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 commercial hedgers and non-commercial speculators 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 from 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.

Keywords: Commodity futures, liquidity provision, speculators, hedgers, theory of normal backwardation, momentum, hedging pressure, risk premium

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1. Introduction

An important question in the commodity futures literature concerns the influence of speculative activity on the functioning of 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, on their part non-commercial “speculators” constitute a heterogeneous group that includes among others 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] It seems unlikely that these investment styles simply originate from passively meeting the hedging demands of commercial market participants, as

[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.

would be required to fit the Keynesian story. Exploring the factors influencing commercial position changes that are unrelated to hedging demand is a central focus of our 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, as noted by Cheng, Kirilenko, and Xiong (CKX, 2015).[2] An alternative explanation, pursued in this paper, emphasizes the importance of considering motives to trade that are separate from insurance provision. We conjecture that much of the short-term net trading by non-commercials creates variation in observed hedging pressure that is not driven by commercial hedging demands. More importantly, this trading demands liquidity from their commercial counterparts, for which commercials receive compensation in the form of a risk premium that is opposite in sign to the premium associated with insurance demand.

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 follows Kaniel, Saar, and Titman (2008) by testing for the predictability of short-term returns

[2] We acknowledge these shortcomings of the CFTC classification, but follow the literature that often uses the terms hedgers and commercials as interchangeably. CKX (2015) contains a detailed discussion of the aggregation of the trader positions. In the end they conclude that their results are robust and also present in the COT and DCOT data.

following net position changes, and use the direction of this return predictability to infer who provides and who consumes liquidity in futures markets.[3] 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[4] that liquidity providers (i.e. commercials) trade as contrarians, while impatient traders (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 mon-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 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 emerges. This leads to another 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-commercials for obtaining price insurance and one premium paid by non-commercials to

[3] 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 leads to the liquidity provision by individual investors and 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.

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

commercial traders for accommodating their short-term liquidity needs.

To further support our liquidity provision hypothesis, we conduct a number of robustness checks. First, we find that the return impact of a given trade is larger and more persistent in "smaller" commodities. Second, using implied commodity volatility as a measure of stress, we document that the willingness of commercials to provide liquidity is lower and the return impact of a given position change is larger when the volatility of a commodity is expected to be high. Finally, following market microstructure literature, we link the willingness to provide liquidity to past capital losses and position imbalances on behalf of commercial traders.

Finally, we address the question why commercial traders provide liquidity to momentum traders, if momentum strategies are profitable? We show that while non-commercial position changes are positively correlated with (past) returns, a large fraction of their trading is orthogonal to momentum. Commercial traders overall benefit from liquidity provision to these trades, although they suffer intermediate-term losses to the component of trading that is momentum-induced. For liquidity provision to make economic sense to commercials, the gains from liquidity provision ought to outweigh the 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 cost of the liquidity demand for 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, while other studies have shown that commercial traders occasionally provide liquidity to non-commercial speculators, for example during the financial crisis (see CKX, 2015), we show that liquidity provision by commercials is an important aspect of the continuous (weekly) rebalancing of positions in commodity futures markets. More importantly, we estimate the premium that commercial hedgers earn from this activity and show that this premium is economically large. Second, we provide a new perspective on the question of why hedgers appear to trade so much: they are induced by the speculators' demand of immediacy and are compensated for providing liquidity to them on the short-term horizon. Third, we explain why previous studies often fail to find a strong correlation between hedging pressure and expected futures returns (see Rouwenhorst and Tang (2012)).[5] 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 insurance demand on future excess returns. Finally, we provide a decomposition of the profits of commercial hedgers and explain why they are willing to trade as contrarians considering that momentum trading by non-commercials is profitable.

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 return.[6] 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 2 summarizes our data and presents some stylized facts about the CFTC position reports and commodity futures returns. Section 3 presents our empirical findings on short-term futures return predictability based on liquidity provision by

[6] In option markets, several studies find that fluctuations in implied volatility reflect buying pressure (see Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009)). 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 (2013) suggest that investors' demand for leverage increases the relative price of high-beta stocks, thereby lowering their expected returns.

commercial market participants. Section 4 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. In Section 5 we estimate a decomposition of the profits and losses of commercial markets participants into components related to hedging, momentum, and liquidity provision. Additional supportive analysis is presented in Section 6, followed by our conclusions in Section 7.

2. Data and Summary Statistics

We use publicly available data provided by the CFTC to study the trading behavior of various types of participants in commodity futures markets. The weekly Commitment of Trader (COT) report details 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.

