 | 119,375 |
| | Cotton | -1.10 | 25.52 | -0.04 | 0.02 | 137,694 |
| | Lumber | 0.80 | 33.38 | 0.02 | 0.09 | 5,156 |
| | Orange Juice | 2.07 | 32.25 | 0.06 | 0.00 | 23,935 |
| | Sugar | 3.35 | 30.33 | 0.11 | 0.00 | 503,497 |
| Average | | 3.22 | 28.34 | 0.12 | 0.00 | 257,780 |

Table 2: **Summary Statistics of Commodity Futures Trader Positions**

This table presents the summary statistics of traders' positions variables for each of the twenty-six commodities, which are calculated using data obtained from the CFTC Commitment of Traders (COT) report. *Spreading pressure* is defined as $SP_{j,t} = \frac{Spreader_{j,t}}{Open\,Interest_{j,t}}$. *Directional speculative pressure* is defined as $DP_{j,t} = \frac{Long^{speculator}_{j,t} - Short^{speculator}_{j,t}}{Open\,Interest_{j,t}}$. *Hedging pressure* is defined as $HP_{j,t} = \frac{Short^{hedger}_{j,t} - Long^{hedger}_{j,t}}{Open\,Interest_{j,t}}$, and *P(HP>0)* is the probability of short hedging. *Net trading* as $Q^i_{j,t} = \frac{NetLong^i_{j,t} - NetLong^i_{j,t-1}}{Open\,Interest_{j,t-1}}$, where $NetLong^i_{j,t}$ is the net long position of trader type $i$ in month $t$ for commodity $j$, and propensity to trade ($PT$) of traders type $i$ in month $t$ for commodity $j$ as $PT^i_{j,t} = \frac{abs(Long^i_{j,t} - Long^i_{j,t-1}) + abs(Short^i_{j,t} - Short^i_{j,t-1})}{Long^i_{j,t-1} + Short^i_{j,t-1}}$. Trader type $i$ indicates hedgers (Hedger), speculators (Specs) or spreaders (Spreader). The sample period is October 6, 1992 through December 29, 2020.

| Sector | Commodity | SP % | | HP % | | | DP % | | \|Q\| % | | Average PT % | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | P(HP>0) | Mean | SD | Hedger | Specs | Specs (no spread) | Specs (spread) |
| Energy | Heating Oil | 11.02 | 6.31 | 8.62 | 8.69 | 83.51 | 2.97 | 6.24 | 2.37 | 1.72 | 13.34 | 11.67 |
| | Natural Gas | 21.94 | 13.79 | -0.69 | 11.14 | 47.01 | -5.71 | 9.69 | 1.58 | 1.36 | 10.44 | 8.23 |
| | WTI Crude Oil | 18.78 | 11.57 | 8.01 | 10.54 | 77.07 | 7.82 | 9.44 | 1.69 | 1.38 | 9.37 | 6.52 |
| | Unleaded/RBOB Gasoline | 9.05 | 5.60 | 16.30 | 11.00 | 89.21 | 14.23 | 9.36 | 2.80 | 2.15 | 12.75 | 15.57 |
| Grains | Corn | 10.81 | 5.05 | 2.28 | 12.87 | 57.80 | 8.58 | 11.86 | 2.31 | 2.18 | 8.01 | 8.21 |
| | Oats | 3.35 | 2.93 | 32.62 | 18.34 | 93.62 | 15.18 | 14.41 | 4.09 | 3.06 | 13.06 | 67.33 |
| | Rough Rice | 6.49 | 3.91 | 8.47 | 23.71 | 62.55 | 1.41 | 18.34 | 3.89 | 3.01 | 13.32 | 36.35 |
| | Soybean Oil | 15.02 | 5.19 | 12.67 | 16.65 | 73.95 | 7.36 | 13.10 | 3.78 | 2.91 | 11.38 | 9.54 |
| | Soybean Meal | 11.43 | 4.33 | 18.30 | 14.52 | 86.64 | 10.43 | 12.00 | 3.39 | 2.65 | 11.70 | 10.86 |
| | Soybeans | 12.79 | 4.13 | 9.31 | 16.46 | 69.00 | 10.29 | 13.70 | 2.73 | 2.55 | 9.01 | 8.50 |
| | Wheat | 13.66 | 6.87 | 0.72 | 14.32 | 46.34 | 0.28 | 12.20 | 2.98 | 2.65 | 7.80 | 10.93 |
| Meats | Feeder Cattle | 11.01 | 5.92 | -7.57 | 10.38 | 23.41 | 10.97 | 13.49 | 2.06 | 2.99 | 9.15 | 18.20 |
| | Lean Hogs | 14.64 | 5.81 | 2.01 | 12.74 | 59.43 | 7.78 | 13.04 | 2.41 | 2.61 | 8.78 | 11.99 |
| | Live Cattle | 12.38 | 5.00 | 6.53 | 10.93 | 69.27 | 12.32 | 11.44 | 1.75 | 2.12 | 7.22 | 9.78 |
| | Frozen Pork Belly | 6.44 | 4.53 | -1.87 | 16.22 | 45.90 | 0.31 | 19.19 | 3.70 | 5.89 | 17.16 | 71.57 |
| Metal | High Grade Copper | 8.57 | 6.43 | 6.69 | 20.31 | 60.24 | 2.98 | 15.75 | 3.88 | 3.16 | 10.71 | 30.67 |
| | Palladium | 2.34 | 2.59 | 40.12 | 28.99 | 83.65 | 33.26 | 24.32 | 4.62 | 3.81 | 9.69 | 72.25 |
| | Platinum | 1.77 | 1.86 | 47.94 | 22.36 | 95.73 | 37.32 | 21.05 | 5.87 | 5.16 | 10.61 | 100.07 |
| | Silver | 10.85 | 5.99 | 38.06 | 16.73 | 99.53 | 22.97 | 13.81 | 3.63 | 3.36 | 8.36 | 11.13 |
| | Gold | 10.19 | 4.83 | 25.39 | 26.48 | 80.80 | 18.28 | 23.59 | 4.81 | 3.99 | 10.28 | 9.39 |
| Soft | Cocoa | 8.37 | 6.42 | 13.04 | 15.97 | 77.07 | 8.49 | 14.78 | 2.76 | 2.43 | 9.31 | 20.62 |
| | Coffee | 10.84 | 5.63 | 11.25 | 16.32 | 68.11 | 5.50 | 15.17 | 3.56 | 3.25 | 10.44 | 13.55 |
| | Cotton | 7.05 | 3.65 | 9.55 | 22.15 | 65.94 | 6.00 | 21.15 | 4.31 | 3.70 | 10.76 | 13.71 |
| | Lumber | 5.98 | 4.27 | 9.52 | 19.89 | 64.45 | 4.24 | 17.67 | 4.45 | 4.39 | 12.70 | 46.71 |
| | Orange Juice | 4.81 | 3.08 | 20.60 | 24.78 | 78.70 | 11.48 | 22.29 | 4.73 | 3.96 | 11.27 | 28.01 |
| | Sugar | 7.03 | 5.08 | 14.43 | 17.93 | 75.31 | 9.41 | 14.13 | 3.61 | 2.57 | 10.54 | 31.67 |
| | Average | 9.87 | 5.41 | 13.55 | 16.94 | 70.55 | 10.16 | 15.05 | 3.38 | 3.04 | 10.66 | 26.27 |

Table 3: **Fama-MacBeth Cross-Sectional Regressions**

This table presents the average coefficients from running Fama-MacBeth cross-sectional regressions of futures excess returns on the lagged (fifty-two week average) spreading pressure ($\overline{SP}$). Included as control variables are basis-momentum ($BM$), hedgers' net position changes ($Q_h$), and/or speculators' net position changes ($Q_s$):

$$R^{(k)}_{j,t+1} = b_0 + b_{\overline{SP}}\overline{SP}_{j,t} + b_{BM}BM_{j,t} + b^h_Q Q^h_{j,t} + b^s_Q Q^s_{j,t} + \epsilon_{j,t+1},$$

where $R^{(k)}_{j,t+k}$ is the return of commodity $j$'s $k$-$th$ nearby contract at week $t+1$. Newey-West t-statistics with four lags and average $R^2$ are reported for each model specification. Panel A, B and C present results for the first-, second- and third-nearby returns, respectively. The sample period is October 5, 1993 through December 29, 2020.

| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Panel A: First-nearby Contract | | | | | | | | |
| $b_{\overline{SP}}$ | -1.81 | | | | -1.80 | -2.00 | -1.98 | -2.03 |
| | (-3.24) | | | | (-3.27) | (-3.43) | (-3.36) | (-3.40) |
| $b_{BM}$ | | 1.14 | | | 1.15 | | | 1.24 |
| | | (2.10) | | | (2.13) | | | (2.01) |
| $b^h_Q$ | | | 3.51 | | | 3.73 | | 1.40 |
| | | | (5.54) | | | (6.01) | | (0.81) |
| $b^s_Q$ | | | | -3.92 | | | -4.08 | -2.53 |
| | | | | (-6.22) | | | (-6.33) | (-1.37) |
| $R^2$ | 6.07% | 6.99% | 4.97% | 4.72% | 12.80% | 11.01% | 10.80% | 21.92% |
| Panel B: Second-nearby Contract | | | | | | | | |
| $b_{\overline{SP}}$ | -1.57 | | | | -1.55 | -1.71 | -1.70 | -1.78 |
| | (-3.09) | | | | (-3.09) | (-3.20) | (-3.18) | (-3.27) |
| $b_{BM}$ | | 1.14 | | | 1.12 | | | 1.22 |
| | | (2.49) | | | (2.44) | | | (2.36) |
| $b^h_Q$ | | | 2.50 | | | 2.74 | | 0.87 |
| | | | (4.23) | | | (4.64) | | (0.57) |
| $b^s_Q$ | | | | -2.92 | | | -3.07 | -2.08 |
| | | | | (-4.86) | | | (-4.96) | (-1.28) |
| $R^2$ | 6.16% | 6.66% | 4.88% | 4.65% | 12.54% | 11.01% | 10.81% | 21.53% |
| Panel C: Third-nearby Contract | | | | | | | | |
| $b_{\overline{SP}}$ | -1.13 | | | | -1.09 | -1.18 | -1.17 | -1.26 |
| | (-2.46) | | | | (-2.43) | (-2.47) | (-2.44) | (-2.57) |
| $b_{BM}$ | | 0.76 | | | 0.79 | | | 0.87 |
| | | (1.84) | | | (1.90) | | | (1.90) |
| $b^h_Q$ | | | 1.82 | | | 2.05 | | 0.61 |
| | | | (3.19) | | | (3.59) | | (0.43) |
| $b^s_Q$ | | | | -2.31 | | | -2.45 | -1.82 |
| | | | | (-3.99) | | | (-4.16) | (-1.22) |
| $R^2$ | 6.04% | 6.49% | 5.01% | 4.77% | 12.25% | 11.02% | 10.80% | 21.34% |

Table 4: **Spreading Pressure Portfolio**

This table presents the summary statistics of commodity futures weekly portfolio returns, where portfolios are constructed by sorting commodity futures on the fifty-two week average of spreading pressure (Panel A), basis-momentum (Panel B), basis (Panel C) or momentum (Panel D). We report annualized mean (Mean), standard deviation (Std. Dev) and Sharpe ratio (SR) of portfolio returns. Basis-momentum is calculated following Boons and Prado (2019) as $\prod_{s=t-11}^{t}\left(1+R_{long,s}^{(0)}\right)-\prod_{s=t-11}^{t}\left(1+R_{long,s}^{(1)}\right)$. Carry (basis) and momentum are defined as $C_t=\frac{\ln F_t^2-\ln F_t^1}{T_2-T_1}$, $M_t=\prod_{s=t-52}^{t}\left(1+R_{long,s}^{(1)}\right)$. *Low3* (*High3*) consists of commodity futures ranked in the bottom (top) three for spreading pressure or basis-momentum, and the rest of twenty commodities constitute the portfolio called *Mid*. *Low3-High3* (*High3-Low3*) represents a long-short portfolio strategy of buying Low3 and shorting High3 (buying High3 and shorting Low3). Following Paschke, Prokopczuk and Simen (2020), we set the (round-trip) transaction cost of each commodity's contract as 0.033% and report the long-short portfolio return excluded transaction cost (Net of Transaction Cost). Portfolios' excess returns are calculated as equal-weighted average excess returns of portfolio constituents. The sample period is October 5, 1993 through December 29, 2020.

| Panel A: $\overline{SP}$ | | | | | |
|---|---|---|---|---|---|
| | Low3 | Mid | High3 | Low3-High3 | Net of Transaction Cost |
| Mean | 10.84 | 2.91 | -5.99 | 16.84 | 15.37 |
| Std. Dev. | 20.55 | 12.64 | 21.87 | 25.25 | 25.25 |
| SR | 0.53 | 0.23 | -0.27 | 0.67 | 0.61 |
| Skewness | -0.12 | -0.45 | 1.02 | -0.49 | -0.50 |
| Kurtosis | 5.17 | 7.48 | 17.71 | 9.63 | 9.68 |
| Panel B: BM | | | | | |
| | Low3 | Mid | High3 | High3-Low3 | Net of Transaction Cost |
| Mean | -5.35 | 2.55 | 12.40 | 17.75 | 15.27 |
| Std. Dev. | 22.77 | 13.24 | 20.02 | 27.36 | 27.36 |
| SR | -0.24 | 0.19 | 0.62 | 0.65 | 0.56 |
| Skewness | 1.23 | -0.37 | -0.06 | -0.76 | -0.77 |
| Kurtosis | 20.14 | 7.39 | 4.53 | 11.75 | 11.84 |
| Panel C: Basis | | | | | |
| | Low3 | Mid | High3 | Low3-High3 | Net of Transaction Cost |
| Mean | 2.66 | 2.72 | 3.04 | -0.38 | -3.48 |
| Std. Dev. | 22.28 | 12.81 | 23.23 | 27.90 | 27.93 |
| SR | 0.12 | 0.21 | 0.13 | -0.01 | -0.12 |
| Skewness | -0.25 | -0.30 | 2.14 | -1.12 | -1.13 |
| Kurtosis | 5.01 | 6.25 | 30.08 | 13.41 | 13.43 |
| Panel D: Momentum | | | | | |
| | Low3 | Mid | High3 | High3-Low3 | Net of Transaction Cost |
| Mean | -3.58 | 2.73 | 9.31 | 12.89 | 10.16 |
| Std. Dev. | 25.63 | 12.44 | 23.79 | 31.71 | 31.75 |
| SR | -0.14 | 0.22 | 0.39 | 0.41 | 0.32 |
| Skewness | 2.33 | -0.32 | -0.16 | -1.54 | -1.54 |
| Kurtosis | 36.57 | 6.13 | 4.62 | 19.30 | 19.35 |

Table 5: **Spreading Pressure Factor: Correlations**

This table presents the summary statistics of spreading pressure factor, i.e., the excess return of long-short spreading pressure portfolios ($R_{\overline{SP}}$). Panel A reports the correlation between the spreading pressure factor and other well-known commodity futures risk factors such the market factor ($R_{Avg}$), basis-momentum ($R_{BM}$), carry ($R_C$) and momentum ($R_M$). Panel B shows the correlation between spreading pressure portfolios and each of four commodity futures sector portfolios (energy, grain, meats, metals, and soft). Low3 (High3) consists of commodity futures ranked in the bottom (top) three for spreading pressure. Low3-High3 represents a long-short portfolio strategy of buying Low3 and shorting High3. Portfolios' excess returns are calculated as equal-weighted average excess returns of portfolio constituents. The p-values are reported in parentheses. The sample period is October 5, 1993 through December 29, 2020.

