# A Tale of Two Premiums: The Role of Hedgers and Speculators in Commodity Futures Markets

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**ABSTRACT**

This paper studies the dynamic interaction between the net positions of traders and risk premiums in commodity futures markets. Short-term position changes are mainly driven by the liquidity demands of non-commercial traders, while long-term variation is primarily driven by the hedging demands of commercial traders. These two components influence expected futures returns with opposite signs. The gains from providing liquidity by commercials largely offset the premium they pay for obtaining price insurance.

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An important question in the commodity futures literature concerns the influence of speculative activity on the price formation in futures markets. According to the traditional view of Keynes (1923) and Hicks (1939), the presence of speculative capital facilitates risk sharing for hedgers who seek insurance against future price fluctuations. A central assumption of the theory of normal backwardation is that the hedging demand for futures is net short, and that hedgers induce speculators to absorb the risk of commodity price fluctuations by setting futures prices at a discount relative to expected future spot prices.

While the view that insurance provision constitutes an important element of commodity futures trading is not controversial per se, there are several reasons to believe that the Keynesian view is an incomplete description of the trading motives of commodity futures markets participants. First, it is often not possible to draw a clear distinction between speculative and hedging activities. Commercial "hedgers" may at times decide to selectively hedge based on their market views and hence their positions can be thought of as having both a hedging as well as a speculative component. Second, non-commercial "speculators" form a heterogeneous group that includes hedge funds, money managers, and index traders. It is likely that these speculators possess motives to trade that are independent of accommodating commercial hedging demands. An example would be commodity trading advisors (CTAs) that have been shown to actively pursue momentum style investment strategies,[1] or institutional investors taking exposure to a commodity index for the purpose of diversification.[2] It seems unlikely that these investment decisions simply originate from passively meeting the hedging demands of commercial market participants, as would be required

[1] Fung and Hsieh (1997, 2001) analyze trend following strategies by hedge funds, which have become a major source of speculative capital over recent decades. Rouwenhorst and Tang (2012) document that changes in speculative positions are positively correlated with relative returns in commodity futures markets. Moskowitz, Ooi and Pedersen (2012) find that speculators follow time-series momentum strategies in many futures markets. Bhardwaj, Gorton, and Rouwenhorst (2014) show that the returns of Commodity Trading Advisors correlate with simple momentum and carry strategies in stocks, currencies, and commodities.
[2] See for example Hamilton and Wu (2015), Basak and Pavlova (2016).

to fit the Keynesian story. Exploring the factors influencing position changes that are unrelated to hedging demands and their impact on expected risk premiums in commodity futures markets is a central focus of this paper.

In light of these conceptual concerns, it is perhaps not surprising that empirical support for the central prediction of the Keynesian view of commodity futures markets has been weak (see Rouwenhorst and Tang (2012) for a literature review). In empirical work, it is common practice to construct a measure of hedging pressure from the weekly reports on trader positions published by the Commodity Futures Trading Commission (CFTC). The test of the theory examines whether variation in hedging pressure – measured as the net short position of commercial traders – helps to predict variation in expected futures risk premiums. One possible reason for the failure to find a strong link is that the CFTC trader classifications do not align with the distinction between speculative and hedging positions. An alternative explanation suggested by Cheng, Kirilenko, and Xiong (2015) (CKX hereafter) and pursued in this paper, emphasizes the importance of considering motives to trade that are separate from insurance provision.[3] We conjecture that much of the short-term trading by non-commercials creates variation in observed hedging pressure that is not driven by commercial hedging motives. More importantly, this trading demands liquidity from their commercial counterparts, for which commercials receive a compensation in the form of a risk premium.

To establish the liquidity provision channel, we examine futures returns following the weekly position changes reported by CFTC, and provide evidence that active trading decisions by non-commercials influence the price setting in commodity futures markets. Our empirical strategy

[3] CKX (2015) show that during the financial crisis, financial traders such as hedge funds and index investors reduced their net long positions in response to market distress. This was facilitated by hedgers who reduced their net short positions as prices fell.

follows Kaniel, Saar, and Titman (2008) by testing for the predictability of short-term returns following position changes, and use the direction of this return predictability to infer who provides and who consumes liquidity in futures markets.[4] We find that during the weeks following a position change, commodities that were bought by non-commercials earn significantly lower returns than commodities that were sold by them. And commodities that are purchased by commercial traders subsequently outperform those that are sold by them. Our empirical findings parallel the prediction from microstructure theory[5] that liquidity providers (i.e., commercials) trade as contrarians, while impatient traders (i.e., non-commercials) consume liquidity and need to offer a price concession to incentivise risk-averse market makers to take the other side of their trades.

The short-term underperformance of commodity futures sold by commercials is opposite to the prediction of the Keynesian view, which associates an increase in commercial selling (hedging) pressure with higher expected risk premiums. We conjecture that variation in hedging pressure has two components: short-term variation that is primarily driven by the liquidity demands of non-commercials, and a longer-term component that stems from changes in the hedging demands of commercial market participants. The latter is relatively stable over short-term horizons due to the slow evolution of underlying production decisions in physical markets. Once we control for the variation in hedging pressure that is induced by short-term trading, the positive relationship between hedging pressure and expected futures risk premiums re-emerges. This leads to the second main finding of our paper, that the expected excess return to a commodity futures contract embeds two return premiums related to position changes: one premium paid by commercials to non-

[4] Kaniel, Saar, and Titman (2008) study the dynamic relation between net individual investor trading and short-horizon returns for a large cross-section of NYSE stocks, and show how the demand of immediacy for trade execution by institutions is met by the liquidity provision by individual investors and leads to predictable returns following their trades. In our context of commodity futures markets, we test for the predictability of short-term returns following position changes by commercial hedgers and non-commercial speculators, and use such return predictability to make inferences about who provides liquidity in these markets.

[5] For example, Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993).

commercials for obtaining price insurance and one premium paid by non-commercials to commercial traders for accommodating their short-term liquidity needs.

To further support our hypothesis, we examine the sensitivity of liquidity provision to the risk environment. First, using option implied commodity volatility as a measure of commodity specific risk, we document that the willingness of commercials to provide liquidity is lower and the return impact of a given position change is larger when risk is expected to be high in commodity markets. By contrast, variation in the VIX does not impact the cost of liquidity provision. This suggests that the commercials who provide liquidity are not financial intermediaries but instead traders in physical markets who use commodity futures to manage their underlying risk exposure. Second, following market microstructure literature, we find that commercials are less willing to provide liquidity when they face more binding capital constraints or when their positions become more imbalanced.

Finally, we address the question why commercial traders provide liquidity to non-commercial traders who follow momentum strategies, if momentum strategies are profitable. We show that while non-commercial position changes are positively correlated with (past) returns, a large fraction of trading by non-commercials is orthogonal to momentum. Commercials benefit from providing liquidity to these uncorrelated trades, although they suffer intermediate-term losses to the component of trading that is momentum-induced. For liquidity provision to make economic sense for commercials, their gains from liquidity provision ought to outweigh their losses to momentum traders. We estimate a decomposition of the total profits (losses) of commercial positions into three components: hedging demand, liquidity provision, and momentum trading. The decomposition shows that (i) on average across commodities, the hedging premium earned by non-commercials is in large part offset by the cost of the liquidity demand induced by their short-term trading needs, and (ii) that the gains to commercials from liquidity provision outweigh their losses from taking the opposite side of momentum trades. This is consistent with the rational pricing of liquidity by commercials.

Our study contributes to the literature on commodity futures in the following ways. First, we document that liquidity provision by commercials is an important aspect of the continuous (weekly) rebalancing of positions in commodity futures markets. It predates the era of "financialization" of commodity markets, and is present before and after the recent financial crisis.[6] Second, we estimate the premium that commercial hedgers earn from this activity and find that this premium is economically large. Third, we provide a new perspective on the question of why "hedgers" appear to trade so much (see Cheng and Xiong (2014)): they are induced by non-commercial demand for immediacy and are compensated for providing liquidity to them on the short-term horizon. Fourth, we explain why previous studies often fail to find a strong correlation between hedging pressure and expected futures returns (see Rouwenhorst and Tang (2012) for a review). We show that variation in hedging pressure embeds two components that predict futures returns with opposite signs, and failure to control for liquidity provision introduces a bias that attenuates the estimated influence of hedging pressure on future excess returns. Finally, our decomposition of trader positions provides an explanation for the low profitability of speculative traders (Rockwell (1967), Chang (1985), and Hartzmark (1987)): the premium they earn from providing price insurance to commercial hedgers is largely offset by the premium they pay for demanding liquidity for their short-term trading needs.

Our study also contributes to the broader literature on demand-based asset pricing, which postulates that changes in the demand for an asset can have a significant impact on its expected

[6] This is distinct from CKX (2015) who show that commercials provided liquidity to non-commercials during the recent financial crises, in response to a shock to intermediary capital.

return.[7] Our study links variation in long-term hedging pressure as well as short-term buying to variation in excess commodity futures returns.

The outline of the paper is as follows. Section I summarizes our data and presents some stylized facts about the CFTC position reports and commodity futures returns. Section II presents our empirical findings on short-term futures return predictability based on liquidity provision by commercial market participants. Section III re-examines the role of hedging pressure for risk premiums and the importance of distinguishing between short-term and long-term variation in trader position imbalances. Section IV examines the sensitivity of the futures return predictability to changes in the risk environment. In Section V we estimate a decomposition of the profits and losses of commercial markets participants into components related to hedging, momentum trading, and liquidity provision. Section VI provides several additional robustness tests, followed by our conclusions in Section VII.

## I. Data and Summary Statistics

We use publicly available data from the CFTC to study the trading behavior of various types of participants in commodity futures markets. The weekly Commitment of Trader (COT) reports detail the aggregate long and short positions of commodity futures market participants by trader type: commercials, non-commercials, and non-reportables. These positions are measured every week on Tuesday, and publicly released three days later, after the market close on Friday. Our data sample covers 26 commodities that are traded on four North American exchanges (NYMEX, NYBOT, CBOT, and CME) from January 2, 1994 to December 31, 2017.

[7] In option markets, Bollen and Whaley (2004) find that investors' demands affect the implied volatility and hence option premium for index options. In the stock market, Shleifer (1986) shows that the price increase of stocks added to the S&P500 index is related to the demand for index funds, and Frazzini and Pedersen (2014) suggest that investors' demand for leverage increases the relative price of high-beta stocks, thereby lowering their expected returns.

The CFTC classifies a trader as "commercial" if she uses futures contracts for hedging purposes as defined in CFTC Regulation 1.3(z), 17 CFR 1.3(z). The CFTC definition underscores that hedging is an important motivation of futures market participation by commercials, but leaves open that certain aspects of their trading can be speculative in nature. Exploring the pricing impact of commercial trading that is not related to hedging is a central focus of this paper. That said, the CFCT definition explains why there is a long tradition in the literature to view commercials as hedgers, and non-commercials as speculators even if the distinction is not always clear.[8] We conduct several robustness checks based on the Disaggregated COT (DCOT) data published by the CFTC since 2006, which uses a finer breakdown of the speculative traders and excludes swap dealers from commercial traders.[9]

Based on the CTFC data we construct three variables to characterize the positions and trading behavior of futures markets participants: hedging pressure (*HP*), net trading (*Q*), and the propensity to trade (*PT*). We follow the convention in the literature and denote the net short position of commercial traders as "hedging pressure," while keeping in mind that these net positions can vary for reasons other than hedging motives: Specifically *HP* is defined as the number of contracts that the commercial traders are short (*CS*) minus the number of contracts that they are long (*CL*), divided by open interest (*OI*), which is defined as the total number of contracts outstanding for commodity $i$ in week $t$:

$$HP_{i,t} = \frac{CS_{i,t} - CL_{i,t}}{OI_{i,t}} - \frac{commercial\ netlong\ position_{i,t}}{OI_{i,t}} \tag{1}$$

For each trader category (i.e., commercials, non-commercials, or non-reportables), we define a

[8] For example, see Houthakker (1957), Rockwell (1967), Chang (1985), Bessembinder (1992), De Roon, Nijman, and Veld. (2000), Moskowitz, Ooi, and Pederson (2012), Hong and Yogo (2012), Acharya, Lochstoer, and Ramadorai (2013).
[9] CKX (2015) find that for the purpose of their study the finer classifications using CFTC internal data yield the same conclusions as those based on the DCOT data.

net trading measure ($Q$) as the net purchase of futures contracts, calculated as the change in their net long position for commodity $i$ from week $t$-1 to week $t$, normalized by the open interest at the beginning of the week:

$$Q_{i,t} = \frac{netlong\ position_{\ i,t} - netlong\ position_{i,t-1}}{OI_{i,t-1}}. \quad (2)$$

If open interest were constant, net trading for commercials in commodity $i$ in week $t$ would be equal to the decrease in hedging pressure between weeks $t$-1 and $t$.

Finally, we define the propensity to trade as the sum of the absolute changes of the aggregate long and the aggregate short positions of each trader category, scaled by their total gross positions at the beginning of the week.[10] For example, the propensity to trade for the commercials is calculated as:

$$PT_{i,t} = \frac{abs\left(CL_{i,t} - CL_{i,t-1}\right) + abs(CS_{i,t} - CS_{i,t-1})}{CL_{i,t-1} + CS_{i,t-1}} \quad (3)$$

Futures price data are obtained from Pinnacle Corp. We construct weekly excess returns (Tuesday-Tuesday) to match the measurement of the positions by the CFTC. We compute the excess return for commodity $i$ in week $t$ using the front-month contract:

$$R_{i,t} = \frac{F_i(t,T) - F_i(t-1,T)}{F_i(t-1,T)} \quad (4)$$

where $F_i(t,T)$ is the futures price at the end of week $t$ for a futures contract maturing on date $T$.[11]

Table I provides summary statistics for our return data and position measures for each of the 26 commodities in our sample. Panel A documents that the average excess return has been positive

[10] This propensity to trade can be understood as an analog to the portfolio turnover rate for stock market investors. Unlike the trading measures which sum to zero, the propensities can be quite different across different types of traders and can vary over time.