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 commercial futures market participation, but leaves open that certain aspects of their trading can be speculative in nature. Exploring 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.[7] In Section 6, we conduct a robustness

[7] For example, see Houthakker (1957), Rockwell (1967), Chang (1985), Bessembinder (1992), DeRoon et al. (2000), Moskowitz, Ooi, and Pederson (2012), Hong and Yogo (2012), Acharya, Lochstoer, and Ramadorai (2013).

check 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.[8]

Based on the CTFC data we construct three variables to characterize the position and trading behaviour of futures markets participants: hedging pressure (*HP*), net trading (*Q*), and the propensity to trade (*PT*). Hedging pressure (*HP*) is defined as the number of contracts that the commercial traders are short (*HS*) minus the number of contracts that they are long (*HL*), divided by open interest (*OI*), which is defined as the total number of contracts outstanding for commodity *i* in week *t*:

$$HP_{i,t} = \frac{HS_{i,t} - HL_{i,t}}{OI_{i,t}} = -\frac{hedgers\ netlong\ position_{i,t}}{OI_{i,t}} \qquad (1)$$

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

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

If open interest were constant, the trading measure for hedgers in commodity *i* 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.[9] For example, the propensity to trade for the commercials is calculated as:

[8] 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.

[9] 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 traders and can vary over time.

$$PT_{i,t} = \frac{abs(HL_{i,t} - HL_{i,t-1}) + abs(HS_{i,t} - HS_{i,t-1})}{HL_{i,t-1} + HS_{i,t-1}} \tag{3}$$

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 excess returns using the nearest-to-maturity (front-month) contract and roll positions on the 7^{th} calendar day of the maturity month into the next-to-maturity contract.[10] The excess return $R_{i,t}$ on commodity *i* in week *t* is calculated as:

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

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

Table 1 provides summary statistics for our return data and position measures for each of the 26 commodities listed in column 1. Columns 2 and 3 show that the average excess return has been positive in 18 out of 26 markets, and has averaged 2.77% per annum across commodities, with an average annualized standard deviation of 27.8%. Column 4 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 volatility of hedging pressure is illustrated in Figure 1, which provides time-series plots of hedging pressure for oil, copper, coffee, and wheat. Weekly changes in hedging pressure are closely linked to the absolute values of net position changes (Q) of the commercial and non-commercial traders, which

[10] If the 7^{th} is not a business day we use the next business day as our roll 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. For example, contracts in the SP-GSCI index are rolled from the fifth to ninth business day of each maturity month with 20% rolled during each day of the five-day roll period.

average as 3.39% and 2.94% of total open interest.[11] The final four columns of Table 1 depict the propensity to trade for both the commercials and non-commercials, which is analogous to the rate of portfolio turnover in the stock market. Columns 9 and 10 show that the propensity to trade is almost twice as high for the non-commercial traders (8.89% per week) as it is for the commercials (5.30% per week). Column 12 indicates 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. In 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 points towards short-term variation in hedging pressure that masks long-term predictability.

Second, there is large weekly variation in hedging pressure. 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 hedgers have to absorb the net short-term trading demands of speculators, changes in hedging pressure will not only reflect their demands for price insurance but also the demand for

[11] Changes in net positions (our trading measure *Q*) differs between hedgers (commercials) and speculators (non-commercials) by the change in the net non-reportable positions.
[12] Table 7 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.

immediacy by speculators to the extent that they follow investment styles that are independent of these hedging plans.

3. Liquidity Provision in Commodity Futures Markets

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

3.1 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 2 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. Non-commercials are momentum traders, while non-commercials trade as contrarians. The smaller traders in the non-reportable category act 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 et al. (2012) and Rouwenhorst and Tang (2012).

3.2 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]

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

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 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 3 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

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[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*.

impact subsequent returns, which suggests that the return predictability reflects a transfer between the reportable (large) players 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 return impact weakens in comparison to the first week. [16]

In both panels, the estimated return impact becomes larger when we include controls. Given that position changes embed a price momentum component (Table 2), by controlling for momentum we more precisely isolate the liquidity impact of position changes. We will return to the impact of momentum on the profitability of liquidity provision by commercials in more detail in Section 5.