Panel A: Spreading Pressure Factor versus well-known factors Correlation

| | $R_{Avg}$ | $R_{\overline{SP}}$ | $R_{BM}$ | $R_C$ | $R_M$ |
|---|---|---|---|---|---|
| $R_{Avg}$ | 1.00 | | | | |
| | (-) | | | | |
| $R_{\overline{SP}}$ | -0.09 | 1.00 | | | |
| | (0.001) | (-) | | | |
| $R_{BM}$ | -0.07 | 0.23 | 1.00 | | |
| | (0.005) | (0.000) | (-) | | |
| $R_C$ | 0.02 | 0.23 | 0.28 | 1.00 | |
| | (0.552) | (0.000) | (0.000) | (-) | |
| $R_M$ | -0.02 | 0.25 | 0.29 | 0.49 | 1.00 |
| | (0.473) | (0.000) | (0.000) | (0.000) | (-) |

Panel B: Spreading Pressure Factor versus Sectors Correlation

| | Energy | Grain | Meats | Metal | Soft |
|---|---|---|---|---|---|
| Low3 | 0.25 | 0.44 | 0.06 | 0.65 | 0.47 |
| | (0.000) | (0.000) | (0.022) | (0.000) | (0.000) |
| High3 | 0.68 | 0.47 | 0.20 | 0.35 | 0.30 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Low3-High3 | -0.38 | -0.04 | -0.13 | 0.23 | 0.12 |
| | (0.000) | (0.121) | (0.000) | (0.000) | (0.000) |

Table 6: **Pricing Model Comparison: Spanning Regressions and GRS Tests**

This table presents the results of spanning regressions and GRS tests by regressing spreading pressure factors ($R_{\overline{SP},t}$) on commodity futures risk ($F_{i,t}$) factors proposed by the extant pricing models:

$$R_{\overline{SP},t} = \alpha + \sum_{i=1}^{K} \beta_i F_{i,t} + \epsilon_t,$$

where $K$ is the number of factors, and $F_{i,t}$ is factor $i$ at time $t$. Panel A reports the regression coefficients in a one-factor model (basis (carry) factor) from Szymanowska et al. (2014), Panel B reports the regression coefficients in a two-factor model (basis-momentum (BM) and the average commodity market factor (Avg)) from Boons and Prado (2019), and Panel C reports the regression coefficients in a three-factor model (carry (C), momentum (M), and the average commodity market factor (Avg)) from Bakshi et al. (2019). Newey-West t-statistics with one lag are calculated (in parentheses), and F-statistics and the p-value of the joint GRS test are also provided in the last two columns. The sample period is October 5, 1993 through December 29, 2020.

| Panel A: One-Factor Model | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta_{Basis}$ | | | $R^2$ | GRS-F | p-val |
| Coefficient | 16.92 | 0.21 | | | 2.41% | 5.05 | 0.00 |
| | (3.55) | (3.46) | | | | | |
| **Panel B. Two-Factor Model** | | | | | | | |
| | $\alpha$ | $\beta_{Avg}$ | $\beta_{BM}$ | | $R^2$ | GRS-F | p-val |
| Coefficient | 13.58 | -0.14 | 0.21 | | 5.66% | 2.99 | 0.03 |
| | (2.73) | (-1.66) | (3.41) | | | | |
| **Panel C. Three-Factor Model** | | | | | | | |
| | $\alpha$ | $\beta_{Avg}$ | $\beta_C$ | $\beta_M$ | $R^2$ | GRS-F | p-val |
| Coefficient | 15.55 | -0.17 | 0.13 | 0.14 | 8.50% | 3.99 | 0.01 |
| | (3.29) | (-2.07) | (3.22) | (3.40) | | | |

Table 7: **Asset Pricing Tests with Spreading Pressure Factor**

This table presents the estimated risk premium on commodity futures risk factors by running Fama-MacBeth cross-sectional asset pricing tests (Panel A-D) and Giglio and Xiu (2021) three-pass regression (Panel E). In Panel A-D, eight different model specifications are considered, and are nested in

$$R_{p,t} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{BM}\beta_{BM,t} + \lambda_C\beta_{C,t} + \lambda_M\beta_{M,t} + \lambda_{Avg,t}\beta_{Avg,t} + \epsilon_{p,t},$$

where $R_{p,t}$ is the return of portfolio $p$ at week $t$, $\lambda$ is factor risk premia, and we estimate $\beta_t$ as a fixed parameter using the entire sample. We use seventeen commodity futures portfolios as test assets, broken down as carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and commodity sector (5). In Panel A, Model (1) and (2) are one-factor models that contains the spreading pressure factor or basis-momentum factor only. In Panel B, Model (3) and (4) add the market average factor (Model (4) is the Boons and Prado (2019) model), and Model (5) is a two factors model by using both spreading pressure factor and basis-momentum factor. In Panel C, Model (6) adds the market average factor to model (5) and Model (7) is the Bakshi, Gao and Rossi (2019) model. Models (8) adds the spreading pressure factor to Models (7). We report two versions of the t-statistics, following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). OLS $R^2$ and GLS $R^2$ (in parentheses) are in the second last column. Generalized version of the Shanken (1985) cross-sectional F-test statistics and their corresponding p-values (in parentheses) are in the last column ($CSRT_{SH}$). Panel E reports the three-pass regression proposed by Giglio and Xiu (2021), using two latent factors. We report the risk premia ($\lambda$), their corresponding standard error (SE), the $R^2$ of the projection of each observed factor onto the two latent factors ($R^2_g$) and the p-value of the test that the observed factor is weak. The observed factors used in this test are market average factor, spreading pressure factor, basis-momentum factor, basis factor and momentum factor. The sample period is October 5, 1993 through December 29, 2020.

Table 7 - **Continued**

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ | $R^2$ | $CSRT_{SH}$ |
|---|---|---|---|---|---|---|---|---|
| Panel A: One-Factor Model | | | | | | | | |
| (1) | 4.01 | 15.17 | | | | | 47.10% | 0.02 |
| | (1.63) | (2.62) | | | | | (27.70%) | (0.06) |
| | [1.50] | [2.66] | | | | | | |
| (2) | 3.87 | | 19.19 | | | | 56.52% | 0.02 |
| | (1.55) | | (3.13) | | | | (26.24%) | (0.03) |
| | [1.34] | | [2.90] | | | | | |
| Panel B: Two-Factor Model | | | | | | | | |
| (3) | -1.91 | 16.85 | | | | 5.18 | 53.04% | 0.02 |
| | (-0.44) | (2.98) | | | | (1.04) | (31.31%) | (0.10) |
| | [-0.45] | [3.13] | | | | [0.98] | | |
| (4) | 0.05 | | 20.02 | | | 3.08 | 59.22% | 0.02 |
| | (0.01) | | (3.34) | | | (0.61) | (29.33%) | (0.05) |
| | [0.01] | | [3.20] | | | [0.66] | | |
| (5) | 4.22 | 11.47 | 15.80 | | | | 66.97% | 0.01 |
| | (1.71) | (2.07) | (2.84) | | | | (43.94%) | (0.60) |
| | [1.52] | [2.09] | [2.47] | | | | | |
| Panel C: Three-Factor Model | | | | | | | | |
| (6) | -2.88 | 13.24 | 16.27 | | | 6.17 | 75.47% | 0.01 |
| | (-0.65) | (2.44) | (2.92) | | | (1.23) | (49.42%) | (0.49) |
| | [-0.71] | [2.52] | [2.61] | | | [1.21] | | |
| (7) | 2.46 | | | 3.77 | 17.42 | 0.56 | 40.74% | 0.02 |
| | (0.56) | | | (0.69) | (2.80) | (0.11) | (15.57%) | (0.02) |
| | [0.61] | | | [0.66] | [3.17] | [0.11] | | |
| Panel D: Four-Factor Model | | | | | | | | |
| (8) | -2.15 | 14.83 | | 1.83 | 14.87 | 5.39 | 65.36% | 0.01 |
| | (-0.49) | (2.76) | | (0.34) | (2.43) | (1.08) | (42.34%) | (0.07) |
| | [-0.46] | [2.85] | | [0.32] | [2.76] | [0.96] | | |
| Panel E: Three-Pass Regression | | | | | | | | |
| $\lambda$ | | 7.40 | 7.20 | 9.77 | 12.6 | 3.26 | | |
| SE | | (3.12) | (2.81) | (3.39) | (4.45) | (2.34) | | |
| $R_g^2$ | | 40.21% | 29.95% | 41.86% | 56.56% | 93.51% | | |
| $p$(weak) | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | |

Table 8: **Spreading Pressure Factor over Time**

This table presents the regression of spreading pressure (and its long and short legs) on different time dummy variables,

$$R_{p,t} = \alpha + \beta_\tau \times \mathbb{I}_\tau + \gamma_p R_{p,t-1} + \varepsilon_{p,t},$$

where $R_{p,t}$ includes the return of spreading pressure ($R_{\overline{SP},t}$), return of spreading pressure long leg ($R_{Long,t}$), and the return of spreading pressure short leg ($R_{Short,t}$). The time dummy used in Model (1) is $I_{t\geq 2005}$, which equals to one when the time is after 2005. Similarly, the time dummy variables used in Model (2), (3), (4) and (5) are $I_{2001\leq t\leq 2005}$, $I_{2003\leq t\leq 2008}$, $I_{2006Sep\leq t\leq 2006Dec}$ and $I_{t=2020}$ respectively. We include the lag of return $R_{p,t-1}$ as a control variable. Newey-West t-statistics with four lags are in parentheses. The sample period is October 5, 1993 through December 29, 2020.

| Model | Variable | $R_{\overline{SP},t}$ | $R_{Long,t}$ | $R_{Short,t}$ |
|---|---|---|---|---|
| (1) | $\alpha$ | 0.19 | 0.25 | 0.06 |
| | | (1.36) | (2.25) | (0.63) |
| | $\beta_{t\geq 2005}$ | 0.21 | -0.07 | -0.30 |
| | | (1.15) | (-0.50) | (-2.02) |
| (2) | $\alpha$ | 0.42 | 0.24 | -0.20 |
| | | (4.38) | (2.91) | (-2.24) |
| | $\beta_{2001\leq t<2005}$ | -0.59 | -0.20 | 0.43 |
| | | (-2.50) | (-1.04) | (2.34) |
| (3) | $\alpha$ | 0.32 | 0.24 | -0.09 |
| | | (3.23) | (3.13) | (-1.03) |
| | $\beta_{2003\leq t<2008}$ | -0.05 | -0.18 | -0.14 |
| | | (-0.21) | (-0.82) | (-0.61) |
| (4) | $\alpha$ | 0.22 | 0.26 | 0.04 |
| | | (1.70) | (2.63) | (0.40) |
| | $\beta_{2006Sep\leq t<2006Dec}$ | 0.16 | -0.12 | -0.29 |
| | | (0.90) | (-0.78) | (-1.93) |

Table 9: **Spreading Pressure and the Term Structure of Futures Prices**

This table reports the predictive regression of the one week-ahead slope and curvature of the commodity futures term structure on spreading pressure ($SP$) and hedging pressure ($HP$):

$$\{Slope_{j,t+1}, Curvature_{j,t+1}\} = \alpha_{t+1} + \mu_j + \beta_{SP}SP_{j,t} + \beta_{HP}HP_{j,t} + \beta_T T^1_{j,t} + \varepsilon_{j,t+1},$$

where $T^1_{j,t}$ is time to maturity of the first nearby contract for commodity $j$ at time $t$. We define the slope of futures curves as $slope_{j,t} = \frac{\ln F^3_{j,t} - \ln F^1_{j,t}}{T^3_{j,t} - T^1_{j,t}}$, and the curvature as $curvature_{j,t} = \frac{\ln F^3_{j,t} - \ln F^2_{j,t}}{T^3_{j,t} - T^2_{j,t}} - \frac{\ln F^2_{j,t} - \ln F^1_{j,t}}{T^2_{j,t} - T^1_{j,t}}$. We report the results for four subgroups as well as for the whole. *Group* indicates the sub-sample depending on the shape of the term structure at time $t$, i.e., 1) positive slope, positive curvature, 2) positive slope, negative curvature, 3) negative slope, positive curvature, and 4) negative slope, negative curvature. *Percentage* (*Mean of SP*) is the proportion of the sample (average spreading pressure) for each group. The regression controls for both time- and commodity-fixed effects, as well as for time to earliest maturity date for each commodity at each point in time. t-statistics based on standard errors clustered at the time dimension are in parentheses. The sample period is from October 6, 1992 to December 29, 2020.

| | | | $Slope_{j,t+1} \times 100$ | | | $Curv_{j,t+1} \times 100$ | | |
|---|---|---|---|---|---|---|---|---|
| Group | Percentage | Mean of SP | $SP_{j,t}$ | $HP_{j,t}$ | $R^2$ | $SP_{j,t}$ | $HP_{j,t}$ | $R^2$ |
| (1) $+Slope$, $+Curv$ | 24.31% | 10.82% | 0.35 | -0.07 | 44.91% | 0.24 | -0.05 | 30.89% |
| | | | (4.64) | (-4.81) | | (2.40) | (-2.28) | |
| (2) $+Slope$,$-Curv$ | 44.75% | 10.75% | 0.35 | -0.10 | 36.59% | -0.12 | -0.04 | 37.29% |
| | | | (5.01) | (-9.33) | | (-1.83) | (-2.80) | |
| (3) $-Slope$, $+Curv$ | 13.38% | 8.40% | 0.54 | -0.08 | 35.27% | 0.32 | -0.05 | 38.45% |
| | | | (4.39) | (-2.77) | | (2.40) | (-1.59) | |
| (4) $-Slope$, $-Curv$ | 17.56% | 9.05% | 0.03 | -0.06 | 37.56% | -0.48 | -0.03 | 39.60% |
| | | | (0.18) | (-1.89) | | (-2.84) | (-0.85) | |
| (5) *All* | 100.00% | 10.18% | 0.87 | -0.22 | 15.64% | -0.05 | -0.07 | 6.18% |
| | | | (12.51) | (-20.04) | | (-0.80) | (-5.49) | |

Table 10: **Asset Pricing Test with Disaggregated Spreading Pressure Factors**

This table reports the results of cross-sectional asset pricing tests with different versions of spreading pressure factors depending on disaggregated spread trader categories from the DCOT report (i.e., money manager, swap dealer, and other reportable):

$$R_{p,t} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{\overline{SP}}^{ManagedMoney}\beta_{\overline{SP}\_ManagedMoney,t} + \lambda_{\overline{SP}}^{OtherReportable}\beta_{\overline{SP}\_OtherReportable,t} + \lambda_{\overline{SP}}^{SwapDealer}\beta_{\overline{SP}\_SwapDealers,t} + \epsilon_{p,t},$$

where $R_{p,t}$ is the return of portfolio $p$. We use seventeen portfolios as test assets, constructed by sorting on carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and sector (5). $\lambda_{\overline{SP},t}$ is the estimated risk premium on the spreading pressure factor based on spreading pressure from overall speculators (i.e., money managers and others), $\lambda_{\overline{SP}}^{ManagedMoney}$ and $\lambda_{\overline{SP}}^{OtherReportable}$ are based on sub-categories of speculator, i.e., money managers and others, respectively, and $\lambda_{\overline{SP}}^{SwapDealer}$ is based on financial intermediaries, i.e., swap dealers. Two versions of t-statistics are reported following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). OLS $R^2$ and GLS $R^2$ (in parentheses) are in the second last column. Generalized version of the Shanken (1985) cross-sectional F-test statistics and their corresponding p-values (in parentheses) are in the last column ($CSRT_{SH}$). The sample period is June 13, 2006 through December 29, 2020.

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{\overline{SP}}^{ManagedMoney}$ | $\lambda_{\overline{SP}}^{OtherReportable}$ | $\lambda_{\overline{SP}}^{SwapDealer}$ | $R^2$ | $CSRT_{SH}$ |
|---|---|---|---|---|---|---|---|
| (1) | 2.28 | 14.63 | | | | 64.97% | 0.02 |
| | (0.57) | (1.72) | | | | (29.61%) | (0.55) |
| | [0.45] | [2.08] | | | | | |
| (2) | 2.73 | | 16.30 | | | 61.87% | 0.02 |
| | (0.70) | | (1.65) | | | (21.88%) | (0.47) |
| | [0.57] | | [2.14] | | | | |
| (3) | 0.86 | | | 17.80 | | 61.52% | 0.02 |
| | (0.21) | | | (1.67) | | (30.74%) | (0.60) |
| | [0.15] | | | [2.02] | | | |
| (4) | 3.96 | | | | 15.61 | 50.71% | 0.02 |
| | (1.03) | | | | (1.49) | (9.44%) | (0.36) |
| | [0.88] | | | | [2.03] | | |
| (5) | 1.49 | 15.83 | | | 7.88 | 66.04% | 0.02 |
| | (0.41) | (1.94) | | | (0.70) | (33.17%) | (0.49) |
| | [0.40] | [2.50] | | | [0.89] | | |
| (6) | -0.99 | | 25.80 | | 4.26 | 73.01% | 0.02 |
| | (-0.25) | | (2.24) | | (0.36) | (33.97%) | (0.53) |
| | [-0.29] | | [2.57] | | [0.44] | | |
| (7) | 1.41 | | | 16.53 | 9.88 | 61.89% | 0.02 |
| | (0.37) | | | (1.54) | (0.92) | (31.38%) | (0.52) |
| | [0.38] | | | [1.85] | [1.24] | | |

Table 11: **Spreading Pressure Factor and Asset Returns**

This table presents the relationship between the spreading pressure factor (and its long and short legs, $R_{i,t}$) and the returns of MSCI Emerging Markets Asia Index, S&P 500, U.S. Dollar Index Futures Contracts, and JP Morgan Treasury Bond Index. We regress the spreading pressure factor (as well as its long and short legs separately) on normalized returns of indices,

$$R_{p,t} = \alpha + \beta_m^a R_{m,t}^a + \beta_\tau \mathbb{I}_\tau + \gamma_n C_{n,t} + \varepsilon_{p,t},$$

where $R_{p,t}$ is the return of SP portfolio and its corresponding long and short legs ($R_{\overline{SP},t}$, $R_{Long,t}$ and $R_{Short,t}$), and $R_m^a$ is the return of MSCI Emerging Markets Asia Index (Panel A), S&P 500 (Panel B), U.S. Dollar Index Futures Contracts (Panel C) and JP Morgan Treasury Bond Index (Panel D). $\mathbb{I}_\tau$ are dummy variables $\mathbb{I}_{2001 \leq t \leq 2005}$ and $\mathbb{I}_{t=2020}$. The control variables ($C_{n,t}$) used in this regression are the growth rate of the Baltic Dry Index, the change in the ten-year breakeven inflation rate and the lag of the spreading pressure return, long or short leg return. We report $\beta_k$, its Newey-West t-statistics with twelve lags and the $R^2$ of the above regression. The sample period is January 5, 1999 through December 29, 2020 (weekly frequency).

| | $\beta_m^a$ | t-stat | $R^2$ |
|---|---|---|---|
| Panel A: MSCI Emerging Markets Asia Index Return | | | |
| Spreading Pressure Factor | 12.45 | (2.48) | 2.38% |
| Long, low spreading pressure commodities | 39.66 | (6.43) | 14.23% |
| Short, high spreading pressure commodities | 26.88 | (5.48) | 10.58% |
| Panel B: S&P 500 Return | | | |
| Spreading Pressure Factor | 6.13 | (1.34) | 2.21% |
| Long, low spreading pressure commodities | 30.04 | (5.76) | 9.80% |
| Short, high spreading pressure commodities | 23.91 | (4.50) | 10.35% |
| Panel C: U.S. Dollar Index Future Contracts Return | | | |
| Spreading Pressure Factor | -6.88 | (-1.35) | 1.70% |
| Long, low spreading pressure commodities | -39.24 | (-7.26) | 15.37% |
| Short, high spreading pressure commodities | -32.38 | (-8.05) | 13.04% |
| Panel D: JP Morgan Treasury Bond Index Return | | | |
| Spreading Pressure Factor | 4.69 | 0.76 | 2.37% |
| Long, low spreading pressure commodities | 1.03 | 0.18 | 5.29% |
| Short, high spreading pressure commodities | -4.73 | -0.87 | 9.38% |