[11] For weeks ending prior to the 7th calendar day of the month, the front contract is defined as the closest to maturity contract available including contracts expiring in the current calendar month. For weeks ending on or after the 7th calendar day, the front month is defined as the closest to maturity contract expiring subsequent to the current calendar month. If the 7th day is not a business day we use the next business day as our cut-off date. Our contract selection strategy generally takes positions in the most liquid portion of the futures curve. Popular commodity indexes follow similar strategy to ensure sufficient liquidity for each component contract in the index.

in 18 out of 26 markets, and has averaged 2.77% per annum across commodities, with an average annualized standard deviation of 27.8%. Panel A also shows that average hedging pressure was positive for 24 out of 26 sample commodities. The large average standard deviation of hedging pressure (17.1% across commodities) implies that net hedging pressure is not always to the short side of the market. The average frequency of commercials being net short was 70.7% across markets, indicating that net long positions by commercials are not uncommon. The high volatility of hedging pressure is illustrated in Figure 1, which provides time-series plots of hedging pressure for oil, copper, wheat, and coffee. Panel B reports summary statistics for the magnitude of weekly position changes by commodity. The absolute values of net position changes (*Q*) of the commercial and non-commercial traders (columns 2 and 3) average 3.39% and 2.94% of total open interest. The remainder of Panel B shows that the average propensity to trade (columns 4 and 5) is almost twice as high for the non-commercial traders (8.89% per week) as it is for commercials (5.30% per week), and that this difference is statistically significant.

These summary statistics motivate the following empirical observations. First, the average net short positions of the commercial traders and the positive average risk premium to long futures positions are broadly consistent with Keynes' theory of normal backwardation. Figure 2 shows that the slope coefficient of a cross-sectional regression of the average risk premium on the average hedging pressure is significantly positive, with a *t*-statistic of 2.89. By contrast, however, there is little predictability of futures returns using hedging pressure at short-term horizons. The average slope coefficient of a Fama-MacBeth cross-sectional regression of weekly futures returns on prior week hedging pressure is insignificantly different from zero (*t*-statistic = -0.61).[12] This suggests that short-term variation in hedging pressure masks long-term return predictability.

[12] Table VI contains the details of these cross-sectional estimates. See also Gorton, Hayashi, and Rouwenhorst (2013) who show that the monthly correlation between returns and hedging pressure is contemporaneous, but not predictive.

Second, there is large variation in hedging pressure at the weekly horizon. In the context of agricultural markets, Cheng and Xiong (2014) have questioned whether the large variation in net short positions of commercial participants can be explained by their attempts to hedge price and output risk. The high propensity to trade by the non-commercials raises the possibility that much of the short-term speculative trading is not motivated by accommodating commercial hedging demands. Since commercials have to absorb the net short-term trading demands of non-commercials, changes in hedging pressure will not only reflect their demands for price insurance but also the demand for immediacy by non-commercials to the extent that they follow investment styles that are independent of these hedging plans.

## II. Liquidity Provision in Commodity Futures Markets

In this section we characterize the short-term trading behavior of commodity market participants and infer the direction of liquidity provision from the predictable component of futures prices following their trading.

### *A. How Do Commercials and Non-Commercials Trade?*

For each trader category identified by the CFTC, we run weekly Fama-MacBeth cross-sectional regressions of their net position change $Q$ on contemporaneous or past excess futures returns and lagged position changes. Table II reports the time series average of the slope coefficients and the corresponding $t$-statistics of the means. We find that changes in position changes are significantly correlated to contemporaneous and lagged commodity futures returns, but the correlations with returns have opposite signs for non-commercials and commercials. On net, non-commercials are momentum traders, while commercials trade as contrarians. The smaller traders in the non-reportable category behave like non-commercials. These cross-sectional results are consistent with early studies in the literature such as Houthakker (1957), as well as the more recent time-series findings of Moskowitz, Ooi, and Pederson (2012) and Rouwenhorst and Tang (2012).

### *B. A Regression Test of Return Predictability and Liquidity Provision*

The strong correlation between positions changes and returns does not identify which group initiates these trades. We infer the direction of liquidity provision by studying the impact of position changes on subsequent futures returns. This approach is inspired by microstructure models as in Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993), which predict that market makers typically trade against price trends and are compensated for providing liquidity through subsequent price reversals.[13] We run predictive Fama-MacBeth regressions of excess returns in weeks $t$+1 and $t$+2 on position changes in week $t$, with and without a set of controls that have been suggested in the literature to capture variation in expected futures returns:[14]

$$R_{i,t+j} = b_0 + b_1 Q_{i,t} + b_2 B_{i,t} + b_3 S_{i,t} \hat{v}_{i,t} + b_4 R_{i,t} + \varepsilon_{i,t+j}, \qquad j=1,2 \qquad (5)$$

where $B_{i,t}$ is the log basis[15], at the end of week $t$, $\hat{v}_{i,t}$ is the annualized standard deviation of the residuals from the regression of commodity futures returns on S&P500 returns (calculated using a

[13] This prediction is supported by empirical studies in equity markets (e.g., Conrad, Hameed, and Niden (1994), Avramov, Chordia, and Goyal (2006), Kaniel, Saar, and Titman (2008)). Our empirical strategy parallels this approach for commodity futures markets.

[14] The (log) basis is motivated by the theory of storage (Working (1949) and Brennan (1958)) and the empirical evidence that links the basis to inventories and the commodity futures risk premium. For example, Fama and French (1987) find that futures basis can forecast the risk premium of commodity futures in time-series regressions. Gorton and Rouwenhorst (2006) and Erb and Harvey (2006) show that sorting commodity futures into portfolios on the basis spreads the returns, and Gorton, Hayashi and Rouwenhorst (2013) empirically link variation of the basis and risk premiums to inventories. The interactive term $S_{i,t}\hat{v}_{i,t}$ is motivated by Bessembinder (1992) as a proxy for priced idiosyncratic risk in commodity futures, based on the work by Hirshleifer (1988). Our lagged return variable captures short-term momentum, as documented by Pirrong (2005), Erb and Harvey (2006), and Miffre and Rallis (2007).

[15] $B_{i,t}$ is defined as $\frac{ln(F_i(t,T_2))-ln(F_i(t,T_1))}{T_2-T_1}$, where $F_i(t,T_1)$ and $F_i(t,T_2)$ are the prices of the closest and next closest to maturity contracts for commodity $i$ in week $t$.

52-week rolling window); $S_{i,t}$ is a sign variable that is equal to 1 when non-commercials are net long and -1 when they are net short.

Panel A of Table III shows that commodities that are bought by the commercials in week *t* earn significantly higher returns in week *t*+1 than commodities sold by them (*t*-statistic = 4.95). The estimated return impact becomes even larger when we include controls for expected returns in our regression (*t*-statistic = 6.60). On the other hand, commodities that are bought by the non-commercials witness a significant predictable price decline in the week subsequent to trading. These estimates provide strong evidence of non-commercials demanding liquidity around weekly position changes. Position changes by non-reportable small traders do not seem to significantly impact subsequent returns, which suggests that the return predictability reflects a transfer between the reportable (large) traders in commodity futures markets. For this reason, we will often suppress the results for non-reportable traders in the remainder of our paper. Panel B shows that the return impact persists in the second week following the position change, although the magnitude becomes smaller in comparison to the first week.

In both panels, the estimated return impact becomes larger when we include controls. Given that position changes embed a price momentum component (Table II), by controlling for momentum we more precisely isolate the liquidity impact of position changes. Inclusion of the control for past returns increases the estimated return impact of position changes because the momentum driven portion of the trading is correlated with future returns with the opposite sign. We will examine the impact of momentum on the profitability of liquidity provision by commercials in more detail in Section V.

The liquidity impact of position changes is robust in sub-periods. The Internet Appendix Table IA.I reports results when we choose 2003 (pre-financialization as defined by Tang and Xiong

(2012)) or 2008 (financial crisis) to demarcate sub-samples. We find similar return impact estimates pre and post. We also examine whether the return impact differs conditional on the direction of hedging pressure itself. The Internet Appendix Table IA.II shows that the return impact of a position change is similar whether commercial positions are net long or net short in a specific commodity.

*C. Insights from the DCOT Data*

Our analysis thus far has focused on the COT data from the CFTC. The advantage of the COT data is its long history, but the disadvantage is its high level of aggregation of positions of potentially dissimilar traders: an example of the latter would be when a financial intermediary institution buys futures to hedge an over-the-counter commodity index swap with an index investor. This long futures hedge would normally be classified as a commercial position, although the underlying motive for the position of the end investor is speculative in nature.

The Disaggregate Commitment of Trader (DCOT) data is published by CFTC since June of 2006 and provides a more detailed breakdown of trader categories. For this shorter period, it offers an opportunity to more accurately isolate the trader categories that demand and provide liquidity in commodity futures markets. The DCOT reports classify commodity futures traders into five groups: (i) producers/merchant/processor/user, (ii) money managers, (iii) swap dealers, (iv) other reportable, and (v) non-reportable (or small investors). The first group, which for brevity we will refer to as producers, comprises market participants that are often thought of have a clear hedging motive, whereas money managers' positions are generally considered to be more "speculative." Swap dealers are separately reported in the DCOT reports, unlike the COT reports where dealers with a hedging exemption would be included in the commercial category. We use the positions of producers in the DCOT reports to construct an alternative proxy for hedging pressure and calculate a corresponding net trading ($Q$) measure defined as before. We find that the net trading measures based on the COT (commercials) and the DCOT (producers) are highly correlated for the period that the samples overlap; the average correlation is 0.90.

Table IV reports the results of re-estimating the futures return-prediction regression equation (5) using the DCOT classifications. We obtain results that closely resemble our findings using the COT data (Table III); the commodity futures that are heavily bought (sold) by the DCOT producers on average earn higher (lower) returns in the week $t$+1 (as shown in Panel A) and $t$+2 (as shown in Panel B). These findings identify producers as short-term liquidity providers.

A natural follow-up question is to ask to whom the producers primarily provide liquidity? And do swap dealers participate in liquidity provision in a similar way as other commercials traders? A comparison of the average slope coefficients on $Q$ across DCOT trader categories in Table IV shows that money managers, which include CTAs and hedge funds, stand out as the primary consumers of liquidity, based on the magnitude and statistical significance of the slope coefficient of their $Q$ measure. We reject the hypothesis that swap dealers are providers of liquidity, as the future return impact of their position changes is insignificantly different from zero. If anything, their negative coefficient on $Q$ indicates they are net consumers of liquidity. The DCOT data supports our conclusions based on the COT data, and suggests that the liquidity provision channel primarily operates between physical commodity market participants as suppliers of liquidity and money managers as consumers of liquidity. We will provide additional evidence to support this hypothesis in Section IV.

*D. Portfolio Sorts on Position Changes*

As a complement to our regression analysis, we construct portfolios by sorting commodities according to past net position changes and compare their post-ranking returns. More precisely, at the end of Tuesday of each week, the measurement day of the COT positions report, we rank the 26 commodity futures in ascending order based on the prior-week net change in the commercials' positions (*Q*). We form five equally-weighted "quintile" portfolios, containing 5, 5, 6, 5, and 5 commodity futures respectively, and calculate the excess returns for these five portfolios during the 40 trading days following the portfolio construction. Because the CFTC report is released after the market close on the Friday following the measurement of positions on Tuesday, we separately report the returns during days 1-4 when the report is not yet released, and days 5-40 when the information contained in the report is in the public domain.

Panel A of Table V summarizes the average excess returns for the sorted portfolios. The second column illustrates the contrarian nature of the trading by the commercials, who intensively buy commodities whose prices have fallen during the prior two weeks (average return = -3.19%), and intensively sell winners (average prior return of 3.72%). The third column shows that during the four days after portfolio formation, commodities in the top quintile (Portfolio 5 with the largest *Q*) earn on average 0.19%, compared to -0.05% for commodities in the bottom quintile (Portfolio 1 with the smallest *Q*). The return difference of 0.24% is significantly different from zero (*t*-statistic = 3.65). The next columns show that a positive return spread persists during days 5-20 following the release of the CFTC report: 0.29% during days 5-10 ($t$ = 3.73) and 0.19% ($t$ = 1.68) during days 11-20. These numbers are economically large: a spread of 73 basis points during the four weeks (1-20 days) following a position change translates to an annualized excess return of about 9% per year. By this measure, the liquidity cost of rebalancing the extreme quintile portfolios exceeds the premium earned by taking a passive long position in the broad market.

Panel B tracks the evolution of position changes of commercials in the quintile portfolios during the weeks following portfolio formation. Induced by the momentum trading of non-commercials, the commercials sell the winners during the first two weeks after the portfolio construction. A similar short-term persistence is present in the buying of losers. However, by week 3 the commercials begin to buy back the commodities they had sold previously, and sell out of the positions that they initially bought. The last column of panel B shows that over the 8-week post-ranking period commercials partially reverse the trades that they implemented during the weeks prior to ranking.

### *E. Summary of Liquidity Provision Results*

Combining our empirical results regarding the short-term interaction between trading behavior and futures returns, a clearer picture starts to emerge about liquidity provision in commodity markets. The commercial traders are on average net short in futures markets and follow contrarian strategies to accommodate the short-term trading demands of non-commercial traders. The commercials increase short positions when the buying pressure from the non-commercials pushes commodity futures prices up, and decrease short positions in response to non-commercial selling pressure. This introduces variation in commercial positions that is unrelated to commercial hedging demands, for which they are compensated in the form of a liquidity provision premium. This is consistent with inventory holding cost models in the microstructure literature that suggest that traders who demand immediacy (e.g., the non-commercials) need to offer a price concession to attract liquidity-supplying orders from other risk-averse investors (e.g., the commercial traders).

## III. The Role of Hedging Pressure Revisited

Liquidity provision to non-commercial traders creates short-term fluctuations in hedging pressure that represents a significant factor in the determination of futures prices. This factor has not been considered in traditional regression tests of the theory of normal backwardation, which has interpreted all movements in hedging pressure as being motivated by the demand for price insurance by commercial hedgers. Our hypothesis is that increases in hedging pressure can either have a positive or a negative influence on expected futures returns depending on whether the change stems from demand for price insurance by commercial "hedgers" or from the demand for liquidity by non-commercial "speculators." In this section we attempt to separate these two effects.