3.3 Portfolio Sorts on Position Changes

As a complement to our regression analysis, we construct portfolios by sorting commodities according to past position changes, and compare their returns post-ranking. More precisely, at the end of Tuesday of each week, the measurement day of the CFTC positions report, we rank the 26 commodity futures in ascending order based on the prior-week change in the commercials' positions (i.e., their Q measure). 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

[16] We introduce sub-sample period tests in the Appendix Table A1. In Panel A of Table A1, we show that our main findings are robust in both the subsample period from 1994 to 2003 and that from 2004 to 2016, that is, before and after the financialization of the commodity futures markets (see Tang and Xiong (2012)). Panel B shows that the return-predicting capability of the commodity traders' position change holds for the subsample period both before and after the 2008 financial crisis. Including other price momentum control variables, such as the return from week t-51 to t-1, does not affect our basic conclusions.

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 4 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 (largest Q) earn on average 0.19%, which is in sharp comparison to -0.05% for commodities in the bottom quintile portfolio (smallest Q). The return difference of 0.24% is significantly different from zero (t-statistic = 3.65). The next columns shows 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 hedgers 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.

3.4 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 (negative serial covariance). 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). Table 5 reports the summary statistics (e.g., mean, median, etc.) for the coefficient estimates averaged across the 26 commodities.[17] 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. 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 et al. (2012) and construct two liquidity provision portfolios based on cross-sectional predictability (XSLIQ) and time 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. Given that a positive (negative) $Q_{i,t}^{Com}$ implies net purchase (sell) by the commercials, this strategy takes a long

[17] Moreover, 80.8% of our sample commodities have positive coefficient estimates for the commercials' position change, and 88.5% of our sample commodities have negative coefficient estimates for the non-commercials' position change. Detailed commodity-level coefficient estimates are available upon request.

position in commodities that are the most intensively bought by the commercials and a short position in commodities sold by them. The return from this strategy captures the liquidity provision compensation received by commercials, and can be written as $R_{t+1}^{XSLIQ} = \sum_{i=1}^{N} w_{i,t}^{XS} R_{i,t+1}$. Denoting μ_R and μ_Q the vectors of expected *t+1* commodity returns and average position changes and Ω is the covariance matrix of next week returns and current position changes, the expected return of the cross-sectional strategy portfolio can be written as:

$$E\left[R_{t+1}^{XSLIQ}\right] = \frac{tr(\Omega)}{N} - \frac{1^T \Omega 1}{N^2} + cov\left(\mu_Q, \mu_R\right) = \frac{(N-1)tr(\Omega)}{N^2} - \frac{(1^T \Omega 1 - tr(\Omega))}{N^2} + cov\left(\mu_Q, \mu_R\right) \quad (6)$$

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 a matrix.

Equation (6) decomposes the cross-sectional strategy returns into three components: (i) an “auto” component that captures the covariance between the position change the next-week commodity futures return for the same commodity, (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. The return to XSLIQ therefore has a time-series component (auto), but 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 or when high return commodities also have high average net position changes. This last component is expected to be small due to the stationarity of positions.

For the construction of the TSLIQ portfolio we choose the portfolio weight of each commodity to be $\frac{1}{N} Q_{i,t}^{Com}$.

The expected time-series strategy portfolio return can be decomposed as:

$$E\left[R_{t+1}^{TSLIQ}\right] = \frac{tr(\Omega)}{N} + \frac{u_Q^T u_R}{N} \tag{7}$$

The time-series strategy overall return is thus decomposed into two components: (i) an "auto" component that is common with the cross-sectional liquidity strategy; and (ii) a "mean-square" effect that is the average product of the means of the net position changes and the futures returns.

The sample average returns of the TSLIQ and XSLIQ portfolios are both significantly positive at 0.71% (*t*-stat = 5.90) and 0.61% (*t*-stat = 5.90) per week respectively. More importantly, the correlation between the two strategies is 0.80, indicative of a large common component to the profitability. Panel B of Table 5 summarizes the decomposition of the average returns and shows that the profitability of both strategies is primarily driven by the common "auto" component of the two portfolios. The large auto component is consistent with our liquidity provision interpretation, whereby trading demand for a commodity influences its subsequent return.

3.5 Major and minor commodities

Are our results driven by the subset of commodities that have a relatively small group of traders? In this section we sort our sample commodities into two equal-half subsample groups based on the average number of traders of a commodity as reported in the COT database. Table 6 documents cross-sectional predictability of returns in both subsamples. The price impact of a trade is quantitatively similar for major and minor commodities in the first week following the position change, but smaller for the major commodities in week 2. The overall two-week price impact for major commodities is therefore larger for the minor commodities, which is consistent with the premise that liquidity effects are inversely related to size.