Table 12: **Spreading Pressure Factor and Economic Uncertainty**

This table presents the relationship between the spreading pressure factor (and its long and short legs, $R_{i,t}$) and shocks to different measures of uncertainty, namely the VIX index, and macroeconomic, financial, and real economic uncertainty. We regress the spreading pressure factor (and its long and short legs separately) on normalized changes in uncertainty measures ($\Delta Uncertainty_{i,t}$),

$$R_{p,t} = \alpha + \beta_i^u \Delta Uncertainty_{i,t} + \beta_\tau \times \mathbb{I}_\tau + \gamma_n C_{n,t} + \varepsilon_t,$$

where $R_{p,t}$ is the return of SP portfolio and its corresponding long and short legs ($R_{\overline{SP},t}$, $R_{Long,t}$ and $R_{Short,t}$), and $\Delta Uncertainty_{i,t}$ is the change of real economic uncertainty (Panel A), VIX (Panel B), financial economic uncertainty (Panel C) and macroeconomic uncertainty (Panel D). $\mathbb{I}_\tau$ are dummy variables $\mathbb{I}_{2001 \leq t \leq 2005}$ and $\mathbb{I}_{t=2020}$. The control variables ($C_{n,t}$) used in this regression are the growth rate of the Baltic Dry Index, the change in the ten-year breakeven inflation rate and the lag of the spreading pressure return, long or short leg return. We report $\beta_i^u$, its Newey-West t-statistics with twelve lags and $R^2$ of the above regression. The sample period is January 5, 1999 through December 29, 2020 (monthly frequency).

| | $\beta_i^u$ | t-stat | $R^2$ |
|---|---|---|---|
| Panel A: Real Economic Uncertainty | | | |
| Spreading Pressure Factor | -30.23 | (-2.69) | 6.66% |
| Long, low spreading pressure commodities | -28.13 | (-1.91) | 10.97% |
| Short, high spreading pressure commodities | 2.44 | (0.20) | 5.92% |
| Panel B: VIX | | | |
| Spreading Pressure Factor | -2.71 | (-0.27) | 2.90% |
| Long, low spreading pressure commodities | -26.53 | (-2.85) | 10.98% |
| Short, high spreading pressure commodities | -24.39 | (-3.06) | 9.32% |
| Panel C: Financial Uncertainty | | | |
| Spreading Pressure Factor | -10.14 | (-0.99) | 4.87% |
| Long, low spreading pressure commodities | -22.64 | (-2.30) | 10.36% |
| Short, high spreading pressure commodities | -10.07 | (-1.47) | 7.38% |
| Panel D: Macro Uncertainty | | | |
| Spreading Pressure Factor | -19.94 | (-1.55) | 6.14% |
| Long, low spreading pressure commodities | -30.10 | (-2.52) | 12.53% |
| Short, high spreading pressure commodities | -8.98 | (-0.84) | 6.52% |

Table 13: **Spread Positions and Index Investment**

This table presents pooled regressions for two models with time and commodity fixed effects, nested in

$$\Delta SpreadPosition_{j,t} = \alpha_t + \mu_j + \beta_{IndexPosition}\Delta IndexPosition_{j,t} + \epsilon_{j,t},$$

where $SpreadPosition_{j,t}$ is spread positions from non-commercials, money managers, other reportables, or swap dealers for commodity $j$ at time $t$, $IndexPosition_{j,t}$ includes $\{LongIndexPosition_{j,t}, NetIndexPosition_{j,t}\}$, $\alpha_t$ and $\mu_j$ are used to control time and commodity fixed effects, respectively. $LongIndexPosition_{j,t}$ is the total long position held by index investors, and $NetIndexPosition_{j,t}$ is the net long position held by index investors. $\Delta Position_{j,t}$ is the change of position, $Position_{j,t}/Position_{j,t-1} - 1$. Panel A shows the results for non-commercials' spread positions. Panels B and C show results for spread positions held by money managers and other reportables, respectively. In Panel D, we show swap dealers' spread positions. Non-commercials spread positions are collected from weekly COT reports, while spread position data at a trader category level come from DCOT reports. The panel shows commodity investment data for twenty commodities, excluding frozen pork belly, lumber, rough rice, oats, orange juice, and palladium. The sample period is December, 2007 through September, 2015 (quarterly frequency).

| Model | $\beta_{LongIndexPosition}$ | $\beta_{NetIndexPosition}$ | $R^2$ |
|---|---|---|---|
| *Panel A: Spread Positions (non-commercials) and Index Positions* | | | |
| (1) | 0.19 | | 16.79% |
| | (2.15) | | |
| (2) | | 0.18 | 16.81% |
| | | (2.15) | |
| *Panel B: Spread Positions (managed money) and Index Positions* | | | |
| (3) | 0.23 | | 14.21% |
| | (2.80) | | |
| (4) | | 0.20 | 14.11% |
| | | (2.39) | |
| *Panel C: Spread Positions (other reportables) and Index Positions* | | | |
| (5) | 0.21 | | 16.79% |
| | (1.30) | | |
| (6) | | 0.23 | 16.81% |
| | | (1.53) | |
| *Panel D: Spread Positions (swap dealers) and Index Positions* | | | |
| (7) | 0.46 | | 11.33% |
| | (0.38) | | |
| (8) | | -1.55 | 11.87% |
| | | (-1.34) | |

Table 14: **Cross-Sectional Asset Pricing Tests for Alternative Risk Channels**

This table presents cross-sectional tests for whether volatility, liquidity, intermediary capital or inventory risks are priced in the commodity market:

$$\begin{aligned} R_{p,t} &= \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda^{mkt}_{var}\beta^{mkt}_{var,t} + \lambda^{avg}_{var}\beta^{avg}_{var,t} + \lambda^{AMI}_{liquidity}\beta^{AMI}_{liquidity,t} \\ &\quad + \lambda^{HKM}_{ICR}\beta^{HKM}_{ICR,t} + \lambda^{GHR}_{INV}\beta^{GHR}_{INV,t} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{p,t}. \end{aligned}$$

Volatility factors are the innovations in aggregate and average commodity market variance ($\Delta var_{mkt,t}$ and $\Delta var_{avg,t}$ ). We construct aggregate commodity market variance ($var_{mkt,t}$) as the sum of daily squared returns of equal-weighted commodity portfolio in week $t$. Average commodity market variance ($var_{avg,t}$) is the equally-weighted average of the sum of the daily squared returns of all commodities in week $t$ (Boons and Prado, 2019). The liquidity measure is the innovations in the aggregate Amihud measure ($\Delta liquidity_{AMI}$). We compute commodity $i$'s Amihud measure as the annual average of daily $\frac{|R_{n,d}|}{Vol_{n,d}}$ by using dollar volume $Vol_{n,d}$ for both front- and second-month contract ($n = 1, 2$) at day $d$. The aggregate Amihud measure is the mean of the median of front- and second-month Amihud illiquidity over all commodities (Boons and Prado, 2019). The intermediary capital risk factor (ICR) is the AR(1) innovations to the intermediary capital ratio scaled by the lagged intermediary capital ratio from He, Kelly and Manela (2017). Inventory risk factor (INV) is the return of the long-short portfolio constructed by going long the three commodities with the lowest normalized inventory levels, and shorting the three commodities with the highest normalized inventory levels. Normalized inventory level at time $t$ is the ratio of the level at time $t$ to its past twelve-month moving average from $t-1$ to $t-12$, which is defined by Gorton, Hayashi and Rouwenhorst (2013). We use seventeen portfolios sorted on carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and sector portfolios (5). Models (1) to (5) are two-factor models contain the market factor and one of either the volatility or the liquidity factors. Models (6) to (10) add the spreading pressure factor. t-statistics of the estimated prices of risk ($\lambda$) are in parentheses below each estimate, which are calculated following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). The sample period of the inventory data is January 4, 2005 through December 26, 2018. The intermediary capital risk factor (ICR) data is from January 4, 2000 to December 26, 2018. The rest of data is between October 5, 1993 to December 29, 2020.

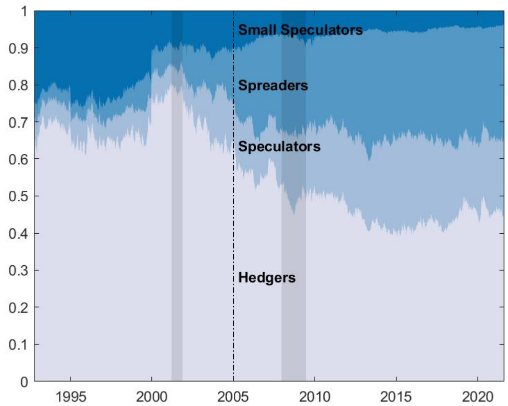
Table 14 - **Continued**

| Model | $\gamma_0$ | $\lambda_{SP}$ | $\lambda_{var}^{mkt}$ | $\lambda_{var}^{avg}$ | $\lambda_{liquidity}^{AMI}$ | $\lambda_{ICR}^{HKM}$ | $\lambda_{INV}^{GHR}$ | $\lambda_{Avg}$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| (1) | 1.21 | | -1.26 | | | | | 0.32 | 31.07% |
| | (0.20) | | (-1.62) | | | | | (0.04) | |
| | [0.12] | | [-1.33] | | | | | [0.03] | |
| (2) | 8.55 | | | -0.88 | | | | -7.03 | 11.57% |
| | (1.45) | | | (-1.03) | | | | (-1.00) | |
| | [1.24] | | | [-0.49] | | | | [-0.90] | |
| (3) | 1.35 | | | | -0.01 | | | 0.34 | 24.63% |
| | (0.20) | | | | (-1.37) | | | (0.04) | |
| | [0.15] | | | | [-1.00] | | | [0.03] | |
| (4) | 0.22 | | | | | 86.54 | | 2.03 | 15.70% |
| | (0.03) | | | | | (2.11) | | (0.37) | |
| | [0.02] | | | | | [0.71] | | [0.28] | |
| (5) | 3.96 | | | | | | 21.81 | -3.89 | 5.25% |
| | (0.79) | | | | | | (0.78) | (-0.62) | |
| | [0.75] | | | | | | [0.49] | [-0.58] | |
| (6) | -1.79 | 17.48 | -0.29 | | | | | 4.17 | 71.29% |
| | (-0.32) | (2.35) | (-0.48) | | | | | (0.64) | |
| | [-0.33] | [2.27] | [-0.44] | | | | | [0.58] | |
| (7) | -0.47 | 17.99 | | -0.88 | | | | 2.78 | 73.62% |
| | (-0.09) | (2.37) | | (-1.03) | | | | (0.43) | |
| | [-0.09] | [2.50] | | [-0.91] | | | | [0.39] | |
| (8) | -1.86 | 17.55 | | | 0.00 | | | 4.30 | 71.03% |
| | (-0.31) | (2.39) | | | (-0.38) | | | (0.62) | |
| | [-0.29] | [2.27] | | | [-0.27] | | | [0.59] | |
| (9) | -2.35 | 17.52 | | | | 106.70 | | 5.02 | 61.14% |
| | (-0.50) | (2.71) | | | | (2.53) | | (0.89) | |
| | [-0.54] | [2.42] | | | | [1.80] | | [0.86] | |
| (10) | 0.73 | 21.26 | | | | | -16.52 | 0.30 | 68.52% |
| | (0.15) | (2.96) | | | | | (-0.60) | (0.05) | |
| | [0.14] | [2.81] | | | | | [-0.51] | [0.04] | |

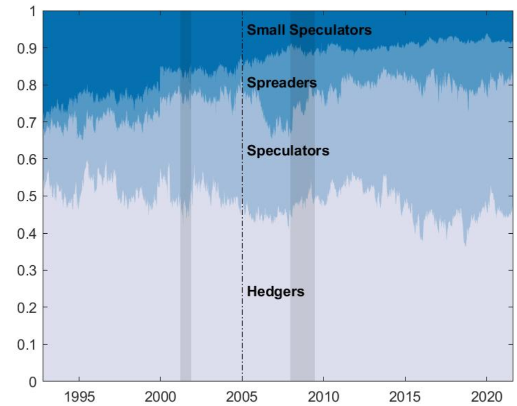
Figure 1: **Commodity Futures Positions by Traders Type**

This figure presents the market share for each of four categories: hedgers (commercials), speculators (non-commercials with directional positions), spreaders (non-commercials with spread positions) and small speculator (non-reportables) for each of five commodity sectors; energy, metals, soft, grains, and meats. The market share of trader type $i$ for commodity $j$ is calculated as $\frac{Long^{i}_{j,t}+Short^{i}_{j,t}}{2\times Open\,Interest_{j,t}}$ and aggregated at the sector level. The sample period is October 6, 1992 through December 29, 2020.

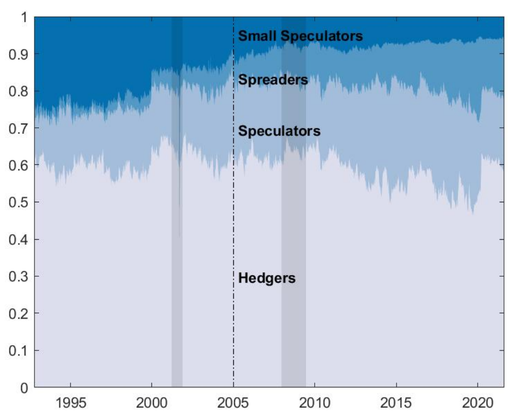
(a) Energy



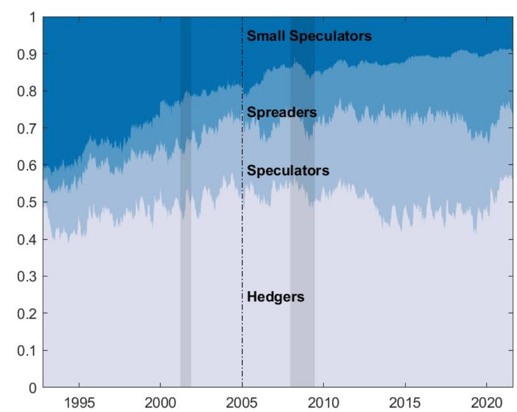

(b) Metals




(c) Softs




(d) Grains




(e) Meats

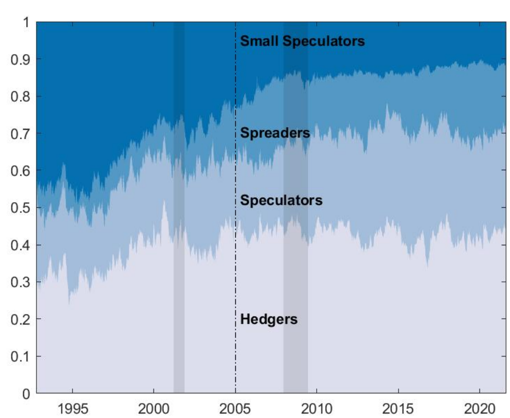
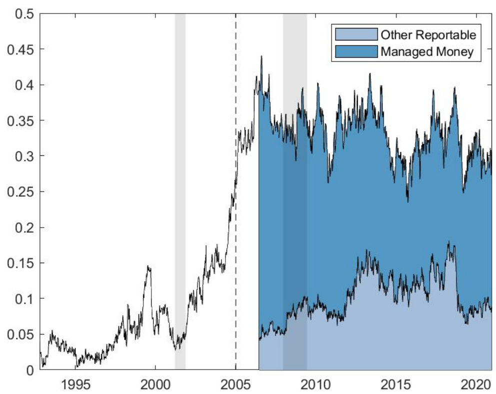


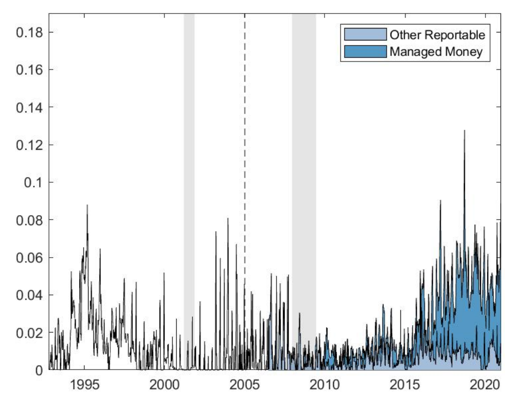
Figure 2: **Spreading Pressure Over Time**

This figure presents the time-series of spreading pressure by aggregated non-commercials (black line) and disaggregated commercials, i.e., money managers (dark blue area) and other reportables (light blue area). It reports six selected commodities, with three of high spreading pressure (natural gas, WTI crude oil, and lean hogs), and three of low spreading pressure (palladium, platinum, and oats). The sample period is October 6, 1992 through December 29, 2020, for aggregated pressure, and June 13, 2006 through December 29, 2020, for disaggregated pressure.