### *A. Regression Tests based on the Smoothed Hedging Pressure*

While the demand for immediacy by non-commercials influences futures prices at short-term horizons (i.e., weekly frequency), we hypothesize that the demand for insurance by commercials is likely to be relatively stable from week to week, and is expected to change slowly over time as output decisions of producers and merchants adjust. Our empirical strategy, therefore, is to distinguish between slow-moving components of hedging pressure that can be used as a proxy for changes in hedging demand and higher frequency movements that are more likely to be associated with liquidity provision. We propose a simple empirical approach in which we calculate a trailing moving average of hedging pressure to remove these short-term fluctuations.

In Table VI, we revisit our basic Fama-MacBeth regression framework for excess futures return predictability including measures of hedging pressure and short-term trading, while controlling for other sources of variation in risk premiums as in Table III. The first specification can be viewed as a traditional regression test of the theory of normal backwardation linking hedging pressure to risk premiums. We find that the average slope coefficient on the key independent variable, lagged hedging pressure ($HP_t$), is not significantly different from zero either in predicting next week returns ($t$-stat = −0.61) or week $t$+2 returns ($t$-stat = 0.96).

Next, we replace $HP_t$ by $\overline{HP}_t$, which is calculated as a trailing 52-week moving average of the net short positions of commercials from week $t$-51 to week $t$ scaled by the open interest in week $t$. This filters out short-term fluctuations in hedging pressure and we will refer to $\overline{HP}$ as *smoothed* hedging pressure. The second regression specification in Table VI shows that the average slope coefficient on smoothed hedging pressure is positive and statistically significant, which is consistent with the prediction of the theory of normal backwardation.

The third specification shows that both short-term position changes $Q$ and smoothed hedging pressure $\overline{HP}$ significantly predict risk premiums in a multivariate regression. The coefficient for smoothed hedging pressure is virtually unaffected by the inclusion of $Q$ in the regression, which indicates that these two variables capture independent sources of variation in risk premiums. Since we have controlled for the futures basis and past returns in our cross-sectional regressions, our liquidity and hedging pressure factors capture variation in risk premiums that is different from previously documented factors such as carry and momentum. Moreover, the coefficients for $Q$ are comparable to the coefficients we found in Table III.

Our analysis helps to explain why simple predictive regressions of excess returns on lagged hedging pressure fail to detect a significant influence (see Rouwenhorst and Tang (2012)). Depending on the source of variation in hedging pressure, there are opposite effects on the futures risk premium. If an increase in hedging pressure is driven by demand for insurance of hedgers, it increases the risk premium, and if it is driven by liquidity demands of non-commercials it lowers the risk premium.

We use the positions of producers from the DCOT data to construct an alternative measure of smoothed hedging pressure. In Table VII we report the results of re-estimating the futures return-prediction regression where we separate the slow-moving component of DCOT producer net positions from the weekly net change in these positions. These results qualitatively resemble our findings for the COT data in Table VI. Table VII shows that the producers, who play an important role in physical markets, influence risk premiums in commodity futures markets in two ways: through the slow-moving component of net-short position (hedging demand), and through their provision of short-term liquidity.

*B. Portfolio Sorting Analysis*

Panel A of Table VIII summarizes the performance of two-way sorted portfolios, constructed by first ranking commodities on smoothed hedging pressure $\overline{HP}$, and then according to prior week net buying activity by commercials ($Q$), both calculated from the COT data, During the first four trading days following the portfolio formation, high $Q$ commodities significantly outperform low $Q$ commodities regardless of the level of hedging pressure. For the next 16 days (days 5-20), the outperformance of high $Q$ commodities is concentrated in the commodities experiencing higher hedging pressure. Overall the return impact of $Q$ is higher for commodities with high hedging pressure. A likely explanation for this finding is that higher smoothed hedging pressure implies stronger hedging demand, and therefore commercials may be more reluctant to deviate from their hedging positions to accommodate the short-term trading needs of non-commercials. After 20 trading days, there is no significant difference between the returns of the commodities in the high and low $Q$ portfolios, which illustrates the temporary nature of the premium for liquidity provision. In contrast, we find that the high $\overline{HP}$ portfolios outperform the low $\overline{HP}$ portfolios at all horizons.

The spread between the two portfolios increases with the length of the investment horizon, which reflects the persistent nature of smoothed hedging pressure.

Panel B of Table VIII presents post ranking net position changes ($Q$) for the double-sorted portfolios. The high $Q$ portfolios experience a brief period of net buying following the portfolio ranking, but witness net selling subsequently. The reverse is true for low $Q$ portfolios, which initially experience a continuation of selling followed by subsequent buybacks.

Overall the documented return and trading patterns are consistent with the mean reversion of temporary deviations of commercial positions from their target levels, induced by liquidity provision to non-commercial traders. Commodities that have poor returns are subsequently sold by non-commercials, thereby reducing observed hedging pressure in the market. The reduction of hedging pressure has a temporary component that is reversed in subsequent weeks. During the weeks of reduced hedging pressure, these commodities temporarily earn higher risk premiums to compensate commercials for their liquidity provision. Similarly, commodities that have good returns are subsequently bought by non-commercials and sold by commercials. This temporarily increases observed hedging pressure of these commodities and lowers their returns.

In the broader context of the literature on commodity futures markets, our findings provide a fresh perspective on traditional tests of the theory of normal backwardation that link commercial hedging pressure to futures risk premiums. Our results highlight the importance of distinguishing between variation in the net positions of commercial traders that is driven by insurance demands, and variation in net positions that is induced by trading of non-commercial market participants that is independent of these hedging demands. We propose a simple way to disentangle these two sources of variation and show that both components significantly predict risk premiums, but in opposite directions. Failing to distinguish between these two separate sources of variation renders the predictive power of hedging pressure for risk premiums to become insignificant. Accounting for liquidity provision allows a sharper estimation of the hedging premium, helping to resolve the debate around the impact of hedging pressure on expected commodity futures returns.

## IV. Further Perspective on Liquidity Provision

In support of our liquidity provision hypothesis, we analyze how liquidity provision varies with the risk environment. Next, we present empirical evidence that short-term return predictability more likely reflects a compensation for liquidity provision instead of commercial traders exploiting private information.

### *A. Variation in the Risk Environment and Liquidity Provision*

How does liquidity provision by commercials vary with changes in the risk environment? In equity markets liquidity provision seems to be reduced in times when the VIX is high, reflecting increased risk to financial intermediaries (e.g., Nagel (2012)). If the liquidity is supplied by swap dealers at financial intermediaries that are classified as commercials by the CFTC, variation in the VIX can be expected to affect liquidity provision in commodity futures markets through this channel. But to the extent that liquidity provision takes place via the trading departments of large commodity producers, as was suggested by our DCOT results in Section II.C, the premium for liquidity provision is expected to be more sensitive to measures of commodity-specific risk than to financial sector risks. We predict that commercials will be more reluctant to engage in "selective hedging" activity and provide liquidity to the non-commercials when the risk for a specific commodity becomes high.

CKX (2015) document that during the recent financial crisis, financial traders experienced a reduction in risk appetite. This caused speculators to cut down their risky positions in commodity futures, which was facilitated by hedgers reducing their net short positions accordingly. They report a contemporaneous correlation between changes in the VIX, trader positions, and commodity futures returns.[16] Our primary focus is on the question of how variation in the risk environment affects the premium commercials charge for liquidity provision. In Panel A of Table IX, we include an interactive dummy to measure the incremental return impact of a position change when the VIX is above the sample median. The coefficient of the interactive VIX dummy is insignificant, implying that conditioning on the VIX does not affect the predictive power of position changes, both at week $t$+1 and week $t$+2 horizons.

To construct a measure of commodity-specific risk, we calculate implied volatilities from options traded on the corresponding commodity futures. Specifically, for each commodity and each day we calculate the implied volatilities for all closest to expiration options with delta values between 0.375 and 0.5 for calls and delta values between -0.5 and -0.375 for puts. We average these implied volatilities to construct a daily implied volatility measure $ComVol_i$ for each commodity.[17] To match the weekly frequency of our returns and positions data, we use Tuesday's implied volatility as our measure of commodity specific risk in week $t$. Next, we define an interactive dummy variable that is equal to one if $ComVol_{i,t}$ is above its full sample median in week $t$. Our hypothesis is that when the volatility for a specific commodity is expected to be high,

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[16] The Internet Appendix Table IA.III shows that if we include the *contemporaneous* change in the VIX in our return regressions, we replicate the significantly negative coefficient reported in CKX (2015). Including changes in the VIX does not change the power of position changes ($Q$) or smoothed hedging pressure ($\overline{HP}$) to predict returns. Moreover, changes in the VIX by itself do not *predict* futures returns.

[17] We construct implied volatilities for the 22 commodities that have options traded on the corresponding futures. The commodities in our sample that do not have options data are platinum, palladium, and Minneapolis wheat. Lean hogs start option trading after 1996. Therefore, we exclude these four commodities from the implied volatility analysis.

commercials will be more reluctant to provide liquidity to non-commercials, leading to an increase of the return impact of a position change for that commodity.

Panel A of Table IX shows that in contrast to measures of financial market risk, commodity-specific risks matter in a way that makes economic sense. The coefficient of the interactive dummy variable on own commodity volatility is positive and significant in regressions of both week $t+1$ and $t+2$. The estimated dummy coefficients are similar in magnitude to the coefficient on $Q_{i,t}$ itself, which indicates that the return impact of a position change roughly doubles when the commodity's volatility is expected to be high (above its median). When we include both the interactive VIX and *ComVol* dummies in our regression, we find that it is the variation in commodity-specific volatility instead of the VIX that matters for the return impact of position changes.

In summary we find no evidence that the liquidity provision behavior of commercial traders is affected by the VIX which is often used as an indicator of financial market risk. Instead, the price of liquidity provision varies with commodity-specific volatility. This suggests that the commercials who provide liquidity are not financial intermediaries but instead traders who have positions in physical markets and use commodity futures to manage their underlying risk exposure.

### *B. Liquidity versus Private Information*

An alternative explanation for why position changes predict futures returns is that the commercial traders exploit private information about the fundamentals of commodity markets. This informational advantage could be the by-product of their activities in the underlying physical commodities markets, which allows them access to information about fundamentals that are not easily observed by non-commercial investors. In this section we present several additional pieces of empirical evidence that favor our interpretation of liquidity provision.

The first is the direction of trading by the commercials in the week prior to the positions report. In the quintile sorts of Table V we documented that the portfolio of commodities in the quintile that is bought most heavily by the commercials on average underperforms those in the quintile that are sold most heavily by them by 6.91% during the two weeks prior to the positions report. This is followed by a partial reversal of 0.64% during the next 40 trading days, leaving (on net) a permanent component to the price change of 6.27%. If the commercial traders possessed private information about the diverging fundamental values of these commodities, we expect the commodity price to change in the same direction as their trading: the price of commodities purchased by the commercials (quintile 5) should simultaneously increase, and the commodities sold by them (quintile 1) should witness a contemporaneous price drop. Instead, we find that the commercials are selling winners and buying losers during the week prior to the report, which is hard to reconcile with private information, but consistent with liquidity provision.[18]

Next, we ask under what circumstances is the cost of liquidity expected to be relatively high? We adopt tests from the market microstructure literature to our context, and label them loosely as the presence of capital loss or order imbalance.

*Capital Loss*: Recent theoretical models suggest that a deterioration of the wealth or the collateral base of market makers can hinder their ability and willingness to provide liquidity.[19] By analogy, when the commercials suffer losses on their futures positions, they have to finance these losses by posting additional collateral. As a result, their willingness to provide liquidity could be

[18] Kaniel, Saar, and Titman (2008) find a similar trading pattern for individual investors in U.S. stock market: the stock price decreases (increases) when individual investors buy (sell). They argue that this observation is opposite to what the private information hypothesis would imply, and is consistent with the hypothesis that individual investors provide liquidity to the stock market (see their page 298). Vayanos and Wang (2012) argue that if an investor's position change co-moves negatively (positively) with prices changes, she provides (consumes) liquidity. Hence, the negative contemporaneous relationship between the position change of the commercial traders and the futures returns documented in Tables II and V indicates that they are liquidity providers.

[19] See Xiong (2001), Kyle and Xiong (2001), Vayanos (2004), and Brunnermeier and Pedersen (2009).

negatively impacted, and the non-commercials would need to offer a larger price concession to persuade the risk-averse commercial traders to absorb their demand for immediacy.[20]

*Order imbalance*: Excess order imbalance can increase the market maker's inventory concern and reduce liquidity in the stock market (e.g., Chordia, Roll, and Subrahmanyam (2002)). In the context of our study, when non-commercials trade in the same direction over several consecutive weeks, the commercials will be pushed further away from their desired hedging positions. As a consequence, they will become less willing to absorb additional trades in that direction going forward, and non-commercials will have to pay a higher price for their liquidity consumption.

In summary, it is our hypothesis that the futures return predictability based on position changes should be stronger following a capital loss for commercials or following weeks during which non-commercials repeatedly trade in the same direction. We test for these hypotheses by constructing interactive dummies that take on the value of 1 when we predict the cost of liquidity to be high: following large losses by the commercial traders, or when the commercials' positions have changed in the same directions in the prior four weeks. The control variables are defined in the same way as equation (5).

The coefficient estimates in Panel B of Table IX show that, consistent with our predictions, the coefficients on the dummy variables are significantly positive in each of these two scenarios. The first specification shows that following large losses of the commercials, the cost of liquidity consumption for non-commercials significantly increases. The regression coefficients indicate that a typical net purchase by the commercials, equal to 3.39% of the open interest, would result in an

[20] Commercial traders face a more binding funding constraint in this scenario even if the loss on their futures hedging positions can be matched by a gain on the value of their physical output. This is because there is a cash flow mismatch – commercial traders need to provide additional capital in a timely manner to meet the marginal calls once they suffer large loss on their futures positions, while the corresponding gains on their physical commodity positions are usually unrealized at this moment.

expected price increase of 8.2 basis points in the next week. But in weeks following a large capital loss of commercials, the return impact of this same position change almost doubles to 15.6 basis points. This finding is consistent with liquidity provision but harder to reconcile with private information. A large loss suggests that the quality of private information signals received by the commercial traders is low, and it is unclear why they can earn higher returns when their private information becomes less precise.