To further quantify these price effects, consider the average absolute position change Q for the commercial traders in the major (3.12%) and minor (3.74%) commodity subsamples. A "typical" commercial purchase would therefore result in an expected price increase of 19.3 basis points (bp) in week *t+1* and 17.5 bp in week *t+2* for minor commodities, and a price increase of 14.9 bp in week *t+1* and 6.3 bp in week *t+2* for major commodities.

We also run time-series return-prediction regression analysis in the major- and minor-commodity subsamples. The results are in Appendix Table A2 and resemble the findings of our cross-sectional methodology that the compensation for the commercials' liquidity provision behavior is stronger and more persistent in the minor commodities.[18]

3.6 Summary of Liquidity Provision Results

Combining our empirical results regarding the short-term interaction between trading behavior and 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 short-term 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 their hedging demands, for which they are compensated in the form of a liquidity provision premium. This is consistent with microstructure models 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).

[18] We also use average trading volume and Open Interest as alternative ways to classify commodities as major and minor. We find similar results between high- and low-volume subsamples, that is, the profitability for the commercials' liquidity provision is larger in the low-volume commodity futures. Our finding that the liquidity-based futures return predictability is more prominent on the "small" commodities that are less traded is in analog with what the literature find on the stock market (e.g., Avramov, Chordia, and Goyal (2006)).

4. The Theory of Normal Backwardation Revisited

Liquidity provision to non-commercial traders creates short-term fluctuations in hedging pressure and represents a factor in the determination of futures prices that is separate from commercial hedging demands. 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 hedgers or from the demand for liquidity by speculators. In this section we attempt to separate these two effects.

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 7, we revisit our basic Fama-MacBeth regression framework for excess return predictability including measures of hedging pressure and short-term trading, while controlling for other sources of variation in risk premiums as in Table 3. 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*), 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* by $\overline{HP}$, which is calculated as a trailing 52-week moving average of hedging pressure.[19] 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 7 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 3.

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.

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[19] We have experimented with a variety of methods to smooth hedging pressure, including the application of a Hodrick-Prescott filter, and an orthogonal decomposition where Q was defined using deviations from smoothed hedging pressure Unreported results show that our findings are robust across methods, and not sensitive to the choice of the length of the moving average window.

In Panel A of Table 8, we provide 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 commercial buying activity, Q. 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. Our conjecture for this observation is that a 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 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 8 presents the trading measure (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 hedging positions from 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 make an important contribution to the empirical design of tests of the theory of normal backwardation. Our results highlight the importance of distinguishing between variation in the net position of the commercial traders that is driven by the insurance demands of hedgers (often called "hedging pressure"), and variation in net positions that reflects short-term "speculative pressure" induced by buying and selling 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 significantly predict risk premiums. Failing to distinguish between these two separate sources of variation renders the predictive power of hedging pressure for risk premiums to become insignificant.

5. Why Commercials Provide Liquidity to Momentum Traders.

We showed 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 the losses to momentum traders. In this section we decompose position changes into a momentum and orthogonal component and trace the profitability of these components of position changes over time. Next, we estimate a decomposition of commercial profits and compare the losses to momentum traders to the benefits of liquidity provision.

5.1 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:

$$Q_{i,t} = a + \varphi \times R_{i,t-1} + e_{i,t}. \quad (8)$$

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 these innovations to momentum signals.[20] The R-squared from regression (8) is 5.28%, 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.[21] To trace out the separate impact of momentum and non-momentum position changes we include them separately in out basis Fama-MacBeth regression:

$$R_{i,t+j} = b_0 + b_1 Q_{nonMOM,i,t} + b_2 Q_{MOM,i,t} + b_3 \overline{HP}_{i,t} + controls + \varepsilon_{i,t+1} \quad j = 1,2 \quad (9)$$

[20] We have tried the alternative decomposition specification of $Q_{MOM,i,t} = a + \varphi \times R_{i,t-1}$ and $Q_{nonMOM,i,t} = e_{i,t}$, and obtain similar results for our analysis in this section.

[21] We also conduct a robustness test, in which we decompose the trading measure Q into Q_{nonMOM} and Q_{MOM} by regressing $Q_{i,t}$ on the lagged returns over the previous four weeks. We find that the R-squared from this decomposition regression with additional lag returns is also low, being 5.76%. Hence, it suggests that our observation that the majority portion of non-commercial's trading is unrelated with past price momentum holds well for different trading measure decomposition specifications.

Table 9 shows that the return impact of momentum and non-momentum trades is quite different. In week 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 negative net price impact of a momentum trade is offset by the positive contribution of momentum. In the second week (*t+2*) the price impact of the non-momentum trade becomes smaller but remains statistically significant, while the point estimate of the momentum component becomes (insignificantly) positive.