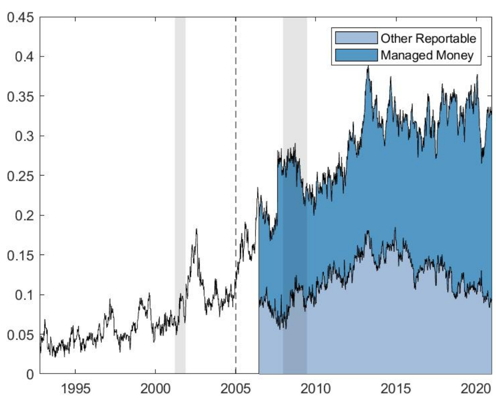
(a) Natural Gas



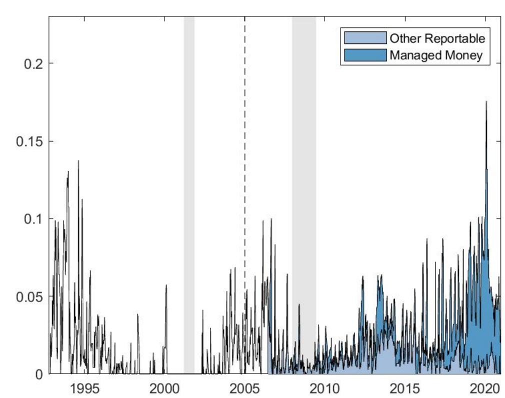

(d) Platinum



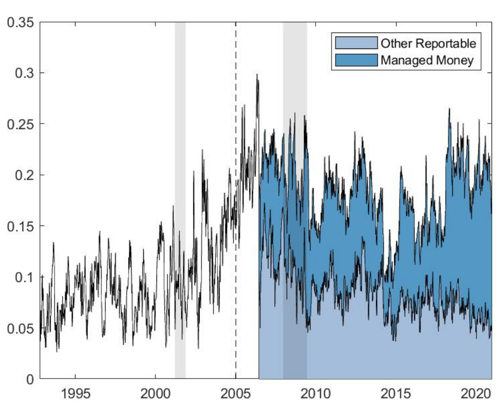

(b) WTI Crude Oil




(e) Palladium




(c) Lean Hogs




(f) Oats

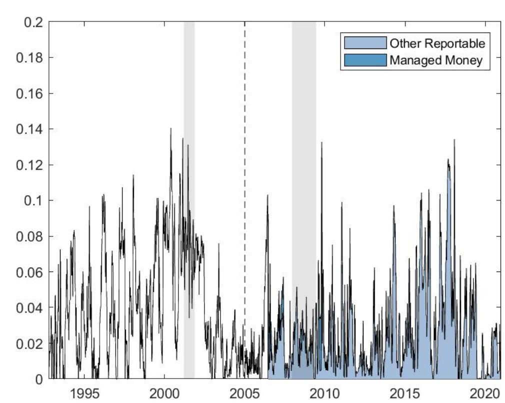
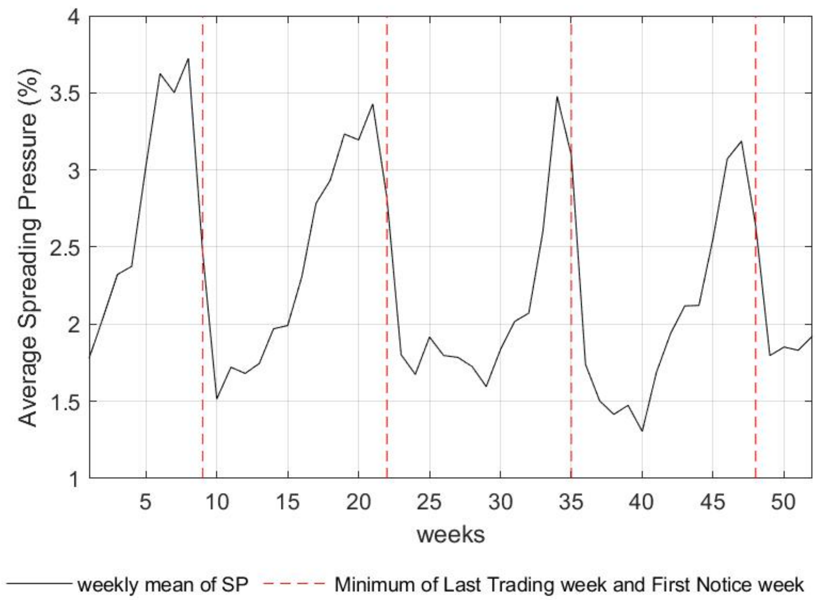


Figure 3: **Spreading Pressure by Week**

This figure presents the weekly average spreading pressure from non-commercials (black line) of palladium and WTI crude oil from October 6, 1992 through December 29, 2020. The red dashed vertical line indicates the week of contract maturity, i.e., the first notice day or the last trading day, whichever comes first.

(a) Palladium




(b) WTI Crude Oil

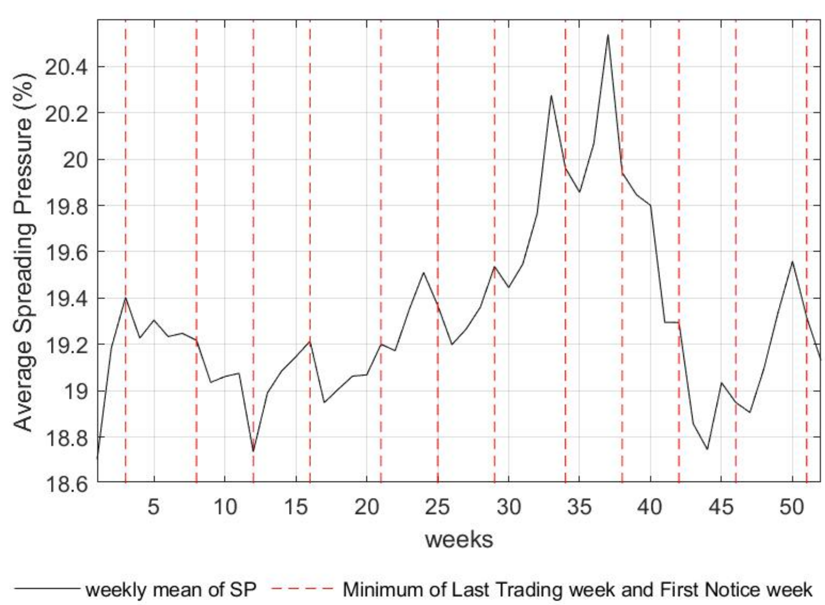
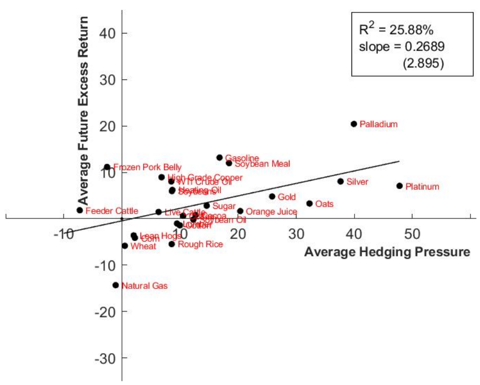


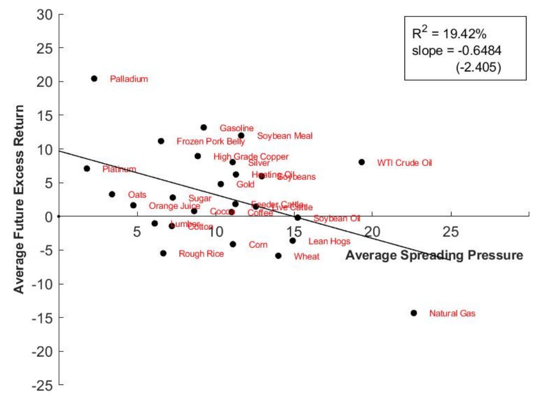
Figure 4: **Trader Positions and Futures Excess Returns**

The figure presents scatter plots of average excess returns of commodity futures over trader position variables (or pressure) and fitted lines by cross-sectional regressions for each of four trader categories over the twenty-six sample commodities. Spreading pressure is defined as speculators' spread positions scaled by total open interest. Hedging pressure is measured by hedgers' net short positions scaled by total open interest. Directional speculative pressure is calculated as speculators' net long positions scaled by total interest. The sample period is October 6, 1992 through December 29, 2020.

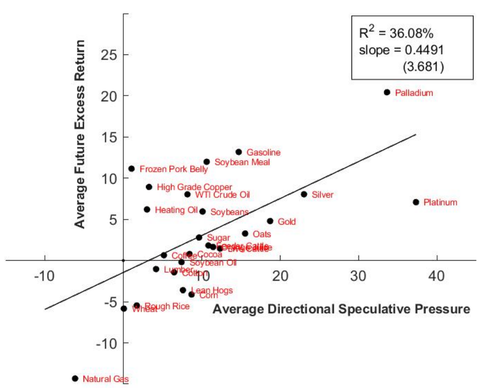
(a) Hedgers




(b) Spreaders




(c) Speculators




(d) Small Speculator

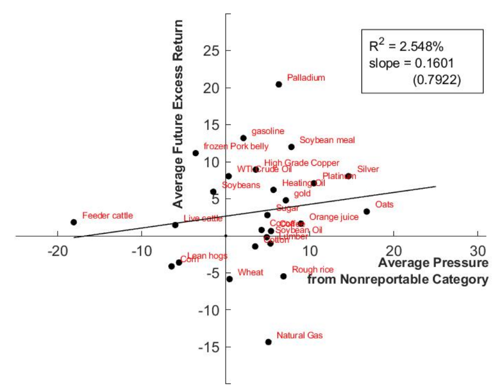
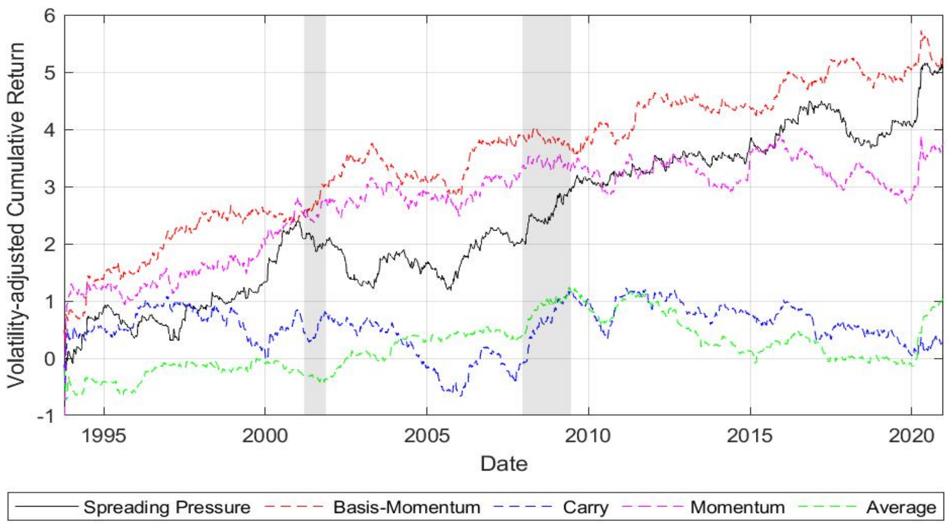


Figure 5: **Cumulative Excess Returns of Commodity Pricing Portfolios**

This figure presents the volatility-adjusted cumulative excess returns for commodity futures pricing portfolios; a long-short portfolio based on carry (basis), momentum, basis-momentum, or spreading pressure, along with an average commodity market factor. The volatility adjustment scales the returns of portfolio $i$ by $\sigma_{MKT}/\sigma_i$, the volatility of commodity market average return over the volatility of portfolio $i$ return (Orłowski et al., 2021). The sample period is October 5, 1993 through December 29, 2020 (for full sample at the top) and January 4, 2005 through December 29, 2020 (post-2005 at the bottom).

(a) Full Sample




(b) Post-2005

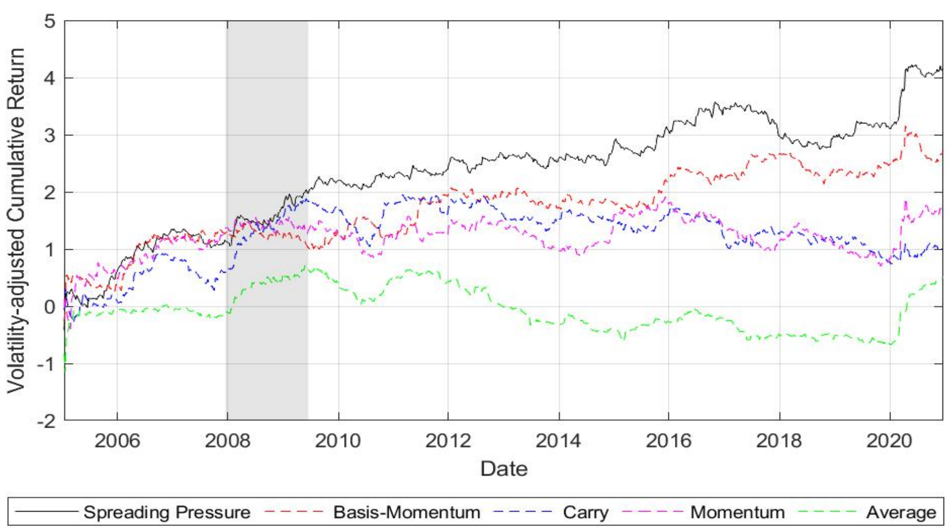


Figure 6: **Information Efficiency of Both Legs of Spreading Pressure Portfolios**

This figure presents the price delay measure (inefficiency) for the long (low spreading pressure) and short (high spreading pressure) legs of the spreading pressure portfolio around 2005 (between 2001 and 2008). Following Hou and Moskowitz (2005) and Brogaard, Ringgenberg, and Sovich (2019), we compute the ratio of $R^2$ from a regression of weekly portfolio returns on four lags of portfolio returns of each leg. The pre-2005 series is normalized to 1, and the post-2005 series is relative to the pre-2005 period.

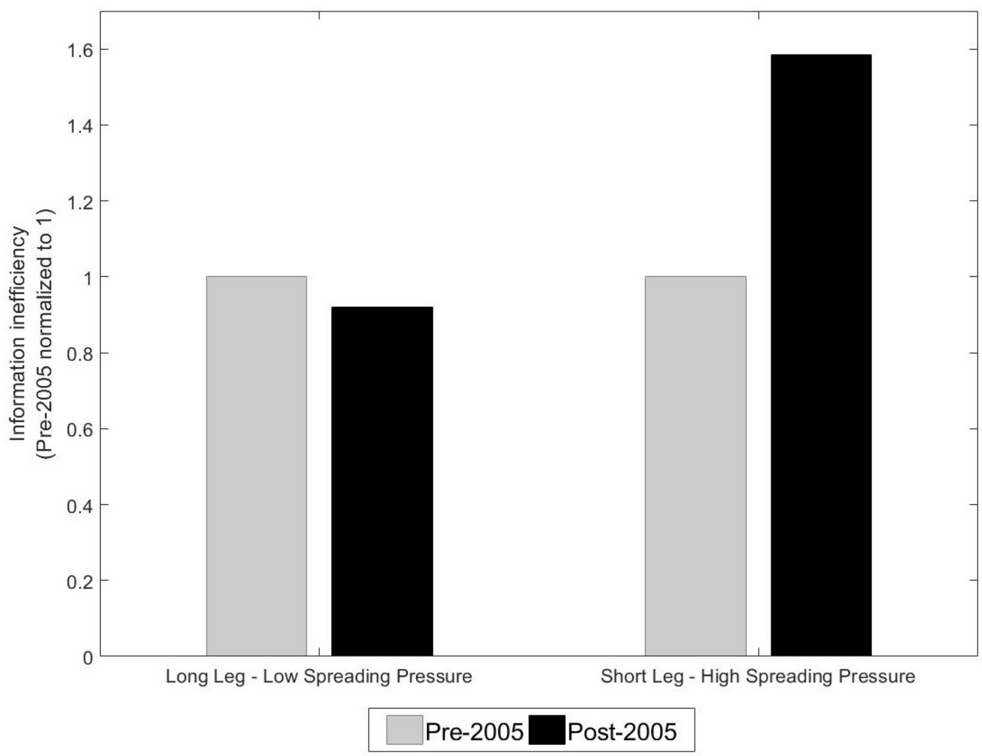
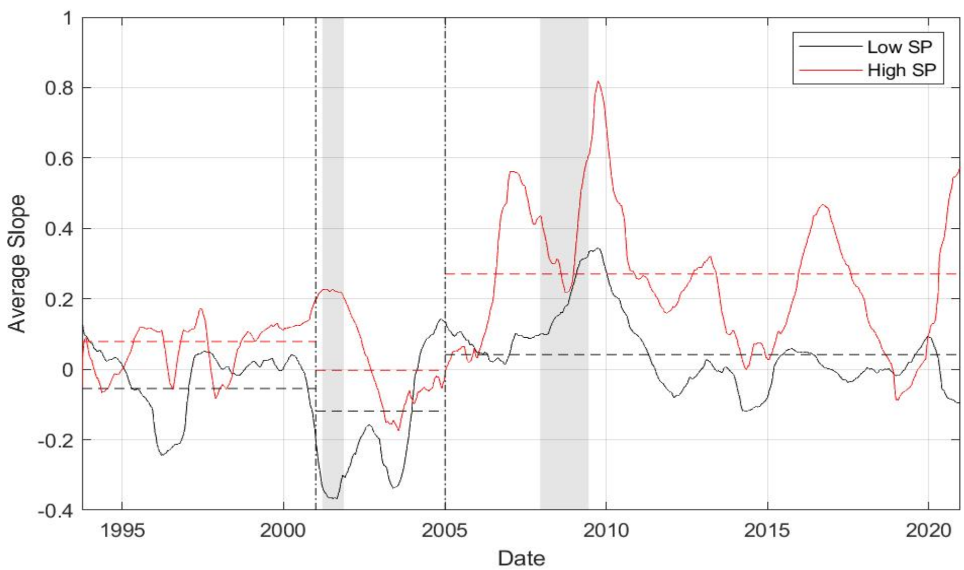


Figure 7: **Spreading Pressure and the Shape of Commodity Futures Curve**

This figure presents the (equal-weighted) average slope and curvature of future curve for commodities in the long (low spreading pressure, black solid line) and short (high spreading pressure, red solid line) legs of the spreading pressure portfolio. The measurements of average slope (panel a) and curvature (panel b) are smoothed 52-weeks averages. The vertical dash lines indicate the beginning of 2001 and 2005 and horizontal dash lines are the average slope and curvature for commodities in the long (black) and short (red) legs of the spreading pressure portfolio in three sub-sample periods, 1993-2000, 2001-2004 and 2005-2020. The sample period is October 5, 1993 through December 29, 2020.