In the second specification, the coefficients for $Q$ and the order imbalance interaction dummy are similar in magnitude. This suggests that the return impact of a position adjustment approximately doubles when net positions of the commercial traders have changed in the same direction in each of the prior four weeks.[21]

In brief, these empirical results support our hypotheses regarding liquidity provision by the commercial traders and are more difficult to reconcile with the private information hypothesis.

## V. Why Do Commercials Provide Liquidity to Momentum Traders?

We have shown that non-commercial position changes are positively correlated with contemporaneous and past futures returns, and that commercials trade as contrarians. If momentum and trend-following strategies are profitable, why are commercial traders willing to take the opposite sides of these trades? For liquidity provision to make sense, the benefits to commercial traders have to exceed their losses to momentum traders. In this section we decompose net position changes into a momentum and an orthogonal component and trace the profitability of these

[21] In the right half of Panel B of Table IX, we report the coefficient estimates of the regression in which we use the futures return in week $t$+2 ($R_{i,t+2}$) as the dependent variable. We find similar results, except that the interactive item based on the capital loss dummy becomes insignificant. This suggests that the collateral-constraint effect on the commercial traders' willingness to provide liquidity last for about one week on the commodity futures markets.

components over time. Next, we estimate a decomposition of the profits of commercial traders and compare their losses to momentum traders to the benefits of liquidity provision.

*A. The Momentum Component of Position Changes*

Momentum trading by non-commercials can take many forms, depending on the exact signal of past performance that each trader employs. Using the most recent week's return $R_{i,t-1}$ as a proxy for the *innovation* to each trader's momentum signal for commodity *i*, we estimate the momentum component of weekly position changes as the fitted value of the following panel regression:

$$Q_{i,t} = a + \varphi \times R_{i,t-1} + e_{i,t}. \qquad (6)$$

We define the momentum portion of trading $Q_{MOM,i,t} = \varphi \times R_{i,t-1}$ as the component of non-commercial position changes that is correlated with past returns, and the non-momentum portion $Q_{nonMOM,i,t} = a + e_{i,t}$ as the component of position changes that is orthogonal to past returns. The R-squared from regression (6) is 4.70%, which implies that the two components of position changes are not equally important. By far the largest fraction of the variation in position changes is unrelated to momentum. To separate the return impact of momentum and non-momentum position changes we modify our benchmark Fama-MacBeth regression as follows:

$$R_{i,t+j} = b_0 + b_1 Q_{nonMOM,i,t} + b_2 Q_{MOM,i,t} + b_3 \overline{HP}_{i,t} + controls + \varepsilon_{i,t+j} \quad j = 1,2 \qquad (7)$$

Table X shows that the overall return impact of momentum and non-momentum trades is quite different. In week *t*+1, the coefficient $b_1$ on $Q_{nonMOM}$ is -6.00 (*t*-stat = -7.08), illustrating the previously documented price impact of trades. By contrast, the coefficient $b_2$ on $Q_{MOM,i,t}$ is insignificantly different from zero, which suggests that the positive contribution of momentum is offset by the negative liquidity cost of a momentum trade. In the second week (*t*+2) the return impact of the non-momentum trade becomes smaller but remains statistically significant, while the point estimate of the momentum component becomes (insignificantly) positive.

We conduct extensive robustness checks on our return decomposition framework, including how different lag structures and controls in the decomposition regression (6) affect the estimated return impact of $Q_{nonMOM}$ and $Q_{MOM}$ in equation (7). The results are summarized in Internet Appendix Tables IA.IV – IA.VI. We find that our conclusions about the differential return impact of momentum versus non-momentum trades are robust across various decomposition specifications and estimation procedures.[22]

To trace the differential return impact of the components of position changes over time, we regress the future cumulative return ($CR$) up to 26 weeks following a position change on $Q_{nonMOM,i,t}$ and $Q_{MOM,i,t}$:

$$CR_{i,t+n} = b_0 + b_{1,n}Q_{nonMOM,i,t} + b_{2,n}Q_{MOM,i,t} + b_{3,n}\overline{HP}_{i,t} + controls + \varepsilon_{i,t+n} \quad (8)$$

The coefficient estimates of $b_{1,1}, b_{1,2}, \dots \dots, b_{1,26}$ and $b_{2,1}, b_{2,2}, \dots \dots, b_{2,26}$ are plotted in Figure 3. It shows that the average cumulative return to non-momentum trades is negative immediately following a trade but then levels off as the price impact subsides. The cumulative return to the momentum component of position changes fluctuates around zero during the first 5-6 weeks but becomes positive over time as the profitability of momentum overtakes the losses associated with liquidity consumption by non-commercials.

[22] We check the robustness of our decomposition of $Q$ into $Q_{nonMOM}$ and $Q_{MOM}$ by regressing $Q_{i,t}$ on additional lagged weekly returns. More specifically, we run the panel regression $Q_{i,t} = a + \sum_{j=1}^{n}\varphi_j R_{i,t-j} + e_{i,t}$, with $n$ = 4, 13, 26, and 52 weeks. We find that the R-squared estimates from these decomposition regressions are similarly low, being 5.24%, 6.32%, 6.49%, and 6.58%, respectively. The corresponding regression coefficients estimates of (9) are presented in the Internet Appendix Table IA.IV. The coefficient $b_1$ on $Q_{nonMOM,i,t}$ is significantly negative across all the $Q_{MOM}/Q_{nonMOM}$ definitions. Internet Appendix Table IA.V gives the results when we use a rolling window to estimate the panel regression in equation (6), when we include additional control variables into equation (6), and the results based on a block bootstrap process. Internet Appendix Table IA.VI repeats these robustness tests when we use a time-series methodology to decompose $Q$.

From Table X and Figure 3, a clearer picture emerges about the benefits to commercial traders from meeting the short-term liquidity demands by non-commercials. Commercials gain from providing liquidity to non-momentum related trading. They eventually lose to the component of positions that is momentum related and held sufficiently long. But given that non-momentum trading is the largest component of short-term position changes, it is likely that it makes overall economic sense for commercials to engage in liquidity provision. In the next section we will make a direct attempt to answer this question by decomposing the profits and losses of commercial traders.

*B. A Profit Decomposition for Commercial Traders*

Our analysis thus far has distinguished between three motives influencing the positions of commercial and non-commercial traders: (i) hedging demand, as approximated by the slow-moving component of hedging pressure, (ii) short-term liquidity provision to noncommercial traders, and (iii) momentum strategies followed by a subset of non-commercial traders. We also have shown that each of these is associated with a return premium: a hedging premium earned by non-commercials linked to hedging pressure, a liquidity provision premium earned by commercials for meeting the short-term trading demands of non-commercials, and a premium earned by non-commercials on the momentum component of their trading. In this section, we estimate a decomposition of the total profit (or loss) of the commercial and non-commercial traders to gauge the relative contribution of each of these three components.

We denote $np_{i,t}$ as a trader's net long position for commodity *i* in week *t*, scaled by open interest in week *t*. As in Section III, we approximate the component of this position that stems from "hedging" motives (denoted as $\overline{np}_{i,t}$) by the average of a trader's net long position from week

$t$−51 to $t$ scaled by the open interest in week $t$. We assume that the deviation of the actual position $np_{\mathrm{i,t}}$ from the smoothed position $\overline{np}_{\mathrm{i,t}}$, that is, $Dnp_{\mathrm{i,t}} = np_{\mathrm{i,t}} - \overline{np}_{\mathrm{i,t}}$, can be attributed to the cumulative effect of past momentum trading or liquidity trading over the previous 52 weeks. We decompose $Dnp_{\mathrm{i,t}}$ by estimating the following panel regression: $Dnp_{\mathrm{i,t}} = \mathrm{a} + \sum_{j=1}^{52} b_j R_{i,t-j} + \varepsilon_{\mathrm{i,t}}$. We define the fitted value $Mnp_{i,t} = \sum_{j=1}^{52} b_j R_{i,t-j}$ as the momentum driven component, and $Lnp_{i,t} = \mathrm{a} + \varepsilon_{\mathrm{i,t}}$ as the liquidity driven component of the deviation of net positions from their smoothed moving average.

In order to translate the decomposition of positions into a decomposition of profits, we can write a trader's profit (standardized by the dollar open interest) in commodity $i$ in week $t$+1 as $\mathrm{Profit}_{\mathrm{i,t+1}} = np_{\mathrm{i,t}} \cdot R_{\mathrm{i,t+1}}$, where $R_{\mathrm{i,t+1}}$ is the futures return in week $t$+1. Substituting in the components of $np_{\mathrm{i,t}}$, the profit in commodity $i$ can be written as the sum of the following three components:

$$\begin{aligned}\mathrm{Profit}_{\mathrm{i,t+1}} &= np_{\mathrm{i,t}} \cdot R_{\mathrm{i,t+1}} = \left(\overline{np}_{i,t} + Mnp_{i,t} + Lnp_{i,t}\right) \cdot R_{\mathrm{i,t+1}} \\ &= \overline{np}_{i,t} \cdot R_{\mathrm{i,t+1}} + Mnp_{i,t} \cdot R_{\mathrm{i,t+1}} + Lnp_{i,t} \cdot R_{\mathrm{i,t+1}} \\ &= \text{“Hedging Demand”} + \text{“Momentum Trading”} + \text{“Liquidity Provision”}\end{aligned}$$

The first component measures the profit or loss from the low-frequency component of positions, which can be thought of as the result of hedging demand; the second component measures the profit from the cumulative effect of past momentum trading, and the final term measures the profits of the component of positions deviations that are not momentum driven, and hence can be attributed to liquidity provision.

Once we obtain the total payoff and its three components described above at the weekly horizon, we compute the time-series average of profits in each commodity for the three trader types. We then divide the profits by the average absolute value of the commercial net positions to construct a measure of percentage gain and loss from the perspective of commercial traders. This illustrates how gains and losses of commercials result in offsetting payoffs to the positions of other futures market participants (because aggregate positions in futures markets add up to zero). We report the cross-sectional means of these commodity-level percentage gains and losses in Table XI.

The table paints an interesting picture of the risk transfers that take place in commodity futures markets. Over the full sample period (Panel A), commercials lose on average 4.71% per anum on the notional value of their positions because their "hedging" positions are on average short in most commodity futures markets and the sample average risk premium on futures has been positive. Not surprisingly, most of the premium accrues to the large non-commercial traders (3.70%) that are net long. In the process of providing liquidity, commercials lose on average to momentum traders (−1.86%), but these losses are relatively small in comparison to the gains from the non-momentum component of liquidity provision (5.27%). This is in line with our finding that momentum trading accounts for a relatively small fraction of short-term position changes. Consistent with rational charging for liquidity by commercials, the overall profit from providing liquidity to short-term trading demands of others is positive (5.27% − 1.86% = 3.41%). And the commercial profits from supplying liquidity provide an important offset to the losses (−4.71%) from hedging pressure. Panel B provides the decomposition when we exclude the recent financial crisis period from 2008/9/15 (the collapse of Lehman Brothers) to 2009/06/30. The results are qualitatively similar, although the commercial losses to momentum traders are somewhat smaller because the profitability of momentum trading increased during the crisis. The results of an analogous profit decomposition based on the DCOT data is available in Internet Appendix Table IA.VII Excluding the financial crisis, the DCOT analysis confirms that the gains to producers from liquidity provision more than compensate for losses to momentum trading and partially offset their losses associated with hedging demand.

The decomposition can also shed new light on the long standing debate in the commodity futures literature whether non-commercial market participants earn a positive return from their speculative activities ((Rockwell (1967), Chang(1985) and Hartzmark (1987)). Our analysis suggests that the low profitability of non-commercials is the result of two opposite effects: the benefit of accommodating commercial hedging demands is largely balanced by the liquidity cost associated with frequent short-term position changes.

## VI. Robustness Tests

We present two final robustness checks on our results. The first asks whether commodity futures returns can be forecasted using only their own past position changes as predictors. This discussion parallels the distinction between cross-sectional momentum and time-series momentum. Next, we examine the stability of our return prediction in major and minor commodities.

### *A. Time-series Return Predictability*

In our interpretation of the cross-sectional regressions and portfolio sorts we link the return of a commodity to its own past position change. As emphasized by Lo and MacKinlay (1990) and Lewellen (2002) it is possible that cross-sectional predictability is driven by the serial covariances with position changes in other commodities instead. To investigate this issue, we (i) directly estimate time-series regressions for individual commodities and (ii) analyze the returns of portfolios formed on cross-sectional and time-series sorts of past position changes.

We run individual commodity time-series return-prediction regressions of next-week futures returns on position changes and the same set of control variables as in equation (5). Panel A of Table XII reports the summary statistics (e.g., mean, median, etc.) for the coefficient estimates averaged across the 26 commodities. There is strong evidence of time-series predictability: in the next week regressions the average slope coefficient is 3.95 (*t*-stat = 4.30) for commercial position changes, and −4.70 (*t*-stat = −4.58) for the non-commercial traders.[23] Time-series predictability persists in week *t*+2, albeit somewhat weaker.

To address whether the cross-sectional predictability is driven by time-series predictability we follow Moskowitz, Ooi, and Pederson (2012) and construct two liquidity provision portfolios based on cross-sectional predictability (XSLIQ) and time-series predictability (TSLIQ). For XSLIQ we choose portfolio weights $w_{i,t}^{XS} = \frac{1}{N}(Q_{i,t}^{Com} - Q_{A,t}^{Com})$, where $Q_{i,t}^{Com}$ is the commercial's net position change in week *t* and $Q_{A,t}^{Com}$ is the average of $Q_{i,t}^{Com}$ across all our sample commodities in week *t*. Intuitively, XSLIQ takes long (short) positions in commodities that are bought (sold) by commercials in proportion to their trading activity in each commodity (i.e., the absolute value of $w_{i,t}^{XS}$). The profit from this strategy can be written as $R_{t+1}^{XSLIQ} = \sum_{i=1}^{N} w_{i,t}^{XS} R_{i,t+1}$, and captures the benefits from liquidity provision received by commercials.