(a) Slope




(b) Curvature

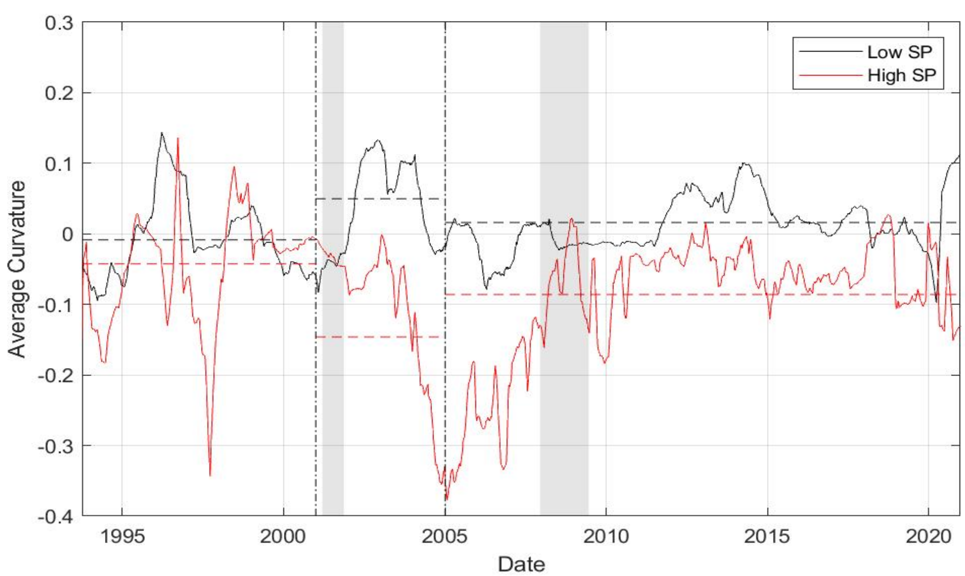


Figure 8: **Number of Spreaders and Average Position Size**

This figure presents the number of spreaders (top figure) and their average position size (bottom figure) in the long/short legs of spreading pressure portfolio. Spreaders' average position size at time $t$ for commodity $i$ is defined as $\frac{SpreadingPosition_t/OI_t}{Num.of Spreaders}$. Spreaders' average position size in the long (short) leg of spreading pressure portfolio is the equal-weighted average of spreaders' average position size for three commodities in the corresponding leg. The measurements in both panels are smoothed to 52-weeks average. The sample period is October 5, 1993 through December 29, 2020.

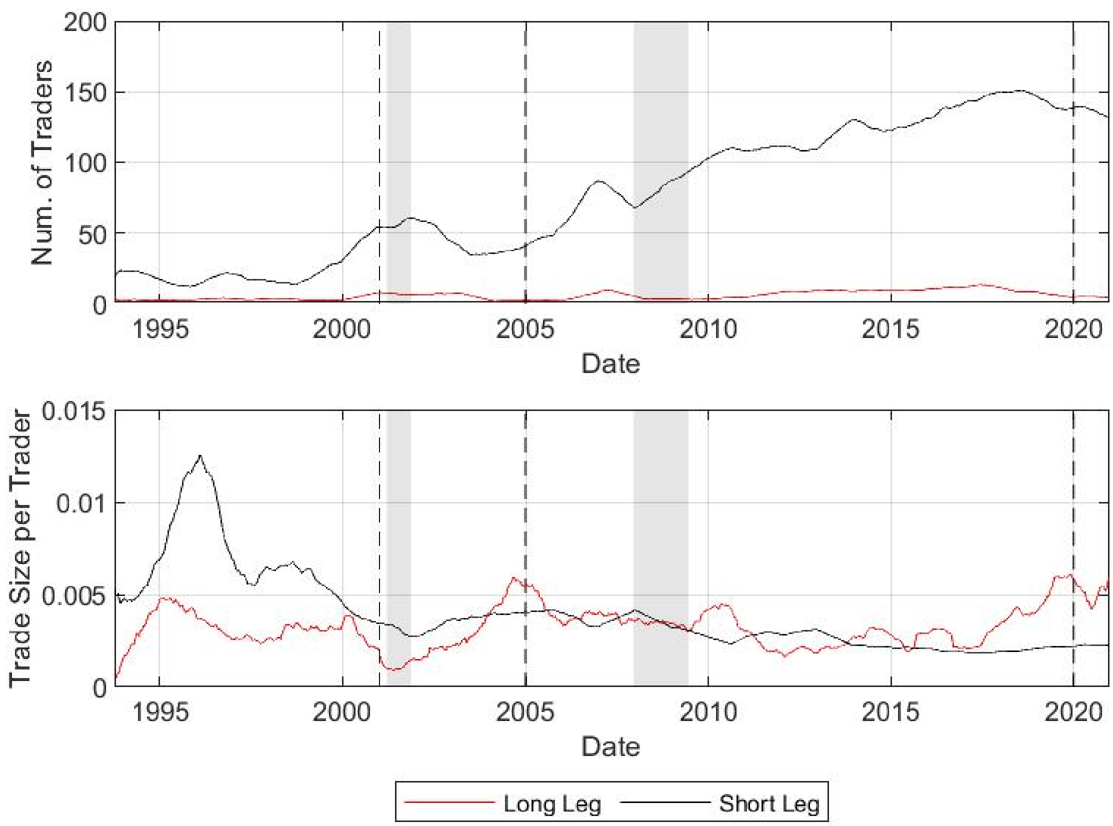
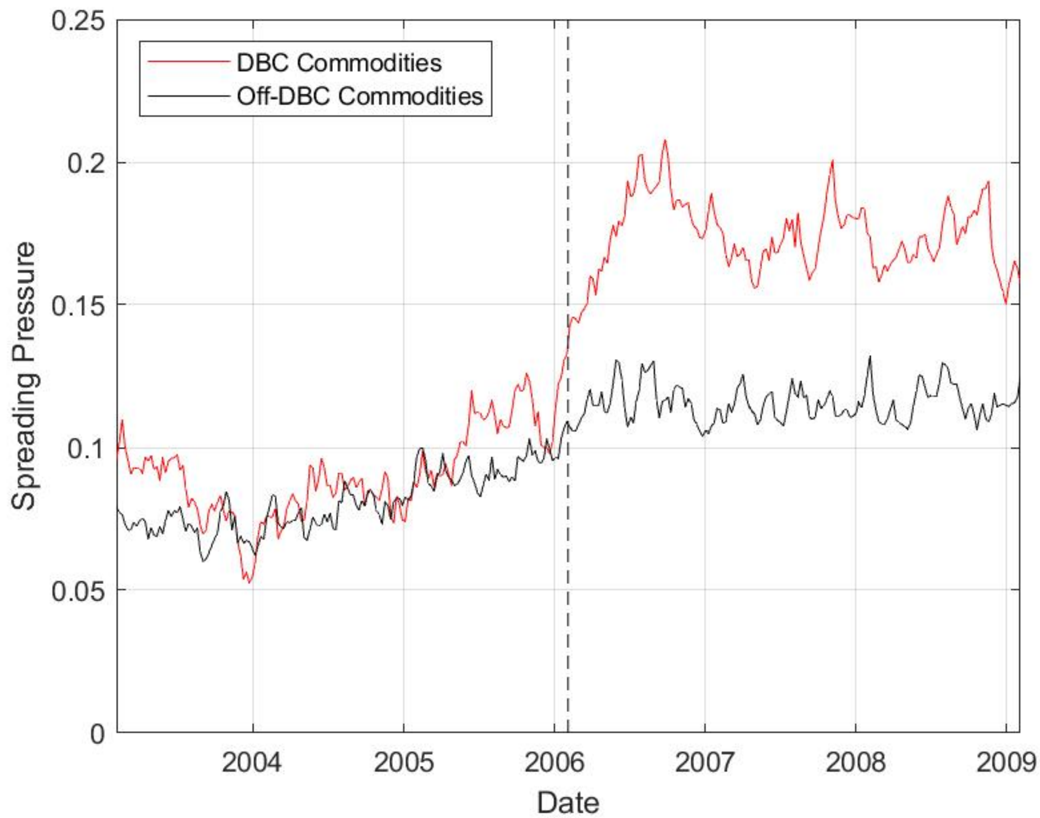


Figure 9: **Spreading Pressure and the Inception of Commodity ETF**

This figure presents the average spreading pressure of the commodities in- and off-DBC ETF (Invesco DB Commodity Index Tracking Fund), respectively. DBC commodities (red line) are commodities in Deutsche Bank Liquid Commodity Index tracked by DBC ETF prior to October 2009, including WTI Crude Oil, Heating Oil, Gold, Corn and Wheat in our sample (Aluminum is not included in our sample). Off-DBC commodities (black line) are the rest of the commodities. The vertical dashed line indicates the inception date of DBC ETF, February 3, 2006. The sample period is three-year before and after the inception date of DBC ETF, covering February 4, 2003 through February 3, 2009.



# Internet Appendix for:

# Spreading Pressure and the Commodity Futures Risk Premium

(Not intended for publication)

Table I-1: **Commodity Annualized Excess Return Summary Statistics**

This table presents the summary statistics of commodity futures returns for which we report annualized mean (Mean), standard deviation (SD), Sharpe ratios (Sharpe) and first-order autocorrelation (AR(1)) of futures front-month returns, as well as average open interest (OI) for each of the twenty-six commodities used in our sample. The first part is for the pre-2005 period (October 6, 1992 through December 28, 2004); and the second part is the post-2005 period (January 4, 2005 through December 29, 2020). The front-month excess return of a commodity in month $t+1$ is defined as $R^{(1)}_{long,t+1} = \frac{F^{(1)}_{t+1}}{F^{(1)}_t} - 1$, where $F^{(1)}_t$ is the price of the front-month futures contract at time $t$.

| Sector | Commodity | Pre-2005 | | | | | Post-2005 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Sharpe | AR(1) | OI | Mean | SD | Sharpe | AR(1) | OI |
| Energy | Heating Oil | 11.94 | 30.82 | 0.39 | -0.03 | 148,299 | -0.13 | 32.47 | 0.00 | 0.04 | 314,792 |
| | Natural Gas | 7.11 | 48.76 | 0.15 | -0.01 | 266,957 | -28.49 | 41.98 | -0.68 | 0.01 | 1,028,072 |
| | WTI Crude Oil | 18.11 | 31.62 | 0.57 | -0.05 | 465,567 | -1.32 | 45.48 | -0.03 | 0.04 | 1,609,619 |
| | Unleaded/RBOB Gasoline | 19.21 | 31.06 | 0.62 | -0.04 | 98,089 | 6.90 | 38.30 | 0.18 | 0.09 | 291,112 |
| Grains | Corn | -8.19 | 21.05 | -0.39 | 0.01 | 942,732 | -0.57 | 28.27 | -0.02 | -0.02 | 1,302,724 |
| | Oats | 0.73 | 27.99 | 0.03 | -0.03 | 33,917 | 6.80 | 32.86 | 0.21 | -0.04 | 10,355 |
| | Rough Rice | -7.83 | 27.09 | -0.29 | 0.02 | 5,499 | -2.98 | 22.83 | -0.13 | 0.05 | 12,041 |
| | Soybean Oil | -0.97 | 21.57 | -0.04 | 0.02 | 120,132 | 1.75 | 23.47 | 0.07 | 0.00 | 345,299 |
| | Soybean Meal | 8.43 | 23.10 | 0.36 | -0.01 | 115,598 | 14.27 | 26.28 | 0.54 | -0.03 | 289,816 |
| | Soybeans | 3.80 | 20.49 | 0.19 | 0.01 | 440,631 | 8.18 | 23.17 | 0.35 | -0.01 | 595,160 |
| | Wheat | -7.19 | 23.03 | -0.31 | 0.00 | 226,253 | -3.61 | 31.07 | -0.12 | -0.02 | 409,861 |
| Meats | Feeder Cattle | 3.63 | 13.58 | 0.27 | -0.08 | 16,003 | 0.99 | 17.28 | 0.06 | -0.08 | 38,224 |
| | Lean Hogs | 0.67 | 26.21 | 0.03 | 0.03 | 40,465 | -5.08 | 28.10 | -0.18 | 0.09 | 213,407 |
| | Live Cattle | 4.50 | 15.79 | 0.29 | -0.07 | 97,510 | -0.05 | 15.99 | 0.00 | -0.05 | 291,084 |
| | Frozen Pork Belly | 16.02 | 37.04 | 0.43 | 0.09 | 5,727 | -8.12 | 29.88 | -0.27 | 0.08 | 2,187 |
| Metal | High Grade Copper | 4.80 | 21.50 | 0.22 | -0.01 | 66,945 | 9.68 | 25.15 | 0.38 | 0.09 | 162,462 |
| | Palladium | 12.13 | 34.75 | 0.35 | 0.05 | 5,186 | 20.66 | 33.45 | 0.62 | -0.03 | 23,129 |
| | Platinum | 11.76 | 19.04 | 0.62 | -0.03 | 14,120 | 3.55 | 24.63 | 0.14 | -0.05 | 47,824 |
| | Silver | 3.35 | 23.24 | 0.14 | 0.03 | 92,569 | 12.00 | 32.41 | 0.37 | -0.03 | 150,687 |
| | Gold | -0.77 | 13.57 | -0.06 | 0.02 | 177,685 | 8.95 | 17.80 | 0.50 | -0.04 | 448,668 |
| Soft | Cocoa | -1.32 | 30.53 | -0.04 | -0.01 | 89,839 | 2.63 | 26.80 | 0.10 | 0.03 | 190,258 |
| | Coffee | 7.83 | 41.97 | 0.19 | -0.02 | 50,077 | -4.51 | 31.75 | -0.14 | -0.03 | 172,324 |
| | Cotton | -4.72 | 23.97 | -0.20 | 0.02 | 66,645 | 1.67 | 26.64 | 0.06 | 0.02 | 191,980 |
| | Lumber | 2.39 | 33.11 | 0.07 | 0.14 | 3,281 | -0.42 | 33.60 | -0.01 | 0.05 | 6,578 |
| | Orange Juice | -6.51 | 28.71 | -0.23 | 0.02 | 26,310 | 8.63 | 34.70 | 0.25 | -0.01 | 22,120 |
| | Sugar | 8.86 | 28.96 | 0.31 | 0.03 | 168,008 | -0.86 | 31.34 | -0.03 | -0.02 | 759,834 |
| Average | | 4.14 | 26.87 | 0.14 | 0.00 | 145,540 | 1.94 | 29.07 | 0.09 | 0.00 | 343,447 |

Table I-2: **Fama-MacBeth Cross-Sectional Predictive Regressions**

This table presents the average coefficients by running Fama-MacBeth cross-sectional regressions of futures excess returns on the two-week (Panel A), three-week (Panel B), four-week (Panel C) lagged (fifty-two week average) spreading pressure ($\overline{SP}$). Included as control variables are basis-momentum ($BM$), hedgers' net position changes ($Q_h$) and/or speculators' net position changes ($Q_s$):

$$R_{j,t+k} = b_0 + b_{\overline{SP}}\overline{SP}_{j,t} + b_{BM}BM_{j,t} + b_Q^h Q_{j,t}^h + b_Q^s Q_{j,t}^s + \epsilon_{j,t+k},$$

where $R_{j,t+k}$ is the return of commodity $j$ at $k$–week ahead week $t$. Newey-West t-statistics with four lags and average $R^2$ are reported for each model specification. Panel A, B and C present results for returns after two-week, three-week and four-week returns, respectively. Newey-West t-statistics with four lags and average $R^2$s are reported for each model specification. The sample period is October 5, 1993 through December 29, 2020.

| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Return*$(t+2)$ | | | | | | | | |
| $b_{\overline{SP}}$ | -1.83 | | | | -1.74 | -2.00 | -1.85 | -1.88 |
| | (-3.29) | | | | (-3.18) | (-3.48) | (-3.27) | (-3.33) |
| $b_{BM}$ | | 0.98 | | | 1.06 | | | 1.11 |
| | | (1.89) | | | (2.02) | | | (1.99) |
| $b_Q^h$ | | | 1.90 | | | 1.86 | | 1.65 |
| | | | (3.09) | | | (3.05) | | (0.98) |
| $b_Q^s$ | | | | -2.25 | | | -2.16 | -0.23 |
| | | | | (-3.38) | | | (-3.28) | (-0.13) |
| $R^2$ | 6.06% | 6.95% | 5.15% | 5.06% | 12.77% | 11.16% | 11.06% | 22.36% |
| *Panel B: Return*$(t+3)$ | | | | | | | | |
| $b_{\overline{SP}}$ | -1.84 | | | | -1.79 | -1.84 | -1.88 | -1.95 |
| | (-3.30) | | | | (-3.28) | (-3.30) | (-3.36) | (-3.60) |
| $b_{BM}$ | | 0.79 | | | 0.84 | | | 0.93 |
| | | (1.50) | | | (1.58) | | | (1.65) |
| $b_Q^h$ | | | 1.26 | | | 1.02 | | 0.94 |
| | | | (1.95) | | | (1.52) | | (0.56) |
| $b_Q^s$ | | | | -1.11 | | | -0.86 | -0.08 |
| | | | | (-1.59) | | | (-1.20) | (-0.04) |
| $R^2$ | 6.06% | 6.90% | 4.88% | 4.79% | 12.70% | 10.82% | 10.73% | 21.69% |
| *Panel C: Return*$(t+4)$ | | | | | | | | |
| $b_{\overline{SP}}$ | -1.84 | | | | -1.85 | -2.11 | -2.04 | -2.33 |
| | (-3.30) | | | | (-3.38) | (-3.74) | (-3.62) | (-4.16) |
| $b_{BM}$ | | 0.66 | | | 0.70 | | | 0.84 |
| | | (1.27) | | | (1.34) | | | (1.50) |
| $b_Q^h$ | | | 1.57 | | | 1.53 | | 3.88 |
| | | | (2.33) | | | (2.25) | | (2.18) |
| $b_Q^s$ | | | | -1.52 | | | -1.48 | 2.38 |
| | | | | (-2.06) | | | (-1.94) | (1.18) |
| $R^2$ | 6.07% | 6.84% | 4.95% | 4.84% | 12.65% | 10.91% | 10.78% | 21.86% |

Table I-3: **Spreading Pressure Portfolio: Different Number of Commodities**

This table presents the summary statistics of commodity futures weekly portfolios returns, where we construct the portfolios by sorting commodity futures on the fifty-two week average of spreading pressure. Panel A, B and C present results of holding two, four and five commodities in long or short leg, respectively. For example, in Panel B, *Low4* (*High4*) consists of commodity futures ranked in the bottom (top) four for spreading pressure or basis-momentum, and the remaining eighteen commodities constitute the portfolio called *Mid*. *Low4-High4* represents a long-short portfolio strategy of buying Low4 and shorting High4. Portfolios' excess returns are calculated as equal-weighted average excess returns of portfolio constituents. The sample period is October 5, 1993 through December 29, 2020.

| Panel A: Two Commodities in Each Leg | | | | | |
|---|---|---|---|---|---|
| | Low2 | Mid | High2 | Low2-High2 | Net of Transaction Cost |
| Mean | 11.58 | 3.06 | -8.79 | 20.37 | 19.35 |
| Std. Dev. | 23.47 | 12.48 | 27.66 | 32.81 | 32.81 |
| Sharpe | 0.49 | 0.24 | -0.32 | 0.62 | 0.59 |
| Skewness | -0.28 | -0.37 | 1.17 | -0.52 | -0.53 |
| Kurtosis | 5.31 | 6.77 | 24.63 | 12.76 | 12.79 |
| Panel B: Four Commodities in Each Leg | | | | | |
| | Low4 | Mid | High4 | Low4-High4 | Net of Transaction Cost |
| Mean | 10.36 | 2.40 | -3.05 | 13.41 | 11.46 |
| Std. Dev. | 18.27 | 12.78 | 19.41 | 21.19 | 21.21 |
| Sharpe | 0.57 | 0.19 | -0.16 | 0.63 | 0.54 |
| Skewness | -0.13 | -0.44 | 0.70 | -0.32 | -0.33 |
| Kurtosis | 4.79 | 7.35 | 11.36 | 6.91 | 6.98 |
| Panel C: Five Commodities in Each Leg | | | | | |
| | Low5 | Mid | High5 | Low5-High5 | Net of Transaction Cost |
| Mean | 8.51 | 2.54 | -2.15 | 10.66 | 8.24 |
| Std. Dev. | 16.8 | 13.04 | 18.21 | 19.21 | 19.22 |
| Sharpe | 0.51 | 0.19 | -0.12 | 0.55 | 0.41 |
| Skewness | -0.11 | -0.42 | 0.51 | -0.27 | -0.29 |
| Kurtosis | 4.75 | 7.17 | 8.21 | 5.87 | 5.92 |

Table I-4: **Alternative Spreading Position Portfolio**

This table presents the summary statistics of commodity futures weekly portfolios returns, where we construct the portfolios by sorting commodity futures on (1) the scaled spreading position, which is the fifty-two week average of speculators' spreading pressure scaled by its fifty-two week standard deviation, (2) weekly spreading pressure, (3) weekly open interest, and (4) spreading pressure crowding, which is the difference between the current week spreading pressure and past 52-week average spreading pressure. *Low3* (*High3*) consists of commodity futures ranked in the bottom (top) three for scaled spreading position, and the remaining twenty commodities constitute the portfolio called *Mid*. *Low3-High3* (*High3-Low3*) represents a long-short portfolio strategy of buying Low3 and shorting High3 (buying High3 and shorting Low3). Portfolio excess returns are calculated as equal-weighted average excess returns of portfolio constituents. The sample period is October 5, 1993 through December 29, 2020.

| | Spreading Position | | | | Weekly Spreading Pressure | | | |
|---|---|---|---|---|---|---|---|---|
| | Low3 | Mid | High3 | Low3-High3 | Low3 | Mid | High3 | Low3-High3 |
| Mean | 11.05 | 2.40 | -3.05 | 14.10 | 11.75 | 2.22 | -2.49 | 14.24 |
| Std. Dev. | 20.39 | 12.34 | 23.92 | 26.29 | 20.25 | 12.44 | 22.88 | 25.34 |
| Sharpe | 0.54 | 0.19 | -0.13 | 0.54 | 0.58 | 0.18 | -0.11 | 0.56 |
| Skewness | -0.02 | -0.39 | 1.00 | -0.55 | -0.17 | -0.39 | 1.19 | -0.90 |
| Kurtosis | 5.36 | 6.80 | 24.96 | 15.00 | 5.20 | 6.55 | 18.29 | 11.92 |
| | Open Interest | | | | Spreading Pressure Crowding | | | |
| | Low3 | Mid | High3 | Low3-High3 | Low3 | Mid | High3 | High3-Low3 |
| Mean | 5.58 | 3.43 | -4.23 | 9.81 | -2.24 | 3.10 | 5.72 | 7.97 |
| Std. Dev. | 19.48 | 12.50 | 24.02 | 26.69 | 18.58 | 13.21 | 19.51 | 22.73 |
| Sharpe | 0.29 | 0.27 | -0.18 | 0.37 | -0.12 | 0.24 | 0.29 | 0.35 |
| Skewness | 0.23 | -0.35 | 0.59 | -0.42 | 0.13 | -0.19 | 0.09 | 0.02 |
| Kurtosis | 4.18 | 6.88 | 13.22 | 8.93 | 4.82 | 6.87 | 4.84 | 3.91 |

Table I-5: **Spreading Pressure Portfolio within Each Sector**

This table presents the summary statistics of commodity futures weekly portfolios returns, where we construct the portfolios by sorting the commodity futures on the fifty-two week average of spreading pressure within five sectors: energy, grains, meats, metals, and soft. *Low1* (*High1*) consists of commodity futures ranked in the bottom (top) for spreading pressure in each sector, and the remaining commodities in each sector constitute the portfolio called *Mid*. *Low1-High1* represents a long-short portfolio strategy of buying Low1 and shorting High1. Portfolio excess returns are calculated as equal-weighted average excess returns of portfolio constituents. The sample period is October 5, 1993 through December 29, 2020.

| | Energy Sector | | | | Grain Sector | | | |
|---|---|---|---|---|---|---|---|---|
| | Low1 | Mid | High1 | Low1-High1 | Low1 | Mid | High1 | Low1-High1 |
| Mean | 10.60 | 6.43 | -10.65 | 21.25 | -0.55 | 1.50 | -0.46 | -0.09 |
| Std. Dev. | 39.10 | 30.58 | 47.24 | 45.49 | 30.07 | 18.41 | 26.50 | 31.81 |
| Sharpe | 0.27 | 0.21 | -0.23 | 0.47 | -0.02 | 0.08 | -0.02 | 0.00 |
| Skewness | -0.34 | 0.06 | 2.07 | -1.06 | 0.38 | 0.13 | 0.38 | 0.42 |
| Kurtosis | 7.99 | 4.39 | 43.99 | 16.30 | 7.26 | 4.31 | 4.95 | 6.83 |
| | Meat Sector | | | | Metal Sector | | | |
| | Low1 | Mid | High1 | Low1-High1 | Low1 | Mid | High1 | Low1-High1 |
| Mean | 3.45 | 1.16 | -1.61 | 5.06 | 16.31 | 6.08 | 10.72 | 5.59 |
| Std. Dev. | 25.67 | 19.15 | 23.45 | 27.59 | 29.33 | 19.51 | 24.71 | 30.22 |
| Sharpe | 0.13 | 0.06 | -0.07 | 0.18 | 0.56 | 0.31 | 0.43 | 0.19 |
| Skewness | 0.92 | 0.46 | 0.06 | 0.38 | 0.04 | -0.65 | 0.23 | 0.22 |
| Kurtosis | 16.13 | 10.91 | 4.41 | 7.41 | 8.02 | 9.08 | 8.39 | 8.35 |
| | Soft Sector | | | | | | | |
| | Low1 | Mid | High1 | Low1-High1 | | | | |
| Mean | 6.22 | 1.53 | -9.24 | 15.46 | | | | |
| Std. Dev. | 31.88 | 17.98 | 29.60 | 39.79 | | | | |
| Sharpe | 0.19 | 0.09 | -0.31 | 0.39 | | | | |
| Skewness | 0.40 | 0.17 | 0.36 | 0.04 | | | | |
| Kurtosis | 4.37 | 4.14 | 4.45 | 3.44 | | | | |

Table I-6: **Cross-Sectional Asset Pricing Tests at the Commodity Level**

This table presents cross-sectional tests for five asset pricing factor models in the commodity level, nested in

$$R_{j,t+1} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{BM}\beta_{BM,t} + \lambda_C\beta_{C,t} + \lambda_M\beta_{M,t} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{j,t+1},$$

where $\beta$ is estimated over a one-year rolling window of weekly returns. In Panel A, Model (1) and (2) are single-factor models that contains the spreading pressure factor or basis-momentum factor only. In Panel B, Model (3) and (4) add the market average factor (Model (4) is the Boons and Prado (2019) model), and Model (5) is a teo factors model by using both spreading pressure factor and basis-momentum factor. In Panel C, Model (6) adds the market average factor to model (5) and Model (7) is the Bakshi, Gao and Rossi (2019) model. Models (8) adds the spreading pressure factor to Models (7). t-statistics are reported following Fama and MacBeth (1973) (in parentheses), and we also present the cross-sectional $R^2$. The sample period is October 5, 1993 through December 29, 2020.

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| Panel A: One-Factor Model | | | | | | | |
| (1) | 2.68 | 9.66 | | | | | 9.07% |
| | (1.12) | (1.93) | | | | | |
| (2) | 3.04 | | 0.33 | | | | 27.68% |
| | (1.26) | | (0.05) | | | | |
| Panel B: Two-Factor Model | | | | | | | |
| (3) | 1.12 | 10.92 | | | | 1.76 | 16.37% |
| | (0.45) | (2.18) | | | | (0.61) | |
| (4) | -0.21 | | 4.26 | | | 3.10 | 35.48% |
| | (-0.09) | | (0.69) | | | (1.05) | |
| (5) | 3.25 | 10.66 | 0.70 | | | | 32.12% |
| | (1.38) | (2.15) | (0.11) | | | | |
| Panel C: Three-Factor Model | | | | | | | |
| (6) | -1.09 | 12.35 | 2.70 | | | 3.99 | 37.25% |
| | (-0.44) | (2.47) | (0.43) | | | (1.37) | |
| (7) | 2.19 | | | 14.12 | -2.26 | 0.69 | 37.24% |
| | (0.87) | | | (1.86) | (-0.33) | (0.23) | |
| Panel D: Four-Factor Model | | | | | | | |
| (8) | 1.41 | 12.83 | | 11.62 | -6.62 | 1.48 | 36.09% |
| | (0.55) | (2.57) | | (1.50) | (-0.97) | (0.50) | |

Table I-7: **Cross-Sectional Asset Pricing Tests including Spreading Returns**

This table presents the estimated risk premium on commodity futures risk factors by running Fama-MacBeth cross-sectional asset pricing tests (Panel A-D) and Giglio and Xiu (2021) three-pass regression (Panel E). In Panel A-D, we regress the average returns of thirty-four commodity-sorted portfolios on their risk exposures. Eight different model specifications are considered, and are nested in

$$R_{p,t} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{BM}\beta_{BM,t} + \lambda_C\beta_{C,t} + \lambda_M\beta_{M,t} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{p,t},$$

where $R_{p,t}$ is the return of portfolio $p$ at week $t$, $\lambda$ is factor risk premia. The portfolios include the nearby and spreading returns of twelve portfolios sorted on spreading pressure, basis momentum and basis-momentum (the High3, Mid, and Low3 portfolios sorted on each signal) and five sector portfolios (energy, grains, meats, metals and softs). In Panel A, Model (1) and (2) are one-factor models that contains the spreading pressure factor or basis-momentum factor only. In Panel B, Model (3) and (4) add the market average factor (Model (4) is the Boons and Prado (2019) model), and Model (5) is a two-factor model by using both spreading pressure factor and basis-momentum factor. In Panel C, Model (6) adds the market average factor to model (5) and Model (7) is the Bakshi, Gao and Rossi (2019) model. Models (8) adds the spreading pressure factor to Models (7). We report two versions of the t-statistics, following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). OLS $R^2$ and GLS $R^2$ (in parentheses) are in the second last column. Generalized version of the Shanken (1985) cross-sectional F-test statistics and their corresponding p-values (in parentheses) are in the last column ($CSRT_{SH}$). Panel E reports the three-pass regression proposed by Giglio and Xiu (2021), using two latent factors. We report the risk premia ($\lambda$), their corresponding standard error (SE), the $R^2$ of the projection of each observed factor onto the two latent factors ($R_g^2$) and the p-value of the test that the observed factor is weak. The observed factors used in this test are market average factor, spreading pressure factor, basis-momentum factor, basis factor and momentum factor. The sample period is October 5, 1993 through December 29, 2020.

Table I-7 - **Continued**

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ | $R^2$ | $CSRT_{SH}$ |
|---|---|---|---|---|---|---|---|---|
| Panel A: One-Factor Model | | | | | | | | |
| (1) | 2.12 | 13.04 | | | | | 27.79% | 0.03 |
| | (1.45) | (2.18) | | | | | (12.03%) | (0.06) |
| | [1.27] | [2.17] | | | | | | |
| (2) | 2.06 | | 16.68 | | | | 34.46% | 0.03 |
| | (1.36) | | (2.65) | | | | (11.40%) | (0.01) |
| | [1.20] | | [2.29] | | | | | |
| Panel B: Two-Factor Model | | | | | | | | |
| (3) | -0.62 | 16.29 | | | | 3.98 | 54.91% | 0.06 |
| | (-1.15) | (2.84) | | | | (1.58) | (14.59%) | (0.00) |
| | [-0.97] | [3.03] | | | | [1.34] | | |
| (4) | -0.49 | | 19.12 | | | 3.58 | 57.63% | 0.03 |
| | (-0.91) | | (3.14) | | | (1.41) | (13.80%) | (0.01) |
| | [-0.71] | | [2.96] | | | [1.20] | | |
| (5) | 2.25 | 9.64 | 13.82 | | | | 40.07% | 0.02 |
| | (1.54) | (1.69) | (2.46) | | | | (19.09%) | (0.15) |
| | [1.43] | [1.61] | [2.06] | | | | | |
| Panel C: Three-Factor Model | | | | | | | | |
| (6) | -0.61 | 12.69 | 15.19 | | | 4.03 | 69.85% | 0.03 |
| | (-1.13) | (2.33) | (2.71) | | | (1.60) | (22.16%) | (0.01) |
| | [-0.94] | [2.44] | [2.34] | | | [1.36] | | |
| (7) | -0.35 | | | 2.59 | 17.22 | 3.17 | 42.58% | 0.05 |
| | (-0.66) | | | (0.47) | (2.73) | (1.24) | (7.96%) | (0.00) |
| | [-0.54] | | | [0.46] | [3.08] | [1.08] | | |
| Panel D: Four-Factor Model | | | | | | | | |
| (8) | -0.62 | 14.55 | | 0.54 | 13.99 | 3.97 | 63.84% | 0.03 |
| | (-1.16) | (2.67) | | (0.10) | (2.28) | (1.58) | (19.27%) | (0.01) |
| | [-1.01] | [2.82] | | [0.09] | [2.50] | [1.37] | | |
| Panel E: Three-Pass Regression | | | | | | | | |
| $\lambda$ | | 6.82 | 6.90 | 9.39 | 11.98 | 3.22 | | |
| SE | | (3.11) | (2.87) | (3.48) | (4.53) | (2.34) | | |
| $R_g^2$ | | 38.69% | 30.68% | 42.97% | 56.98% | 93.36% | | |
| $p$(weak) | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | |

Table I-8: **Cross-Sectional Asset Pricing Tests: Additional Managed Portfolios**

This table presents Fama-MacBeth cross-sectional asset pricing tests results of a three-factor model by using additional managed portfolios as testing assets (Panel A) and Giglio and Xiu (2021) three-pass regression by using seventy-five portfolios (Panel B). There are seventeen baseline portfolios, broken down as carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and commodity sector (5). We construct additional testing portfolios by interacting the baseline portfolios with a conditioning variable, including open interest growth ($\Delta OI$), return of US dollar index ($R_{USD}$) or change in commodity volatility ($\Delta Vol$). In panel A, we report factor risk premia ($\lambda$), two versions of the t-statistics, following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). OLS $R^2$ and GLS $R^2$ (in parentheses) are in the second last column. Generalized version of the Shanken (1985) cross-sectional F-test statistics and their corresponding p-values (in parentheses) are in the last column ($CSRT_{SH}$). Panel B reports the three-pass regression proposed by Giglio and Xiu (2021), using two latent factors and 75 testing portfolios, include the nearby of baseline portfolios (17), spreading return of baseline portfolios (17), baseline portfolios interacted with open interest growth (17), baseline portfolios interacted with return of US dollar index (17) and baseline portfolios interacted with change in commodity volatility (17). We report the risk premia ($\lambda$), their corresponding standard error (SE), the $R^2$ of the projection of each observed factor onto the two latent factors ($R^2_g$) and the p-value of the test that the observed factor is weak. The observed factors used in this test are market average factor, spreading pressure factor, basis-momentum factor, basis factor and momentum factor. The sample period is October 5, 1993 through December 29, 2020.

| Panel A: Fama-Macbeth Regression | | | | | | |
|---|---|---|---|---|---|---|
| Conditional Variable | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_{Avg}$ | $R^2$ | $CSRT_{SH}$ |
| $\Delta OI$ | -0.12 | 12.75 | 16.15 | 3.52 | 77.85% | 0.02 |
| | (-0.60) | (2.34) | (2.90) | (1.41) | (34.54%) | (0.72) |
| | [-0.68] | [2.47] | [2.57] | [1.21] | | |
| $R_{USD}$ | -0.13 | 12.72 | 16.19 | 3.57 | 77.84% | 0.02 |
| | (-0.73) | (2.34) | (2.91) | (1.43) | (35.12%) | (0.85) |
| | [-0.80] | [2.46] | [2.58] | [1.25] | | |
| $\Delta Vol$ | -1.32 | 12.74 | 15.95 | 4.70 | 73.49% | 0.03 |
| | (-1.03) | (2.33) | (2.85) | (1.70) | (36.08%) | (0.20) |
| | [-0.71] | [2.49] | [2.59] | [1.24] | | |

| Panel B: Three-Pass Regression | | | | | |
|---|---|---|---|---|---|
| | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ |
| $\lambda$ | 6.41 | 6.56 | 8.85 | 11.30 | 2.98 |
| SE | (2.99) | (2.83) | (3.39) | (4.43) | (2.31) |
| $R^2_g$ | 37.96% | 30.78% | 42.39% | 56.59% | 92.47% |
| $p$(weak) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table I-9: **Asset Pricing Tests with Spreading Pressure Factor: Post-2005**

This table presents the estimated risk premium on commodity futures risk factors by running Fama-MacBeth cross-sectional asset pricing tests. Eight different model specifications are considered, and are nested in

$$R_{p,t} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{BM}\beta_{BM,t} + \lambda_C\beta_{C,t} + \lambda_M\beta_{M,t} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{p,t},$$

where $R_{p,t}$ is the return of portfolio $p$ at week $t$, $\lambda$ is factor risk premia. We use seventeen commodity futures portfolios as test assets, broken down as carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and commodity sector (5). In Panel A, Model (1) and (2) are single-factor models that contains the spreading pressure factor or basis-momentum factor only. In Panel B, Model (3) and (4) add the market average factor (Model (4) is the Boons and Prado (2019) model), and Model (5) is a teo factors model by using both spreading pressure factor and basis-momentum factor. In Panel C, Model (6) adds the market average factor to model (5) and Model (7) is the Bakshi, Gao and Rossi (2019) model. Models (8) adds the spreading pressure factor to Models (7). We report two versions of the t-statistics, following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). OLS $R^2$ and GLS $R^2$ (in parentheses) are in the second last column. Generalized version of the Shanken (1985) cross-sectional F-test statistics and their corresponding p-values (in parentheses) are in the last column ($CSRT_{SH}$). The sample period is January 4, 2005 through December 29, 2020.