We denote $\mu_Q = [\mu_{Q,1}, \mu_{Q,2}, \dots, \mu_{Q,N}]'$ where $\mu_{Q,i} = E[Q_{i,t}^{Com}]$, and $\mu_R = [\mu_{R,1}, \mu_{R,2}, \dots, \mu_{R,N}]'$ where $\mu_{R,i} = E[R_{i,t+1}]$. If we further define $\Omega = \mathrm{E}[(Q_t - \mu_Q)(R_{t+1} - \mu_R)']$, where $Q_t = [Q_{1,t}^{Com}, Q_{2,t}^{Com}, \dots, Q_{N,t}^{Com}]'$ and $R_{t+1} = [R_{1,t+1}, R_{2,t+1}, \dots, R_{N,t+1}]'$, the expected profit of the cross-sectional strategy portfolio can be written as:

$$E\left[R_{t+1}^{XSLIQ}\right] = \frac{tr(\Omega)}{N} - \frac{1^T\Omega 1}{N^2} + cov\left(\mu_Q, \mu_R\right) = \frac{(N-1)tr(\Omega)}{N^2} - \frac{(1^T\Omega 1 - tr(\Omega))}{N^2} + cov\left(\mu_Q, \mu_R\right) \quad (9)$$

where $cov(\mu_Q, \mu_R)$ is the cross-sectional covariance of $\mu_{R,i}$ and $\mu_{Q,i}$, and *tr*(.) denotes the trace of

[23] Moreover, 80.8% (88.5%) of our sample commodities have positive (negative) coefficient estimates for the position change of commercials (non-commercials).

a matrix.

Equation (9) decomposes the expected cross-sectional strategy return (XSLIQ) into three components: (i) an “auto” component that captures the covariance between a commodity’s position changes and its next-week futures return, (ii) a “cross” component that captures how position changes in one commodity affect next-week returns for other commodities, and (iii) a “mean-level” effect variable that captures the cross-sectional covariance of unconditional means of $Q_t$ and $R_{t+1}$, across commodities. Aside from a time series (auto) component, the return to XSLIQ can also result from a negative cross component when positive (commercial) position changes in one commodity are followed by lower subsequent returns in other commodities (cross) or when high return commodities also have high average net position changes (mean-level).

For the construction of the time-series portfolio we establish a long position in commodity *i* at the end of week *t* when $Q_{i,t}^{Com}$ is positive and a short position when $Q_{i,t}^{Com}$ is negative, sizing the position in proportion to the magnitude of $Q_{i,t}^{Com}$. We define the profit of TSLIQ strategy as the average of the time-series portfolio returns across all commodities, with the weight of each commodity (i.e., $w_{i,t}^{TS}$) equal to $\frac{1}{N} Q_{i,t}^{Com}$. The expected profit of the time-series strategy portfolio can be decomposed as:

$$E\left[R_{t+1}^{TSLIQ}\right] = \frac{tr(\Omega)}{N} + \frac{\mu_Q^T \mu_R}{N} \tag{10}$$

and has two components: (i) an “auto” component that represents the covariance between a commodity's position change and its next-week futures return; and (ii) a “mean-square” effect that is the product of the means of the net position changes and the futures returns. We divide the total profit of the XSLIQ and TSLIQ strategies by the average portfolio size (the sum of the absolute value of $w_{i,t}^{XS}$ or $w_{i,t}^{TS}$), to obtain the percentage portfolio returns. Panel B of Table XII shows that the sample average returns of the XSLIQ and TSLIQ portfolios are significantly positive: 0.18%

($t$-stat = 5.90) and 0.21% ($t$-stat = 5.50) per week respectively. The correlation between the returns of the two strategies is 0.80, indicative of a large common component to their profitability. More importantly, the return decomposition of XSLIQ and TSLIQ shows that the profitability of both strategies is almost entirely driven by the "auto" component of returns. The cross-sectional and time-series portfolio decomposition results are consistent with our liquidity provision interpretation, whereby position changes in a commodity influence its own subsequent return.

*B. Major and Minor Commodities*

Do our results hold in the subsample of "major" commodities or are they primarily driven by the subset of commodities that have a relatively small number of reporting traders or commodities with relatively small open interest? In Table XIII, we report results where we sort our sample commodities into two equal-half subsample groups based on the average number of traders or the open interest as reported in the COT database. When sorting on the number of traders we find that the price impact of a trade is quantitatively similar for major and minor commodities in the first week, but becomes smaller and insignificant for the major commodities in week $t$+2. When we sort commodities by average open interest, the week $t+2$ return predictability remains intact for major commodities, and the difference between the two groups largely disappears. Whether liquidity effects are inversely related to measures of market size, therefore, depends on the precise definition of market importance.

To further quantify these price effects, consider the average absolute position change $Q$ for the commercial traders in the major (3.13%) and minor (3.72%) subsamples that are defined by the number of traders. A typical commercial purchase would result in an expected price increase of 19.2 basis points (bp) in week $t$+1 and 17.4 bp in week $t$+2 for minor commodities, and a price increase of 15.0 bp in week $t$+1 and 6.3 bp in week $t$+2 for major commodities. For subsamples defined by open interest, the corresponding price effects would be 15.2 bp ($t$+1) and 11.4 ($t$+2) for minor commodities, and 16.3 bp ($t$+1) and 13.8 bp ($t$+2) for major commodities.

## VII. Conclusions

We document that non-commercial traders, who are often viewed as speculators in commodity futures markets, demand short-term liquidity from their commercial counterparts. For this liquidity provision, non-commercial traders pay a premium which manifests itself through the subsequent relative underperformance of the commodities they buy and outperformance of the commodities they sell. We show that the cost for non-commercials to obtain liquidity increases when the volatility for a commodity is expected to be high, when commercials face more binding capital constraints, or when commercial positions become more imbalanced.

Our study shows that commodity futures prices embed two premiums related to positions: one associated with low-frequency changes in hedging pressure, and one linked to short-term position changes initiated by non-commercials. The opposite signs of these two premiums can explain why previous empirical tests of the theory of normal backwardation often fail to find an influence of hedging pressure on risk premiums without controlling for liquidity provision. It can also explain why prior research has documented that the profits from speculative activity have been low.

The premium for liquidity provision helps to explain why commercials willingly take the opposite side of profitable momentum trading by non-commercials. We find that commercials incur losses to the component of non-commercial trading that is momentum related, but more than make up for these losses by earning a liquidity premium from the large fraction of short-term trading that is orthogonal to momentum. The overall benefits of liquidity provision allow commercials to recapture a large portion of the premium paid to non-commercials for obtaining price insurance in commodity markets. The paper provides an empirical example of how directional trading by a large subset of market participants lowers the expected returns earned by them.

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Figure 1: Hedging Pressure of Oil, Copper, Wheat, and Coffee

The figure shows the time series of weekly hedging pressure for oil, copper, wheat, and coffee over the period from 1994/01/02 to 2017/12/31. The hedging pressure is defined as the net short position of commercial traders divided by total open interest.

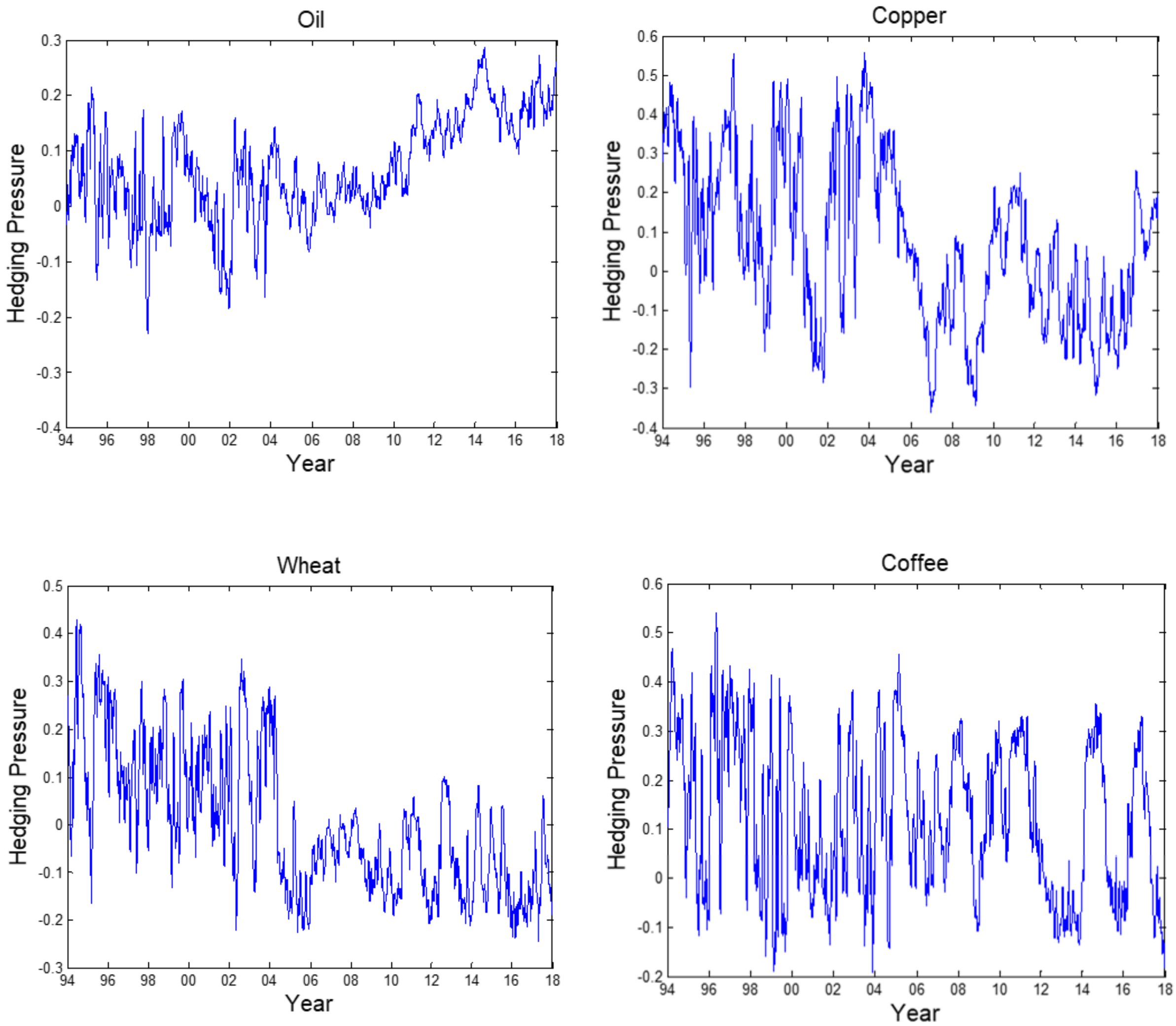

Figure 2: Average Futures Excess Returns and Average Hedging Pressure

The figure provides a scatter plot of the average futures excess return and average hedging pressure for the 26 sample commodities between 1994 and 2017. The cross-sectional regression line has a slope coefficient of 0.27 with *t*-statistic of 2.89 and an $R^2$ of 26%.

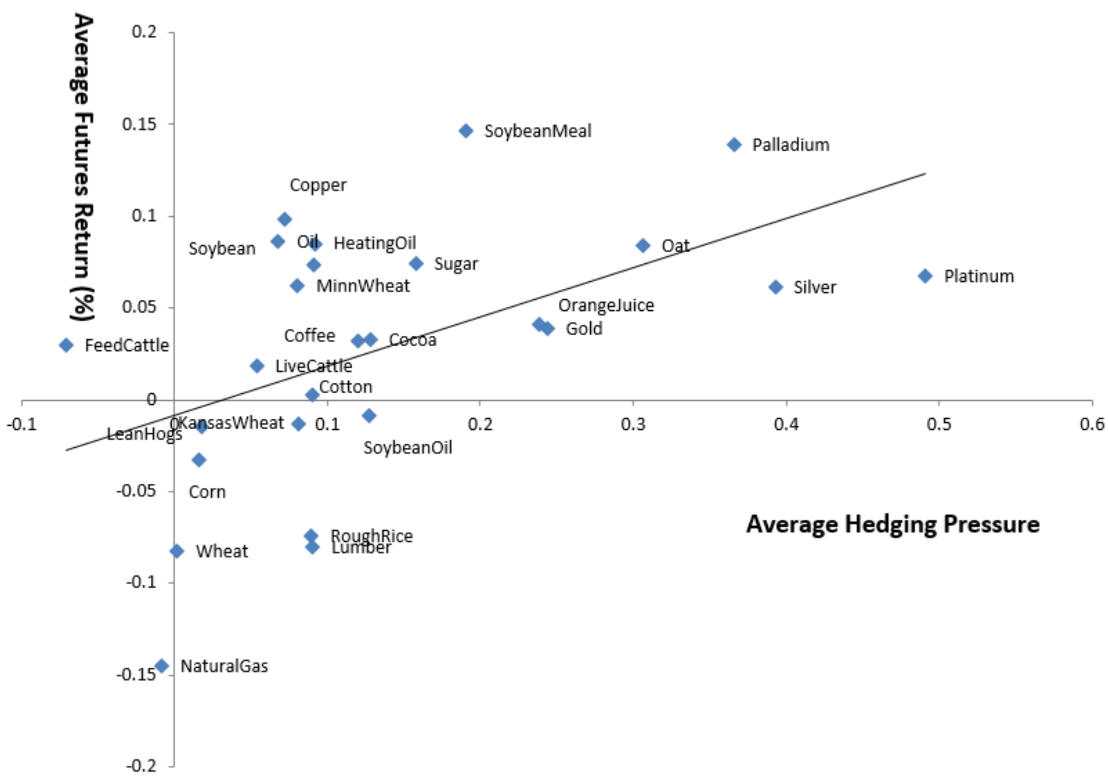

Figure 3: Cumulative Return Impact of Liquidity- and Momentum-driven Position Changes

The figure plots the slope coefficients $b_{1,\mathrm{n}}$ and $b_{2,\mathrm{n}}$ estimated from the following panel regression to measure the return impact of position changes of non-commercial traders:

$$CumulR_{i,t+n} = b_0 + b_{1,n}Q_{nonMOM,i,t} + b_{2,n}Q_{MOM,i,t} + b_{3,\mathrm{n}}\overline{HP}_{i,t} + controls + \varepsilon_{i,t+\mathrm{n}}$$

with n ∈ {1, … … ,26}. $CumulR_{i,t+n}$ is the cumulative return of commodity *i* from week *t*+1 to *t*+n. $Q_{nonMOM,i,t}$ is the component of non-commercial position changes in week *t* that is orthogonal to the futures return in week *t*-1 (i.e., the liquidity-driven position change), and $Q_{MOM,i,t}$ is the component of non-commercial position changes in week *t* that is correlated to the futures return in week *t*-1 (i.e., the momentum-driven position change).