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ | $R^2$ | $CSRT_{SH}$ |
|---|---|---|---|---|---|---|---|---|
| Panel A: Single Factor Model | | | | | | | | |
| (1) | 3.55 | 16.97 | | | | | 67.50% | 0.02 |
| | (1.01) | (2.21) | | | | | (30.10%) | (0.34) |
| | [0.90] | [2.13] | | | | | | |
| (2) | 3.27 | | 16.99 | | | | 42.96% | 0.03 |
| | (0.93) | | (1.98) | | | | (8.89%) | (0.12) |
| | [0.77] | | [1.85] | | | | | |
| Panel B: Two Factors Model | | | | | | | | |
| (3) | -0.85 | 18.18 | | | | 3.32 | 70.45% | 0.02 |
| | (-0.16) | (2.40) | | | | (0.53) | (36.96%) | (0.28) |
| | [-0.16] | [2.37] | | | | [0.49] | | |
| (4) | 2.26 | | 17.33 | | | -0.10 | 43.12% | 0.04 |
| | (0.42) | | (2.11) | | | (-0.02) | (13.53%) | (0.01) |
| | [0.52] | | [1.90] | | | [-0.02] | | |
| (5) | 3.71 | 15.79 | 9.12 | | | | 69.13% | 0.02 |
| | (1.06) | (2.14) | (1.27) | | | | (32.05%) | (0.43) |
| | [0.89] | [2.20] | [1.02] | | | | | |
| Panel C: Three Factors Model | | | | | | | | |
| (6) | -1.55 | 16.85 | 9.91 | | | 4.07 | 73.26% | 0.02 |
| | (-0.29) | (2.29) | (1.38) | | | (0.64) | (40.38%) | (0.18) |
| | [-0.31] | [2.41] | [1.10] | | | [0.58] | | |
| (7) | 3.99 | | | 7.53 | 13.45 | -1.97 | 33.45% | 0.02 |
| | (0.77) | | | (1.03) | (1.59) | (-0.31) | (4.86%) | (0.22) |
| | [0.86] | | | [0.96] | [1.74] | [-0.30] | | |
| Panel D: Four Factor Model | | | | | | | | |
| (8) | -0.88 | 19.21 | | 3.73 | 7.08 | 3.36 | 71.49% | 0.02 |
| | (-0.17) | (2.70) | | (0.52) | (0.88) | (0.53) | (39.17%) | (0.25) |
| | [-0.17] | [2.64] | | [0.52] | [0.93] | [0.51] | | |

Table I-10: **Cross-Sectional Asset Pricing Tests at the Commodity Level: Post-2005**

This table presents cross-sectional tests for five asset pricing factor models in the commodity level, nested in

$$R_{j,t+1} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{BM}\beta_{BM,t} + \lambda_C\beta_{C,t} + \lambda_M\beta_{M,t} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{j,t+1},$$

where where $R_{p,t}$ is the return of portfolio $p$ at week $t$, $\lambda$ is factor risk premia and $\beta$ is estimated over a one-year rolling window of weekly returns. In Panel A, Model (1) and (2) are single-factor models that contains the spreading pressure factor or basis-momentum factor only. In Panel B, Model (3) and (4) add the market average factor(Model (4) is the Boons and Prado (2019) model), and Model (5) is a teo factors model by using both spreading pressure factor and basis-momentum factor. In Panel C, Model (6) adds the market average factor to model (5) and Model (7) is the Bakshi, Gao and Rossi (2019) model. Models (8) adds the spreading pressure factor to Models (7). t-statistics are reported following Fama and MacBeth (1973) (in parentheses), and we also present the cross-sectional $R^2$. The sample period is January 4, 2005 through December 29, 2020.

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| Panel A: Single Factor Model | | | | | | | |
| (1) | 0.62 | 15.43 | | | | | 55.02% |
| | (0.17) | (2.31) | | | | | |
| (2) | 1.80 | | -2.66 | | | | 43.86% |
| | (0.50) | | (-0.32) | | | | |
| Panel B: Two Factors Model | | | | | | | |
| (3) | -0.51 | 17.47 | | | | 1.41 | 64.56% |
| | (-0.14) | (2.60) | | | | (0.33) | |
| (4) | -0.76 | | 3.07 | | | 1.66 | 53.61% |
| | (-0.22) | | (0.38) | | | (0.38) | |
| (5) | 1.63 | 15.22 | 0.02 | | | | 65.19% |
| | (0.47) | (2.26) | (0.00) | | | | |
| Panel C: Three Factors Model | | | | | | | |
| (6) | -2.26 | 17.72 | 1.88 | | | 3.18 | 73.81% |
| | (-0.64) | (2.62) | (0.23) | | | (0.75) | |
| (7) | 0.50 | | | 16.21 | -0.02 | 0.40 | 77.39% |
| | (0.14) | | | (1.66) | (-0.00) | (0.09) | |
| Panel D: Four Factor Model | | | | | | | |
| (8) | -0.47 | 19.33 | | 14.79 | -3.63 | 1.36 | 75.68% |
| | (-0.13) | (2.89) | | (1.46) | (-0.40) | (0.31) | |

Table I-11: **Cross-Sectional Asset Pricing Tests including Spreading Returns: Post 2005**

This table presents the estimated risk premium on commodity futures risk factors by running Fama-MacBeth cross-sectional asset pricing tests. Eight different model specifications are considered, and are nested in

$$R_{p,t} = \gamma_0 + \lambda_{\overline{SP}}\beta_{\overline{SP},t} + \lambda_{BM}\beta_{BM,t} + \lambda_C\beta_{C,t} + \lambda_M\beta_{M,t} + \lambda_{Avg}\beta_{Avg,t} + \epsilon_{p,t}.$$

where $R_{p,t}$ is the return of portfolio $p$ at week $t$, $\lambda$ is factor risk premia. We use seventeen commodity futures portfolios as test assets, broken down as carry (3), momentum (3), basis-momentum (3), spreading pressure (3), and commodity sector (5). We regress the average returns of thirty-four commodity-sorted portfolios on their risk exposures. The portfolios include the nearby and spreading returns of twelve portfolios sorted on spreading pressure, basis momentum and basis-momentum (the High3, Mid, and Low3 portfolios sorted on each signal) and five sector portfolios (energy, grains, meats, metals and softs). In Panel A, Model (1) and (2) are single-factor models that contains the spreading pressure factor or basis-momentum factor only. In Panel B, Model (3) and (4) add the market average factor (Model (4) is the Boons and Prado (2019) model), and Model (5) is a teo factors model by using both spreading pressure factor and basis-momentum factor. In Panel C, Model (6) adds the market average factor to model (5) and Model (7) is the Bakshi, Gao and Rossi (2019) model. Models (8) adds the spreading pressure factor to Models (7). We report two versions of the t-statistics, following Shanken (1992) (in parentheses) and Kan, Robotti and Shanken (2013) (in square brackets). OLS $R^2$ and GLS $R^2$ (in parentheses) are in the second last column. Generalized version of the Shanken (1985) cross-sectional F-test statistics and their corresponding p-values (in parentheses) are in the last column ($CSRT_{SH}$). The sample period is January 4, 2005 through December 29, 2020.

| Model | $\gamma_0$ | $\lambda_{\overline{SP}}$ | $\lambda_{BM}$ | $\lambda_C$ | $\lambda_M$ | $\lambda_{Avg}$ | $R^2$ | $CSRT_{SH}$ |
|---|---|---|---|---|---|---|---|---|
| Panel A: Single Factor Model | | | | | | | | |
| (1) | 1.82 | 14.56 | | | | | 46.72% | 0.03 |
| | (0.91) | (1.81) | | | | | (16.24%) | (0.56) |
| | [0.74] | [1.74] | | | | | | |
| (2) | 1.65 | | 13.91 | | | | 27.53% | 0.04 |
| | (0.83) | | (1.54) | | | | (4.80%) | (0.23) |
| | [0.71] | | [1.41] | | | | | |
| Panel B: Two Factors Model | | | | | | | | |
| (3) | -0.36 | 17.51 | | | | 2.84 | 64.84% | 0.02 |
| | (-0.50) | (2.29) | | | | (0.77) | (17.98%) | (0.96) |
| | [-0.42] | [2.21] | | | | [0.68] | | |
| (4) | -0.10 | | 16.83 | | | 2.12 | 39.63% | 0.01 |
| | (-0.14) | | (2.00) | | | (0.57) | (6.04%) | (0.99) |
| | [-0.10] | | [1.80] | | | [0.46] | | |
| (5) | 1.88 | 13.91 | 6.50 | | | | 47.10% | 0.03 |
| | (0.96) | (1.83) | (0.87) | | | | (17.29%) | (0.70) |
| | [0.86] | [1.78] | [0.73] | | | | | |
| Panel C: Three Factors Model | | | | | | | | |
| (6) | -0.34 | 16.29 | 8.83 | | | 2.88 | 66.50% | 0.03 |
| | (-0.47) | (2.21) | (1.23) | | | (0.78) | (19.32%) | (0.48) |
| | [-0.38] | [2.34] | [0.94] | | | [0.63] | | |
| (7) | 0.01 | | | 7.06 | 13.48 | 1.77 | 29.04% | 0.04 |
| | (0.02) | | | (0.95) | (1.57) | (0.48) | (1.95%) | (0.12) |
| | [0.01] | | | [0.90] | [1.70] | [0.40] | | |
| Panel D: Four Factor Model | | | | | | | | |
| (8) | -0.43 | 19.09 | | 2.47 | 6.11 | 2.93 | 66.72% | 0.03 |
| | (-0.61) | (2.69) | | (0.34) | (0.76) | (0.80) | (19.07%) | (0.53) |
| | [-0.55] | [2.66] | | [0.33] | [0.77] | [0.76] | | |

Table I-12: **Spreading Pressure and the Term Structure of Futures Prices**

This table reports the predictive regression of the one week-ahead slope and curvature of the commodity futures term structure on spreading pressure and hedging pressure:

$$\{Slope_{j,t+1}, Curvature_{j,t+1}\} = \alpha_{t+1} + \gamma_j + \beta_{SP} SP_{j,t} + \beta_{HP} HP_{j,t} + \varepsilon_{j,t+1}.$$

We define the slope of the futures curves as $slope_{j,t} = \frac{\ln F^3_{j,t} - \ln F^1_{j,t}}{T_3 - T_1}$, and the curvature as $curvature_{j,t} = \frac{\ln F^3_{j,t} - \ln F^2_{j,t}}{T_3 - T_2} - \frac{\ln F^2_{j,t} - \ln F^1_{j,t}}{T_2 - T_1}$. We report the results for four subgroups as well as the whole group. *Group* indicates the sub-sample depending on the shape of the term structure at time $t$, i.e., 1) positive slope, positive curvature, 2) positive slope, negative curvature, 3) negative slope, positive curvature, and 4) negative slope, negative curvature. *Percentage* (*Mean of SP*) denotes the proportion of the sample (average spreading pressure) for each group. The regression controls for both time- and commodity-fixed effects, as well as for time to earliest maturity date, for each commodity at each point in time. t-statistics, based on standard errors clustered at the time dimension, are in parentheses. The sample period in Panel A is October 6, 1992 through January 4, 2005, and in Panel B is January 4, 2005 through December 29, 2020.

| | | | $Slope_{j,t+1} \times 100$ | | | $Curv_{j,t+1} \times 100$ | | |
|---|---|---|---|---|---|---|---|---|
| Group | Percentage | Mean of SP | $SP_{j,t}$ | $HP_{j,t}$ | $R^2$ | $SP_{j,t}$ | $HP_{j,t}$ | $R^2$ |
| Panel A: Pre-2005 | | | | | | | | |
| (1) +*Slope*, +*Curv* | 22.66% | 6.32% | 0.06 | -0.04 | 44.50% | 0.10 | -0.03 | 32.10% |
| | | | (0.41) | (-2.16) | | (0.40) | (-0.77) | |
| (2) +*Slope*,−*Curv* | 40.51% | 6.73% | 0.23 | -0.08 | 34.36% | -0.12 | -0.03 | 41.10% |
| | | | (1.75) | (-5.34) | | (-0.78) | (-1.25) | |
| (3) −*Slope*, +*Curv* | 17.34% | 5.59% | 0.45 | -0.07 | 34.05% | 0.42 | -0.07 | 34.73% |
| | | | (1.84) | (-1.69) | | (1.63) | (-1.66) | |
| (4) −*Slope*, −*Curv* | 19.49% | 5.82% | -0.55 | -0.08 | 37.65% | -1.08 | -0.07 | 38.03% |
| | | | (-1.51) | (-1.77) | | (-2.84) | (-1.38) | |
| (5) *All* | 100.00% | 6.27% | 0.37 | -0.13 | 14.21% | -0.70 | -0.08 | 6.87% |
| | | | (3.01) | (-8.02) | | (-4.72) | (-3.77) | |
| Panel B: Post-2005 | | | | | | | | |
| (1) +*Slope*, +*Curv* | 25.42% | 13.65% | 0.36 | -0.11 | 45.80% | 0.39 | -0.07 | 31.00% |
| | | | (4.38) | (-6.15) | | (3.10) | (-3.09) | |
| (2) +*Slope*,−*Curv* | 47.70% | 13.15% | 0.27 | -0.15 | 38.97% | -0.27 | -0.04 | 35.61% |
| | | | (3.81) | (-9.04) | | (-3.89) | (-2.55) | |
| (3) −*Slope*, +*Curv* | 10.58% | 11.65% | 0.02 | -0.15 | 39.03% | 0.08 | -0.08 | 43.69% |
| | | | (0.21) | (-3.43) | | (0.57) | (-1.44) | |
| (4) −*Slope*, −*Curv* | 16.30% | 12.30% | 0.02 | 0.03 | 39.34% | -0.36 | 0.04 | 42.93% |
| | | | (0.24) | (0.70) | | (-2.70) | (0.78) | |
| (5) *All* | 100.00% | 13.00% | 0.24 | -0.34 | 18.95% | 0.20 | -0.06 | 6.19% |
| | | | (3.65) | (-23.40) | | (2.52) | (-3.58) | |

Table I-13: **Commodity Portfolios Sorted on Spreading Pressure at the Trader Category Level (DCOT report)**

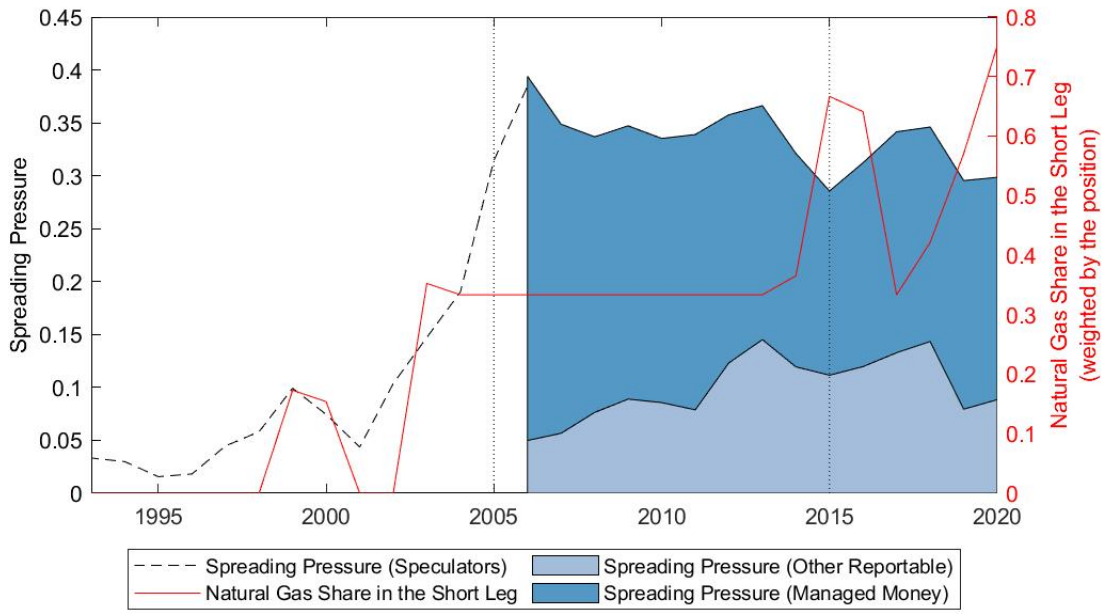
This table presents the summary statistics of commodity futures weekly portfolio returns, where we construct the portfolios by sorting commodity futures on the fifty-two week average of spreading pressure from money managers, other reportables, swap dealers, and all non-commercials. *Low3* (*High3*) consists of commodity futures ranked in the bottom (top) three for spreading pressure or basis-momentum, and the remaining twenty commodities constitute the portfolio called *Mid*. *Low3-High3* (*High3-Low3*) represents a long-short portfolio strategy of buying Low3 and shorting High3 (buying High3 and shorting Low3). Portfolios' excess returns are calculated as equal-weighted average excess returns of portfolio constituents. The sample period is June 13, 2006 through December 29, 2020.

| | Spreading Pressure (Money Managers) | | | | Spreading Pressure (Other Reportable) | | | |
|---|---|---|---|---|---|---|---|---|
| | Low3 | Mid | High3 | Low3-High3 | Low3 | Mid | High3 | Low3-High3 |
| Mean | 6.23 | 1.67 | -6.34 | 12.57 | 7.76 | 1.49 | -6.74 | 14.50 |
| Std. Dev. | 22.17 | 14.49 | 26.60 | 27.14 | 23.67 | 14.84 | 24.82 | 28.51 |
| Sharpe | 0.28 | 0.12 | -0.24 | 0.46 | 0.33 | 0.10 | -0.27 | 0.51 |
| Skewness | -0.13 | -0.54 | 1.31 | -0.83 | -0.50 | -0.20 | 1.67 | -1.49 |
| Kurtosis | 4.91 | 6.82 | 16.31 | 12.11 | 7.62 | 6.00 | 42.41 | 25.69 |
| | Spreading Pressure (Swap Dealers) | | | | Spreading Pressure | | | |
| | Low3 | Mid | High3 | Low3-High3 | Low3 | Mid | High3 | Low3-High3 |
| Mean | 6.62 | 1.76 | -7.29 | 13.92 | 7.51 | 2.32 | -11.72 | 19.23 |
| Std. Dev. | 19.77 | 14.69 | 29.50 | 29.69 | 22.53 | 14.49 | 25.49 | 26.51 |
| Sharpe | 0.34 | 0.12 | -0.25 | 0.47 | 0.33 | 0.16 | -0.46 | 0.73 |
| Skewness | 0.06 | -0.39 | 1.63 | -1.23 | -0.11 | -0.58 | 1.33 | -0.91 |
| Kurtosis | 3.33 | 6.17 | 25.64 | 20.10 | 5.33 | 7.78 | 18.61 | 13.36 |

Figure I-1: **Spreading Pressure and Commodity Turnover**

This figure presents commodity annualized turnover and the annual average of spreading pressure from all speculators, for managed money only, and for other reportable only. The figure includes two commodities, natural gas and platinum. The sample period is 1993 through 2020.

(a) Natural Gas




(b) Platinum

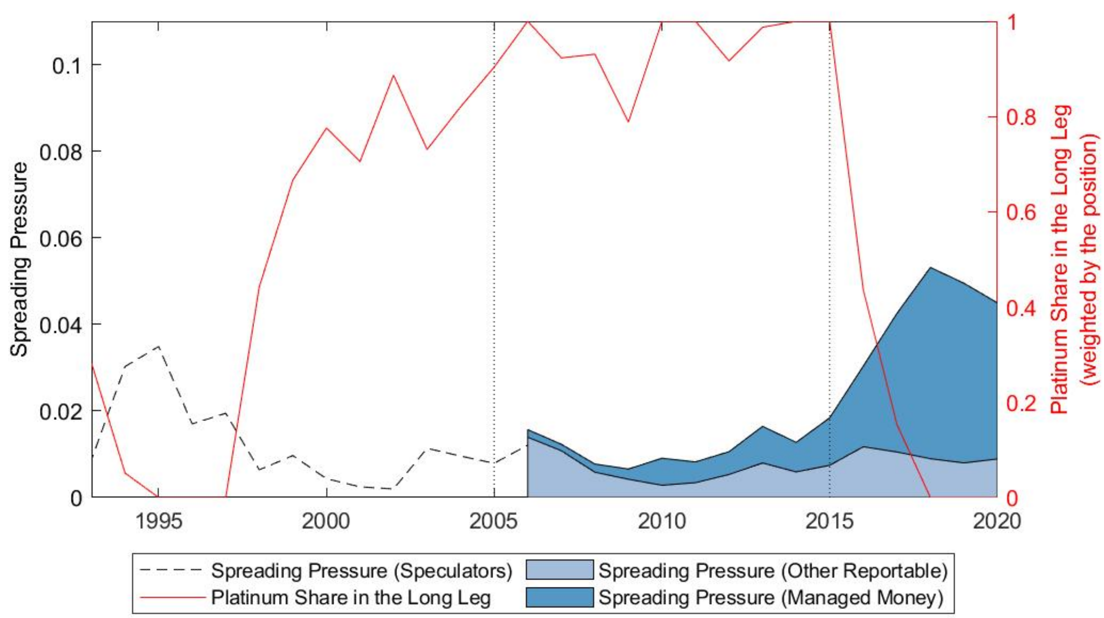


Figure I-2: **Commodity Turnover in SP Trading Strategy**

This figure shows the turnover of twenty-six commodities in spreading pressure portfolio long and short legs. The turnover is measured as the logarithm of number of times one commodity was a member in long leg (red) or short leg (black), respectively. Commodities with * on the x-axis are components of the S&P GSCI Index, and commodities with ** are components of the Bloomberg Commodity Index (DJ-UBSCI) but not components of the S&P GSCI Index. The sample period is October 5, 1993 through December 29, 2020.

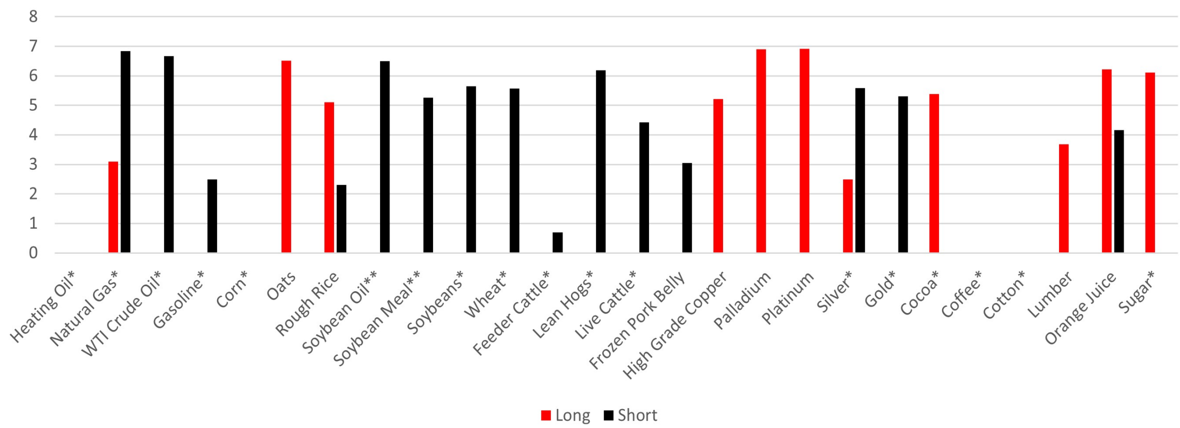
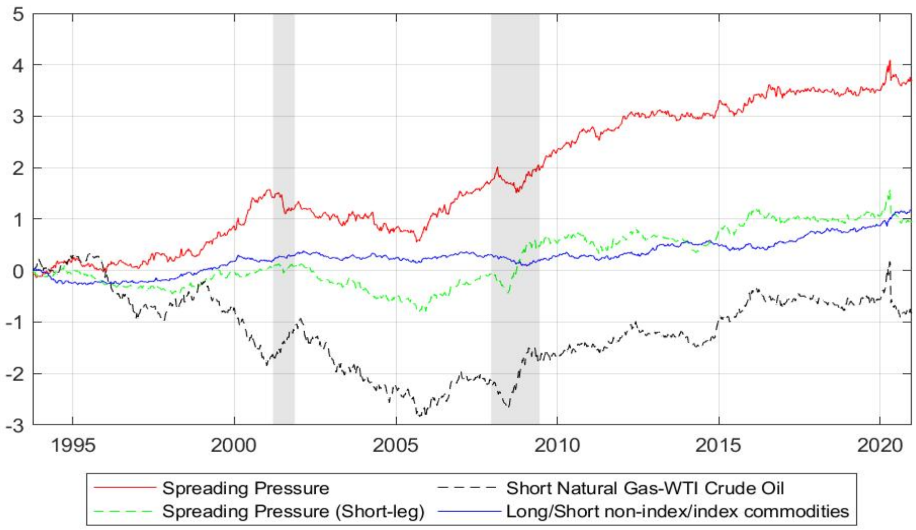


Figure I-3: **Cumulative Excess Returns of Commodity Pricing Portfolios**

This figure presents cumulative exess returns for commodity futures pricing portfolios: a long-short portfolio based on spreading pressure, the short leg of the spreading pressure portfolio, a portfolio by shorting natural gas and WTI crude oil, and a portfolio constructed by going long on off-index commodities and shorting index commodities. The sample period in Figure (a) is October 5, 1993 through December 29, 2020 , and in Fugure (b) is January 4, 2005 through December 29, 2020.

(a) Full Sample




(b) Post-2005

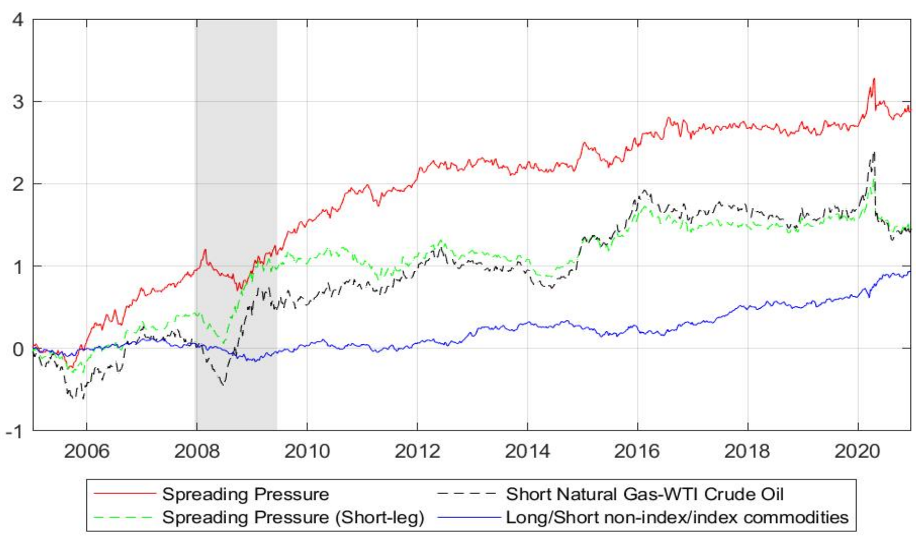
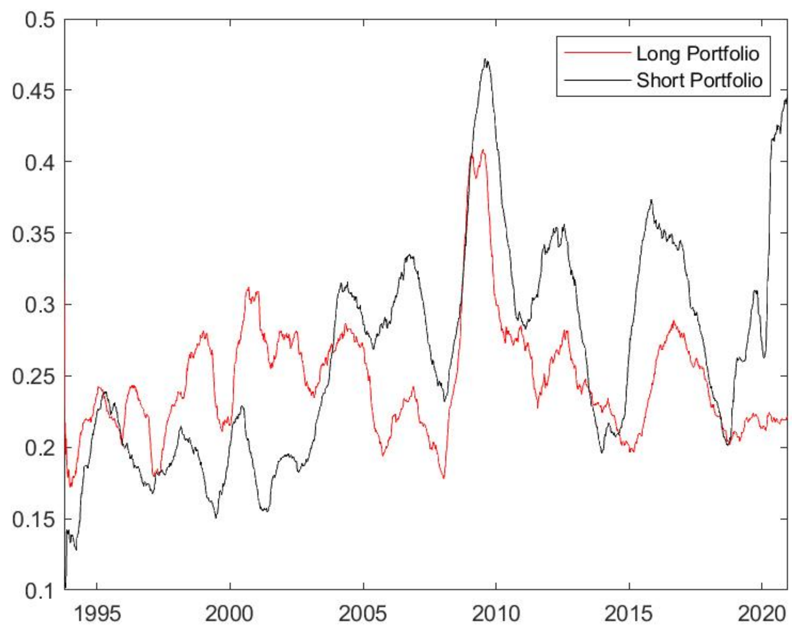


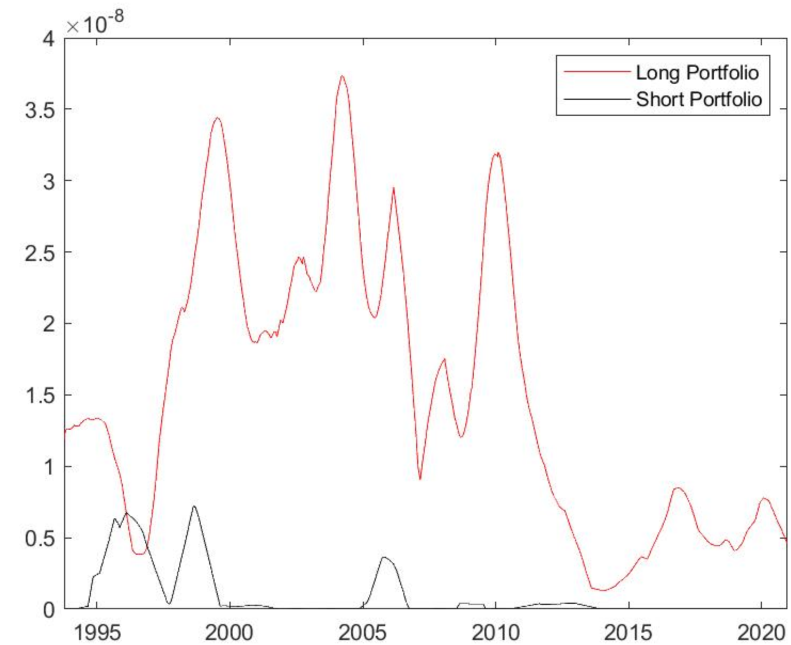
Figure I-4: **Volatility and Liquidity of Both Legs of Spreading Pressure Portfolios**

This figure presents 52-week moving average volatility and illiquidity for the long and short legs of the spreading pressure portfolio. The sample period is October 5, 1993 through December 29, 2020.

(a) Volatility



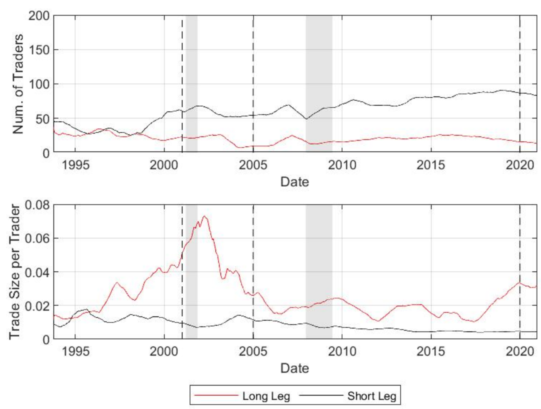

(b) (Il)liquidity



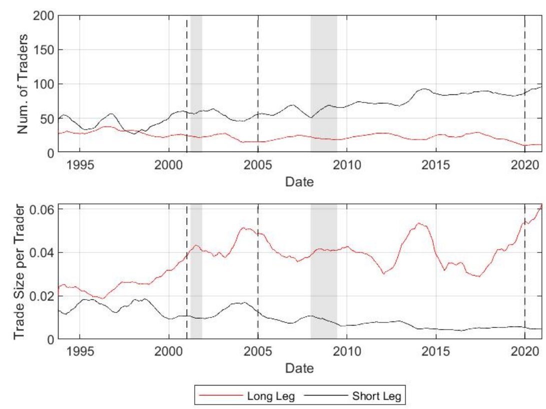
## Figure I-5: **Number of Traders and Average Position Size**

This figure presents the number of traders (top figure in each panel) and their average position size (bottom figure in each panel) in the long/short legs of spreading pressure portfolio. The types of traders included in this figure are (1) hedgers with long position (Panel A), (2) hedgers with short position (Panel B), (3) speculators with long position (Panel C), (4) speculators with short position (Panel D). Traders' average position size at time $t$ for commodity $i$ is defined as $\frac{TraderPosition_t/OI_t}{Num.ofTraders}$. Traders' average position size in the long (short) leg of spreading pressure portfolio is the equal-weighted average of traders' average position size for three commodities in the corresponding leg. All measurements are smoothed to 52-weeks average. The sample period is October 5, 1993 through December 29, 2020.

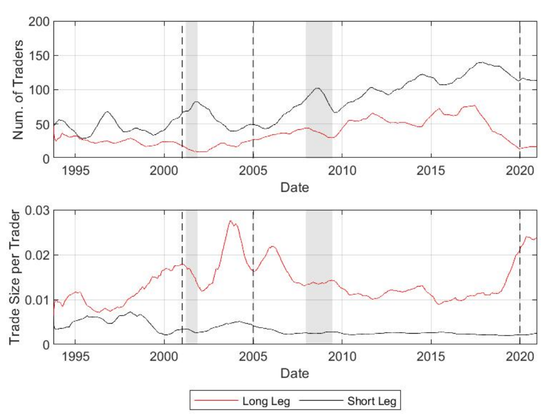
(a) Hedger Long




(b) Hedger Short




(c) Speculator Long




(d) Speculator Short