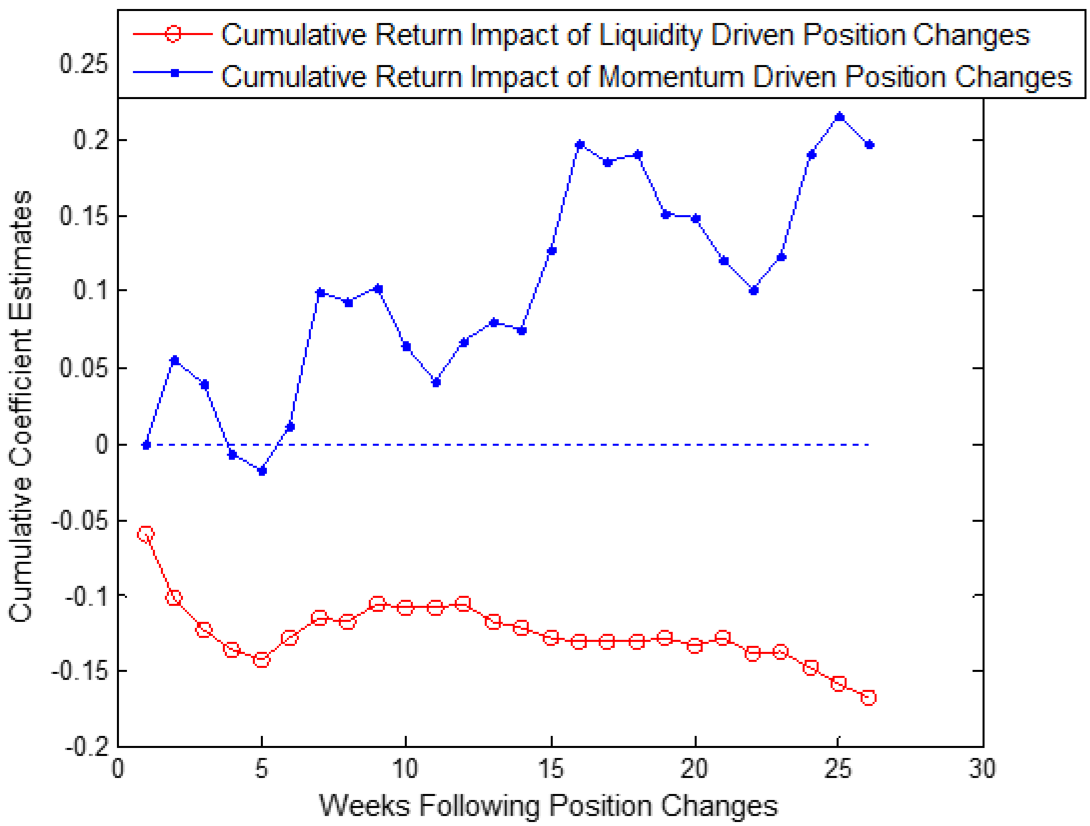

Table I
Summary Statistics

The table provides summary statistics of the commodity futures price data and positions data obtained from weekly CFTC Commitment of Traders (COT) report between January 1994 and December 2017. In Panel A we report the summary statistics of the commodity futures excess return and hedging pressure. The excess return in week *t* is defined as: $R_{i,t} = (F_i(t,T) - F_i(t-1,T))/F_i(t-1,T)$, where $T$ denotes the maturity of the front-month futures contract for commodity *i*. Hedging pressure, *HP* for commodity *i*, is defined as the net short (short minus long) position of commercial traders in commodity futures contracts divided by total open interest, i.e., $HP_{i,t} = (CS_{i,t} - CL_{i,t})/OI_{i,t}$. The probability of short hedging pressure, Prob(HP>0), is defined as the fraction of weeks when commercial traders hold net short positions for a given commodity.

In Panel B we report the description of the commercial and non-commercial traders' net trading measures and their propensity to trade measures. We define the net trading measure *Q* as the weekly change of the net long position normalized by open interest, that is, $Q_{i,t} = (net\ long\ position_{i,t} - net\ long\ position_{i,t-1})\ /\ OpenInterest_{i,t-1}$. We then report the time-series average of the *absolute value* of the trading measure for the commercial and non-commercial traders. We also examine the difference of the propensity of adjusting portfolio positions between the non-commercial and commercial traders. We denote NCL, NCS, CL, and CS as the size of the non-commercials' long position, the non-commercials' short position, the commercials' long position, and the commercials' short position respectively, and then define the propensity to trade as $PT_{i,t}^{COM} = \frac{abs(CL_{i,t} - CL_{i,t-1}) + abs(CS_{i,t} - CS_{i,t-1})}{CL_{i,t-1} + CS_{i,t-1}}$ and $PT_{i,t}^{nonCOM} = \frac{abs(NCL_{i,t} - NCL_{i,t-1}) + abs(NCS_{i,t} - NCS_{i,t-1})}{NCL_{i,t-1} + NCS_{i,t-1}}$. The *t*-statistic for the difference between the non-commercial and commercial traders' propensity-to-trade is calculated by using Newey-West standard errors with four lags.

Panel A: Summary Statistics of the Excess Return and Hedging Pressure

| Commodity | Annualized Excess Return (in %) | | Hedging Pressure (*HP*)% | | |
|---|---|---|---|---|---|
| | Mean | Standard Deviation | Mean | Standard Deviation | Prob (HP > 0) |
| Oil | 8.65 | 33.44 | 6.78 | 9.26 | 77.14 |
| Heating Oil | 8.51 | 31.49 | 9.19 | 8.87 | 83.69 |
| Natural Gas | -14.50 | 45.57 | -0.83 | 11.64 | 46.52 |
| Platinum | 6.72 | 21.85 | 49.11 | 22.47 | 95.92 |
| Palladium | 13.88 | 33.69 | 36.57 | 32.78 | 80.90 |
| Silver | 6.16 | 28.51 | 39.29 | 16.48 | 100.00 |
| Copper | 9.80 | 24.51 | 7.20 | 21.06 | 60.43 |
| Gold | 3.86 | 16.24 | 24.38 | 26.91 | 79.70 |
| Wheat | -8.27 | 28.70 | 0.17 | 14.53 | 43.88 |
| KC Wheat | -1.32 | 27.41 | 8.13 | 13.78 | 70.50 |
| Minn Wheat | 6.21 | 26.15 | 8.06 | 12.35 | 72.82 |
| Corn | -3.24 | 26.41 | 1.63 | 12.91 | 55.32 |
| Oat | 8.37 | 33.68 | 30.63 | 18.11 | 93.45 |
| Soybean | 7.36 | 23.07 | 9.08 | 16.35 | 70.10 |
| Soybean Oil | -0.84 | 23.32 | 12.69 | 17.03 | 73.14 |
| Soybean Meal | 14.67 | 26.85 | 19.07 | 14.86 | 85.61 |
| Rough Rice | -7.40 | 25.47 | 8.93 | 23.92 | 63.47 |
| Cotton | 0.23 | 28.43 | 9.06 | 22.24 | 65.55 |
| Orange Juice | 4.08 | 32.51 | 23.89 | 23.35 | 83.85 |
| Lumber | -8.02 | 31.01 | 9.05 | 20.01 | 63.71 |
| Cocoa | 3.26 | 29.59 | 12.80 | 16.64 | 74.66 |
| Sugar | 7.45 | 31.78 | 15.78 | 17.71 | 77.62 |
| Coffee | 3.21 | 37.38 | 12.04 | 15.68 | 70.02 |
| Lean Hogs | -1.48 | 25.63 | 1.77 | 13.24 | 57.79 |
| Live Cattle | 1.82 | 15.71 | 5.37 | 10.98 | 64.99 |
| Feeder Cattle | 2.96 | 15.08 | -7.08 | 10.59 | 25.98 |
| Average | 2.77 | 27.83 | 13.57 | 17.07 | 70.65 |

Panel B: Summary Statistics of the Commercials and Non-Commercials' Trading Measures and their Propensity to Trade Measures

| Commodity | Average Absolute Value of Net Position Change ($\|Q\|$) % | | Average Propensity to Trade *(PT)* % | | | |
|---|---|---|---|---|---|---|
| | Commer-cials | Non-Commercials | Commer-cials | Non-Commercials | Difference | (*t-stat*) |
| Oil | 1.72 | 1.42 | 3.20 | 6.07 | 2.87 | 11.49 |
| Heating Oil | 2.49 | 1.81 | 4.18 | 9.24 | 5.06 | 14.37 |
| Natural Gas | 1.62 | 1.38 | 3.69 | 6.80 | 3.11 | 8.90 |
| Platinum | 5.94 | 5.19 | 7.15 | 10.46 | 3.31 | 10.66 |
| Palladium | 4.42 | 3.60 | 5.91 | 9.56 | 3.65 | 7.05 |
| Silver | 3.68 | 3.43 | 5.49 | 7.09 | 1.61 | 10.11 |
| Copper | 3.97 | 3.23 | 5.39 | 9.95 | 4.57 | 15.31 |
| Gold | 4.93 | 4.09 | 5.97 | 7.98 | 2.01 | 9.28 |
| Wheat | 3.03 | 2.67 | 4.95 | 6.59 | 1.64 | 11.01 |
| KC Wheat | 2.83 | 2.37 | 4.61 | 9.29 | 4.69 | 12.66 |
| Minn Wheat | 2.83 | 2.18 | 5.61 | 15.93 | 10.31 | 8.29 |
| Corn | 2.37 | 2.24 | 3.51 | 6.22 | 2.71 | 17.37 |
| Oat | 4.02 | 2.98 | 6.35 | 12.02 | 5.67 | 17.46 |
| Soybean | 2.78 | 2.62 | 4.48 | 6.88 | 2.40 | 18.13 |
| Soybean Oil | 3.89 | 3.02 | 5.01 | 7.78 | 2.77 | 15.11 |
| Soybean Meal | 3.45 | 2.68 | 4.59 | 8.08 | 3.49 | 17.79 |
| Rough Rice | 3.75 | 2.86 | 5.93 | 10.96 | 5.03 | 11.54 |
| Cotton | 4.42 | 3.81 | 5.02 | 9.20 | 4.18 | 15.03 |
| Orange Juice | 4.86 | 4.06 | 6.06 | 10.17 | 4.11 | 17.32 |
| Lumber | 4.56 | 4.46 | 12.94 | 12.20 | -0.73 | -1.79 |
| Cocoa | 2.77 | 2.42 | 3.40 | 8.33 | 4.94 | 17.38 |
| Sugar | 3.62 | 2.60 | 4.31 | 9.09 | 4.78 | 12.06 |
| Coffee | 3.79 | 3.42 | 4.94 | 9.19 | 4.25 | 16.15 |
| Lean Hogs | 2.54 | 2.69 | 4.84 | 7.49 | 2.65 | 13.02 |
| Live Cattle | 1.79 | 2.17 | 3.22 | 5.93 | 2.70 | 18.44 |
| Feeder Cattle | 2.11 | 3.09 | 7.04 | 8.54 | 1.50 | 6.59 |
| Average | 3.39 | 2.94 | 5.30 | 8.89 | 3.59 | 12.72 |

Table II

Weekly Position Changes, and Contemporaneous and Lagged Returns

The table reports the average slope coefficients and R-squared of weekly Fama-MacBeth cross-sectional regressions of the net position change (scaled by open interest) $Q_{i,t}$ in week *t*, on an intercept, the contemporaneous futures excess return ($R_{i,t}$) or the lagged return ($R_{i,t-1}$) and the lagged position change ($Q_{i,t-1}$). Separate regressions are run for each of three trader types using CFTC COT classifications: commercials, non-commercials and others (non-reportables). The *t*-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

| | Commercials | | Non-Commercials | | Non-Reportables | |
|---|---|---|---|---|---|---|
| $R_{i,t}$ | -0.65 | | 0.52 | | 0.13 | |
| | (*-37.87*) | | (*36.07*) | | (*20.55*) | |
| $R_{i,t-1}$ | | -0.21 | | 0.23 | | 0.02 |
| | | (*-18.47*) | | (*22.05*) | | (*4.11*) |
| $Q_{i,t-1}$ | | 0.18 | | 0.16 | | -0.02 |
| | | (*19.16*) | | (*17.38*) | | (*-2.54*) |
| $R^2$ | 24.44% | 17.79% | 20.97% | 17.94% | 10.19% | 12.96% |

## Table III
## Return Predictability Following Position Changes: Regression Approach

The table reports the average slope coefficients and R-squared of weekly Fama-MacBeth cross-sectional regressions of the commodity futures excess return in weeks $t$+1 (Panel A) and $t$+2 (Panel B) on an intercept, the net position change (scaled by open interest) $Q_{i,t}$ in week $t$, both with and without a set of controls for expected returns. The controls are the log futures basis ($B_{i,t}$), excess return in week $t$ ($R_{i,t}$), and $S_{i,t}\hat{v}_{i,t}$ where $v$ is the annualized standard deviation of the residuals from a rolling 52-week regression of futures excess returns on SP500 returns and $S$ is an indicator variable that is 1 when the non-commercials are net long and -1 when the non-commercials are net short. Separate regressions are run for each of three trader types using CFTC COT classifications: commercials, non-commercials, and non-reportables. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

Panel A: Dependent Variable: $R_{i,t+1}$

| Coefficient Estimates (×100) | Commercials | | Non-Commercials | | Non-Reportables | |
|---|---|---|---|---|---|---|
| $Q_{i,t}$ | 3.07 | 4.59 | -3.84 | -5.24 | -1.35 | -2.33 |
| | (*4.95*) | (*6.60*) | (*-5.98*) | (*-7.30*) | (*-0.91*) | (*-1.57*) |
| $B_{i,t}$ | | -0.47 | | -0.47 | | -0.48 |
| | | (*-2.71*) | | (*-2.72*) | | (*-2.73*) |
| $S_{i,t}\hat{v}_{i,t}$ | | -0.05 | | -0.02 | | -0.04 |
| | | (*-0.41*) | | (*-0.14*) | | (*-0.39*) |
| $R_{i,t}$ | | 4.51 | | 4.45 | | 2.14 |
| | | (*4.34*) | | (*4.33*) | | (*2.29*) |
| $R^2$ | 4.82% | 25.40% | 4.59% | 25.28% | 4.24% | 25.03% |

Panel B: Dependent Variable: $R_{i,t+2}$

| Coefficient Estimates (×100) | Commercials | | Non-Commercials | | Non-Reportables | |
|---|---|---|---|---|---|---|
| $Q_{i,t}$ | 2.11 | 3.08 | -2.44 | -3.49 | -2.39 | -1.06 |
| | (*3.43*) | (*4.31*) | (*-3.65*) | (*-4.37*) | (*-1.55*) | (*-0.67*) |
| $B_{i,t}$ | | -0.28 | | -0.28 | | -0.32 |
| | | (*-1.63*) | | (*-1.62*) | | (*-1.85*) |
| $S_{i,t}\hat{v}_{i,t}$ | | -0.06 | | -0.06 | | -0.05 |
| | | (*-0.51*) | | (*-0.50*) | | (*-0.42*) |
| $R_{i,t}$ | | 1.98 | | 1.57 | | -0.13 |
| | | (*1.83*) | | (*1.47*) | | (*-0.14*) |
| $R^2$ | 4.98% | 25.02% | 4.85% | 24.94% | 4.48% | 24.77% |

Table IV

Weekly Return Predictability Following Position Changes: DCOT Dataset

The table reports the average slope coefficients of weekly Fama-MacBeth cross-sectional regressions of the futures excess return in week $t$+1 (Panel A) and week $t$+2 (Panel B) on an intercept, the net position change (scaled by open interest) $Q_{i,t}$ in week $t$, with the same set of control variables as in Table III. Separate regressions are run for each of the trader category based on the CFTC DCOT classifications: producers/merchant/processor/user, money managers, swap dealers, other reportables, and non-reportables. The sample period is from June 2007 to December 2017. The table reports the time-series average of slope coefficients and R-squared estimate from the weekly cross-sectional regression. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

Panel A: Dependent Variable: $R_{i,t+1}$

| Coefficient Estimates (×100) | Producer | Money Manager | Swap Dealer | Other Reportable | Non-Reportable |
|---|---|---|---|---|---|
| $Q_{i,t}$ | 8.14 | -6.19 | -3.32 | -0.97 | -2.20 |
| | (*6.18*) | (*-4.39*) | (*-1.20*) | (*-0.40*) | (*-0.77*) |
| $B_{i,t}$ | -0.65 | -0.73 | -0.73 | -0.69 | -0.71 |
| | (*-2.36*) | (*-2.62*) | (*-2.65*) | (*-2.49*) | (*-2.54*) |
| $S_{i,t}\hat{v}_{i,t}$ | -0.06 | -0.11 | -0.09 | -0.09 | -0.09 |
| | (*-0.30*) | (*-0.57*) | (*-0.50*) | (*-0.47*) | (*-0.50*) |
| $R_{i,t}$ | 4.51 | 4.17 | 1.13 | 1.36 | 1.63 |
| | (*2.98*) | (*2.61*) | (*0.82*) | (*0.97*) | (*1.17*) |
| $R^2$ | 25.39% | 25.40% | 24.21% | 24.45% | 24.45% |

Panel B: Dependent Variable: $R_{i,t+2}$

| Coefficient Estimates (×100) | Producer | Money Manager | Swap Dealer | Other Reportable | Non-Reportable |
|---|---|---|---|---|---|
| $Q_{i,t}$ | 4.93 | -4.89 | -3.55 | 4.18 | -0.11 |
| | (*3.77*) | (*-3.41*) | (*-1.33*) | (*1.65*) | (*-0.03*) |
| $B_{i,t}$ | -0.52 | -0.50 | -0.46 | -0.50 | -0.50 |
| | (*-1.84*) | (*-1.82*) | (*-1.69*) | (*-1.79*) | (*-1.79*) |
| $S_{i,t}\hat{v}_{i,t}$ | -0.13 | -0.12 | -0.14 | -0.16 | -0.12 |
| | (*-0.66*) | (*-0.63*) | (*-0.77*) | (*-0.82*) | (*-0.62*) |
| $R_{i,t}$ | 2.03 | 1.91 | -0.68 | 0.02 | -0.98 |
| | (*1.36*) | (*1.22*) | (*-0.51*) | (*0.01*) | (*-0.74*) |
| $R^2$ | 24.41% | 24.20% | 23.35% | 23.98% | 23.82% |

Table V

Return Predictability Following Position Changes: Portfolio Sorting Approach

On Tuesday of each week, commodities are ranked based on the change in the net position of commercial traders, *Q*. We sort commodities into five "quintile" portfolios containing 5, 5, 6, 5, 5 commodities each, respectively. The table reports the average futures excess returns (Panel A) and average position changes (Panel B) of the commercial traders (normalized by the open interest on the day of ranking) on the quintile portfolios during the 10 trading days prior to ranking and the 40 trading days following the ranking. Because the CFTC measures positions on Tuesdays but publishes the positions after the market close on Friday, we separately calculate the post ranking excess returns for days 1-4 and days 5-40. The *t*-statistics for the difference in the means of the top and bottom quintiles are in parentheses, adjusted using the Newey-West method using four lags.

Panel A: Average Excess Returns (in %)

| | -10 to 0 days | 1-4 days | 5-10 days | 11-20 days | 21-40 days | 1-40 days |
|---|---|---|---|---|---|---|
| Portfolio 1 (smallest Q) | 3.72 | -0.05 | -0.09 | 0.08 | 0.44 | 0.37 |
| Portfolio 2 | 1.59 | 0.02 | 0.00 | 0.05 | 0.16 | 0.24 |
| Portfolio 3 | 0.02 | 0.07 | 0.07 | 0.15 | 0.14 | 0.42 |
| Portfolio 4 | -1.51 | 0.15 | 0.07 | 0.14 | 0.15 | 0.50 |
| Portfolio5 (largest Q) | -3.19 | 0.19 | 0.20 | 0.27 | 0.34 | 1.01 |
| Portfolio 5 − Portfolio 1 | -6.91 | 0.24 | 0.29 | 0.19 | -0.10 | 0.64 |
| (*t*-stat) | | *(3.65)* | *(3.73)* | *(1.68)* | *(-0.58)* | *(2.64)* |

Panel B: Average Position Changes of the Commercial Traders (in %)

| | -2 to 0 weeks | 1 week | 2 week | 3-4 weeks | 5-8 weeks | 1-8 weeks |
|---|---|---|---|---|---|---|
| Portfolio 1 (smallest Q) | -7.72 | -1.55 | -0.22 | 0.51 | 0.82 | -0.44 |
| Portfolio 2 | -2.38 | -0.54 | -0.22 | 0.08 | 0.15 | -0.53 |
| Portfolio 3 | 0.19 | -0.04 | -0.03 | -0.03 | 0.00 | -0.10 |
| Portfolio 4 | 2.54 | 0.48 | 0.05 | -0.43 | -0.50 | -0.39 |
| Portfolio5 (largest Q) | 7.54 | 1.40 | 0.06 | -0.86 | -1.67 | -1.07 |
| Portfolio 5 − Portfolio 1 | 15.26 | 2.95 | 0.28 | -1.37 | -2.49 | -0.63 |
| (*t*-stat) | | *(26.86)* | *(2.63)* | *(-7.46)* | *(-8.38)* | *(-1.70)* |

Table VI
Return Predictability, Smoothed Hedging Pressure, and Position Changes

The table reports the average slope coefficients and R-squared of weekly Fama-MacBeth cross-sectional regressions of the futures excess return ($R_{i,t+j}$) in week $t+j$ ($j$=1,2) on an intercept, lagged hedging pressure $HP_{i,t}$, lagged smoothed hedging pressure $\overline{HP}_{i,t}$, lagged net position changes of commercials $Q_{i,t}$ and the same set of control variables as defined in Table III. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

| Coefficient Estimates (×100) | Dependent Variable: $R_{i,t+1}$ | | | Dependent Variable: $R_{i,t+2}$ | | |
|---|---|---|---|---|---|---|
| $HP_{i,t}$ | -0.09 | | | 0.14 | | |
| | (*-0.61*) | | | (*0.96*) | | |
| $\overline{HP}_{i,t}$ | | 0.52 | 0.47 | | 0.53 | 0.45 |
| | | (*3.50*) | (*2.90*) | | (*3.67*) | (*2.96*) |
| $Q_{i,t}$ | | | 4.75 | | | 2.45 |
| | | | (*6.39*) | | | (*3.72*) |
| Controls | yes | yes | yes | yes | yes | yes |
| $R^2$ | 25.84% | 25.68% | 29.78% | 25.41% | 25.20% | 29.46% |

Table VII
Hedging Pressure and Liquidity Provision: DCOT Data

The table examines the impact of hedging pressure and weekly position changes for risk premiums comparing two different measures of hedging pressure. The first is based on net commercial positions from the Commitment of Traders (COT) Report the second is based on the net positions of traders in the producers/merchant/processor/user category as reported in the Disaggregate Commitment of Traders (DCOT) Report. The sample period is from June 2007 to December 2017. The table reports the time-series average of slope coefficients and R-square of weekly Fama-MacBeth cross-sectional regressions of the futures excess return in week *t*+1 (Panel A) and week *t*+2 (Panel B) on an intercept, lagged smoothed hedging pressure ($\overline{HP}_{i,t}$), and lagged net position changes ($Q_{i,t}$) of the producers/merchant/processor/user category, with and without a set of control variables as defined in Table III. The *t*-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

Panel A: Dependent Variable: $R_{i,t+1}$

| Coefficient Estimates (×100) | DCOT data without controls | DCOT data with controls | COT data without controls | COT data with controls |
|---|---|---|---|---|
| $\overline{HP}_{i,t}$ | 0.64 | 0.48 | 0.57 | 0.50 |
| | (*2.55*) | (*1.73*) | (*2.43*) | (*1.86*) |
| $Q_{i,t}$ | 5.16 | 8.07 | 4.58 | 6.68 |
| | (*4.21*) | (*5.89*) | (*3.59*) | (*4.90*) |
| Controls | no | yes | no | yes |
| $R^2$ | 10.23% | 29.67% | 10.89% | 29.68% |

Panel B: Dependent Variable: $R_{i,t+2}$

| Coefficient Estimates (×100) | DCOT data without controls | DCOT data with controls | COT data without controls | COT data with controls |
|---|---|---|---|---|
| $\overline{HP}_{i,t}$ | 0.71 | 0.57 | 0.57 | 0.38 |
| | (*2.75*) | (*2.13*) | (*2.62*) | (*1.63*) |
| $Q_{i,t}$ | 2.46 | 4.49 | 2.24 | 4.08 |
| | (*2.01*) | (*3.27*) | (*1.93*) | (*3.14*) |
| Controls | no | yes | no | yes |
| $R^2$ | 10.70% | 28.75% | 10.89% | 29.12% |

Table VIII
Returns and Position Changes of Double Sorted Portfolios
on Smoothed Hedging Pressure and Position Changes

This table studies commodity futures return predictability based on previous week's smoothed hedging pressure $\overline{HP}$ and the commercial traders' lagged position changes $Q$. At the end of each Tuesday, we split our 26 sample commodities into two groups of 13 based on their relative ranking on smoothed hedging pressure $\overline{HP}$. Within each group of 13, we then sort commodities based on the commercial traders' $Q$, assigning 6 to Low $Q$ and 7 to the High $Q$ cohort. Panel A reports the average futures excess returns on the double sorted portfolios, and Panel B reports the average position changes of the commercial traders (normalized by the open interest of the ranking day) in the days and weeks subsequent to the sorting. Since the CFTC measures positions on Tuesdays and publishes the positions after the market close on Friday, we separately calculate the average of the post ranking returns for days 1-4 and days 5-40. The $t$-statistics for the difference in the means of the top and bottom halves are adjusted using the Newey-West method using four lags.

Panel A: Average Excess Returns (in %)

| | Low $Q$ | High $Q$ | H – L $Q$ | $t$-stat |
|---|---|---|---|---|
| | *Days 1-4* | | | |
| Low $\overline{HP}$ | -0.10 | 0.10 | 0.21 | (*3.76*) |
| High $\overline{HP}$ | 0.05 | 0.22 | 0.17 | (*2.89*) |
| H – L $\overline{HP}$ | 0.16 | 0.12 | | |
| ($t$-statistics) | (*2.51*) | (*2.10*) | | |
| | *Days 5-20* | | | |
| Low $\overline{HP}$ | -0.11 | -0.06 | 0.05 | (*0.35*) |
| High $\overline{HP}$ | 0.20 | 0.69 | 0.49 | (*3.97*) |
| H – L $\overline{HP}$ | 0.31 | 0.76 | | |
| ($t$-statistics) | (*1.77*) | (*4.85*) | | |
| | *Days 21-40* | | | |
| Low $\overline{\mathrm{HP}}$ | -0.08 | -0.16 | -0.08 | (*-0.57*) |
| High $\overline{\mathrm{HP}}$ | 0.63 | 0.58 | -0.05 | (*-0.36*) |
| H – L $\overline{\mathrm{HP}}$ | 0.71 | 0.74 | | |
| ($t$-statistics) | (*3.68*) | (*3.68*) | | |
| | *Days 1-40* | | | |
| Low $\overline{HP}$ | -0.29 | -0.12 | 0.17 | (*0.83*) |
| High $\overline{HP}$ | 0.88 | 1.49 | 0.61 | (*3.16*) |
| H – L $\overline{HP}$ | 1.16 | 1.60 | | |
| ($t$-statistics) | (*3.57*) | (*5.15*) | | |

Panel B: Average Position Change of the Commercial Traders (in %)

| | Low $Q$ | High $Q$ | H – L $Q$ | *t*-stat |
|---|---|---|---|---|
| | *1 Week* | | | |
| Low $\overline{HP}$ | -0.89 | 0.35 | 1.24 | (*17.78*) |
| High $\overline{HP}$ | -0.86 | 0.96 | 1.82 | (*19.62*) |
| H – L $\overline{HP}$ | 0.03 | 0.61 | | |
| (*t*-statistics) | (*0.30*) | (*7.76*) | | |
| | *2-4 weeks* | | | |
| Low $\overline{HP}$ | -0.51 | -0.75 | -0.24 | (*-1.57*) |
| High $\overline{HP}$ | 0.74 | -0.22 | -0.96 | (*-5.10*) |
| H – L $\overline{HP}$ | 1.25 | 0.53 | | |
| (*t*-statistics) | (*5.26*) | (*2.62*) | | |
| | *5-8 weeks* | | | |
| Low $\overline{HP}$ | -0.16 | -1.19 | -1.03 | (*-5.90*) |
| High $\overline{HP}$ | 0.90 | -0.28 | -1.18 | (*-4.82*) |
| H – L $\overline{HP}$ | 1.06 | 0.91 | | |
| (*t*-statistics) | (*3.86*) | (*3.30*) | | |
| | *Week 1-8* | | | |
| Low $\overline{HP}$ | -1.56 | -1.59 | -0.03 | (*-0.11*) |
| High $\overline{HP}$ | 0.78 | 0.46 | -0.32 | (*-0.99*) |
| H – L $\overline{HP}$ | 2.34 | 2.05 | | |
| (*t*-statistics) | (*5.53*) | (*5.20*) | | |

## Table IX Factors Affecting Liquidity Provision

In Panel A, we measure the incremental return impact of a position change by defining dummy variables $D(VIX)_t$ and $D(ComVol)_{i,t}$ that take on the value 1 when either the VIX is above its full sample median, or when the implied volatility for an individual commodity is above its sample median in that week. In Panel B, we define a dummy variable $D(CLoss)_{i,t}$ that is equal to one when the losses (measured over the prior 4 weeks) of commercial positions in commodity *i* are above the sample median. $D(OIB)_{i,t}$ is one when the position changes of commercial traders for commodity *i* were in the same direction (buying or selling) in the prior four weeks from *t-3* to *t*. These interactive dummies are part of a predictive panel with include commodity fixed effects: $R_{i,t+1} = b_0 + b_1\overline{HP}_{i,t} + b_2 Q_{i,t} + b_3 Q_{i,t} D(\cdot)_t + controls + \varepsilon_{i,t+1}$ . Variables are defined in the same way as in Table VII. The *t*-statistics are adjusted by the Newey-West method with four lags.

Panel A: Liquidity Provision Conditional on VIX and Commodity Volatility

| Coefficient Estimates (×100) | Dependent Variable: $R_{i,t+1}$ | | | Dependent Variable: $R_{i,t+2}$ | | |
|---|---|---|---|---|---|---|
| $Q_{i,t}$ | 4.08 | 2.72 | 3.22 | 2.41 | 1.76 | 1.73 |
| | (*5.76*) | (*4.87*) | (*4.41*) | (*3.39*) | (*3.09*) | (*2.41*) |
| $Q_{i,t} \times D(VIX)_t$ | -0.73 | | -0.98 | 0.26 | | 0.05 |
| | (*-0.82*) | | (*-1.10*) | (*0.29*) | | (*0.06*) |
| $Q_{i,t} \times D(ComVol)_{i,t}$ | | 2.26 | 2.37 | | 1.88 | 1.87 |
| | | (*2.43*) | (*2.55*) | | (*2.05*) | (*2.04*) |
| $\overline{HP}_{i,t}$ | 0.44 | 0.42 | 0.42 | 0.41 | 0.40 | 0.40 |
| | (*2.28*) | (*2.20*) | (*2.19*) | (*2.17*) | (*2.10*) | (*2.10*) |
| Controls | yes | yes | yes | yes | yes | yes |
| $R^2$ | 0.29% | 0.34% | 0.34% | 0.23% | 0.24% | 0.24% |

Panel B: Capital Constraint and Order Imbalance Effects

| Coefficient Estimates (×100) | Dependent Variable: $R_{i,t+1}$ | | Dependent Variable: $R_{i,t+2}$ | |
|---|---|---|---|---|
| $Q_{i,t}$ | 2.42 | 2.83 | 2.12 | 1.90 |
| | (*4.22*) | (*5.72*) | (*3.45*) | (*3.56*) |
| $Q_{i,t} \times D(CLoss)_{i,t}$ | 2.17 | | 1.01 | |
| | (*2.49*) | | (*1.16*) | |
| $Q_{i,t} \times D(OIB)_{i,t}$ | | 2.49 | | 3.35 |
| | | (*2.29*) | | (*3.10*) |
| $\overline{HP}_{i,t}$ | 0.39 | 0.33 | 0.35 | 0.29 |
| | (*2.20*) | (*1.85*) | (*1.96*) | (*1.64*) |
| Controls | yes | yes | yes | yes |
| $R^2$ | 0.31% | 0.32% | 0.22% | 0.26% |

## Table X
## Returns Following Momentum-driven versus Non-Momentum Position Changes

We decompose the non-commercials' trading measure $Q$ into two components by running the panel regression $Q_{i,t} = a + \varphi \times R_{i,t-1} + e_{i,t}$. We define $Q_{MOM,i,t} = \varphi \times R_{i,t-1}$, as the component of non-commercials' position changes that can predicted by the past returns ($R_{i,t-1}$), and $Q_{nonMOM,i,t} = a + e_{i,t}$, as the component unrelated to past returns.

Next, we use these two components of position changes to predict next week futures returns. The table reports the average slope coefficients and R-squared of weekly Fama-MacBeth cross-sectional regressions of the futures excess return ($R_{i,t+j}$) in week $t+j$ ($j$=1,2) on an intercept, the two components of position changes, smoothed lagged hedging pressure $\overline{HP}_{i,t}$, and the same set of control variables as in Table III. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

| Coefficient Estimates (×100) | Dependent Variable: $R_{i,t+1}$ | Dependent Variable: $R_{i,t+2}$ |
|---|---|---|
| $Q_{nonMOM,i,t}$ | -6.00 | -4.13 |
| | (*-7.08*) | (*-4.94*) |
| $Q_{MOM,i,t}$ | -0.11 | 5.64 |
| | (*-0.03*) | (*1.54*) |
| $\boldsymbol{\overline{HP}_{i,t}}$ | 0.44 | 0.39 |
| | (*2.77*) | (*2.55*) |
| Controls | yes | yes |
| $R^2$ | 36.05% | 35.83% |

Table XI
Profit Attribution of Commercial Traders

In this table we decompose the profits and losses of commercial traders into three components: hedging demand, momentum trading, and liquidity provision. We first calculate "Hedging Demand" as the 52-week moving average of past net positions. The deviation between actual position and smoothed position is decomposed into a component that can be predicted based on past futures returns and a residual. The former is labeled as "Momentum Trading", and the latter is labelled as "Liquidity Provision". We multiply the position components described above by the next-week futures return to compute the corresponding profit components. We then take their time-series averages and divide them by the average absolute value of the commercial net positions to obtain an *percentage* annual profit measure from the perspective of the commercial traders. The column "Commercials" provides the average annual percentage profit to commercials averaged across all sample commodities. The next two columns provide a breakout of the offsetting gains and losses to the other traders (i.e., Non-Commercials and Non-Reportables). In Panel A, we decompose the profit or loss based on the entire available COT sample period from 1994/01/02 to 2017/12/31. In Panel B, we exclude the financial crisis period from 2008/9/15 (the collapse of Lehman Brothers) to 2009/06/30 (the economy bottom date by NBER) from our profit decomposition analysis.

Panel A: Profit decomposition based on the full sample COT data

| | Commercials | Non-Commercials | Non-Reportables |
|---|---|---|---|
| Hedging Demand | -4.71% | 3.70% | 1.01% |
| Momentum Trading | -1.86% | 1.71% | 0.15% |
| Liquidity Provision | 5.27% | -3.63% | -1.65% |
| Total Profit/Loss | -1.30% | 1.79% | -0.49% |

Panel B: Profit decomposition excluding the financial crisis

| | Commercials | Non-Commercials | Non-Reportables |
|---|---|---|---|
| Hedging Demand | -5.09% | 4.18% | 0.91% |
| Momentum Trading | -0.50% | 0.58% | -0.08% |
| Liquidity Provision | 4.63% | -3.14% | -1.50% |
| Total Profit/Loss | -0.96% | 1.62% | -0.66% |

Table XII
Time-Series Return Predictability

In Panel A we conduct time-series regressions in which, for each commodity, we regress the futures excess return ($R_{i,t+j}$) in week $t+j$ ($j$=1,2) on an intercept, the net position change (scaled by open interest) $Q_{i,t}$ in week $t$, and the same set of control variables as in Table III. We then report the cross-sectional mean and median for the coefficient estimates (multiplied by 100) obtained at the commodity-level time-series regressions described above. The $t$-statistics for the mean of the coefficient estimates are in parentheses. In Panel B we decompose the cross-sectional liquidity strategy return $R^{XSLIQ}$ and the time-series liquidity strategy return $R^{TSLIQ}$ into its various components, as proposed in Moskowitz, Ooi, and Pedersen (2012).

Panel A: Time-series Futures Return Prediction Regressions

| | | | | |
|---|---|---|---|---|
| Dependent Variable = $R_{i,t+1}$ | | | | |
| | Commercials | | | |
| | $Q_{i,t}$ | $B_{i,t}$ | $S_{i,t}\hat{v}_{i,t}$ | $R_{i,t}$ |
| Mean | 3.95 | -0.29 | -0.08 | 1.98 |
| (*t-statistics*) | *(4.30)* | *(-1.05)* | *(-0.77)* | *(2.51)* |
| Median | 3.63 | -0.09 | -0.06 | 2.52 |
| | Non-Commercials | | | |
| | $Q_{i,t}$ | $B_{i,t}$ | $S_{i,t}\hat{v}_{i,t}$ | $R_{i,t}$ |
| Mean | -4.70 | -0.28 | -0.06 | 1.74 |
| (*t-statistics*) | *(-4.58)* | *(-1.01)* | *(-0.62)* | *(2.41)* |
| Median | -3.63 | -0.12 | -0.02 | 2.39 |
| Dependent Variable = $R_{i,t+2}$ | | | | |
| | Commercials | | | |
| | $Q_{i,t}$ | $B_{i,t}$ | $S_{i,t}\hat{v}_{i,t}$ | $R_{i,t}$ |
| Mean | 1.94 | -0.41 | -0.06 | 1.01 |
| (*t-statistics*) | *(2.37)* | *(-1.46)* | *(-0.64)* | *(0.89)* |
| Median | 1.49 | -0.24 | -0.02 | 1.32 |
| | Non-Commercials | | | |
| | $Q_{i,t}$ | $B_{i,t}$ | $S_{i,t}\hat{v}_{i,t}$ | $R_{i,t}$ |
| Mean | -1.82 | -0.42 | -0.05 | 0.52 |
| (*t-statistics*) | *(-1.68)* | *(-1.48)* | *(-0.53)* | *(0.47)* |
| Median | -1.52 | -0.26 | -0.02 | 0.74 |

Panel B: Return Decompositions

| Cross-sectional strategy weekly return: $R^{XSLIQ}$ | | | |
|---|---|---|---|
| Auto | Cross | Mean level | Total |
| 0.21% | -0.02% | -0.00% | 0.18% |

| Time-series strategy weekly return: $R^{TSLIQ}$ | | |
|---|---|---|
| Auto | Mean Squared | Total |
| 0.21% | -0.00% | 0.21% |

Table XIII
Return Predictability: Major and Minor Commodities

In this table we conduct a Fama-MacBeth regression of commodity futures excess returns ($R_{i,t+j}$) in week $t+j$ ($j$=1,2) on an intercept, the net position change (scaled by open interest) $Q_{i,t}$ in week $t$, and the same set of control variables as in Table III, for the sub-sample of major and minor commodities separately. We divide the 26 sample commodities into two equal halves, according to the average Total Number of Traders or the average Open Interest, both of which are available from the COT database. We report the time-series average of the weekly cross-sectional regression coefficient estimates and the average R-squared for these two sub-samples. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with four lags.

| Coefficient Estimates (×100) | Major | | Minor | |
|---|---|---|---|---|
| | Commercials | Non-Commercials | Commercials | Non-Commercials |
| *Major and Minor Commodities Classified by Average Total Number of Traders* | | | | |
| Dependent Variable: $R_{i,t+1}$ | | | | |
| $Q_{i,t}$ | 4.79 | -4.92 | 5.16 | -5.44 |
| | (*3.77*) | (*-3.54*) | (*5.28*) | (*-5.31*) |
| *controls* | yes | yes | yes | yes |
| $R^2$ | 43.82% | 43.98% | 39.51% | 39.73% |
| Dependent Variable: $R_{i,t+2}$ | | | | |
| $Q_{i,t}$ | 2.02 | -2.28 | 4.68 | -5.23 |
| | (*1.55*) | (*-1.55*) | (*4.61*) | (*-4.85*) |
| *controls* | yes | Yes | yes | yes |
| $R^2$ | 42.93% | 42.92% | 40.08% | 40.01% |
| *Major and Minor Commodities Classified by Average Open Interest* | | | | |
| Dependent Variable: $R_{i,t+1}$ | | | | |
| $Q_{i,t}$ | 5.18 | -4.90 | 4.10 | -5.30 |
| | *(4.27)* | *(-3.55)* | *(3.95)* | *(-4.88)* |
| *controls* | yes | yes | yes | yes |
| $R^2$ | 44.50% | 44.41% | 39.65% | 39.56% |
| Dependent Variable: $R_{i,t+2}$ | | | | |
| $Q_{i,t}$ | 4.39 | -4.67 | 3.08 | -4.20 |
| | *(2.89)* | *(-2.88)* | *(3.02)* | *(-3.60)* |
| *controls* | yes | yes | yes | yes |
| $R^2$ | 44.82% | 44.65% | 39.25% | 39.20% |