To trace out 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 the $Q_{nonMOM,i,t}$ and $Q_{MOM,i,t}$:

$$CR_{i,t+n} = b_0 + b_{1,n}Q_{nonMOM,i,t} + b_{2,n}Q_{MOM,i,t} + b_{3,n}\overline{HP}_{i,t} + controls + \varepsilon_{i,t+n} \quad (10)$$

The coefficient estimates of $b_{1,1}, b_{1,2}, \ldots \ldots, b_{1,26}$ and $b_{2,1}, b_{2,2}, \ldots \ldots, b_{2,26}$ 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 stays flat during the first 5-6 weeks, but becomes positive over time as the continuation of momentum profits overtakes the losses associated with liquidity provision.

From Table 9 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 the non-momentum trading is the larger component of short-term position changes, it is likely that it makes overall economic sense for them to provide liquidity. In the next section we will attempt to make a direct attempt to decompose the profits and losses of commercial traders.

5.2 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 associated linked to hedging pressure, a liquidity provision premium earned by commercials for meeting the short-term trading demands of non-commercial, and a momentum premium earned by the component of short-term trading that is paid to non-commercials. 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.

As in section 4, we define the component of this position driven by "hedging" motives as the average of net long position of commercials from week $t-51$ to t, normalized by the open interest at time t, denoted by $\overline{np}_{\mathrm{i,t}}$. We assume that the deviation of the actual open-interest denominated position (denoted as $np_{\mathrm{i,t}}$) from the smoothed position $Dnp_{\mathrm{i,t}} = np_{\mathrm{i,t}} - \overline{np}_{\mathrm{i,t}}$ can be attributed to the cumulative effect of past momentum trading or to liquidity trading by non-commercials over the past 52 weeks. We decompose $Dnp_{\mathrm{i,t}}$ by estimating the following panel regression: $Dnp_{\mathrm{i,t}} = \mathrm{a} + \mathrm{b} \cdot \sum_{j=1}^{52} R_{\mathrm{i,t-j}} + \varepsilon_{\mathrm{i,t}}$. We define the fitted value $Mnp_{i,t} = \mathrm{b} \cdot \sum_{j=1}^{52} R_{\mathrm{i,t-j}}$ 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 the profits of a trader in commodity *i* in week *t+1* as $\text{Profit}_{\text{i,t+1}} = np_{\text{i,t}} \cdot OI_{\text{i,t}} \cdot P_{\text{i,t}} \cdot R_{\text{i,t+1}}$, where $OI_{\text{i,t}}$ is the open interest of commodity *i* in week *t*, $P_{\text{i,t}}$ is the nominal dollar value of each futures contract (= the commodity futures price in week *t* multiplied by the contract size), and $R_{\text{i,t+1}}$ is the futures return in week *t*+1. Substituting in the components of *np*, the profit in commodity *i* can be written as the sum of three components:

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

The first component measures the profits and losses 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.

We scale the profits in each commodity for each trader by the net position of commercial traders to construct a measure of % gains and losses from the perspective of commercials. By scaling the payoffs of all traders by the net position of commercials we illustrate how gains and losses of commercials result in offsetting payoffs on the positions of other the futures market participants (by virtue of the fact that for every long there is an offsetting short position). Once we obtain the total payoff and its components described above at the weekly horizon, we compute their time-series average for each commodity *i*, and report the mean of the cross-commodity averages in Table 10.

The table paints an interesting picture of the risk transfers that take place in commodity futures markets. Commercials lose about 4.71% on the notional value of their positions due to the fact that they 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 findings 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 profits from providing liquidity provide an important offset to the losses (−4.71%) due to hedging pressure. These results shed a new light on a long standing debate in the commodity futures literature, whether non-commercials market participants earn a positive return from their speculative activities (see Rouwenhorst and Tang (2012) and references therein). It appears that the benefits of accommodating commercial short positions are largely offset by the cost associated with frequent short-term position changes.

6. Further Perspectives on Liquidity Provision

6.1. Variation in the Risk Environment and Liquidity Provision

How is the liquidity provision behavior of commercials affected by 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)). To the extent that liquidity provision takes place via the trading departments of large commodity producers or their hedging departments, their liquidity provision behavior may be more sensitive to measures of commodity-specific risk than to financial sector risks.

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.[22] 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 11, 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, meaning that the VIX does not contribute to predicting the return impact of position changes, both at the week 1 and week 2 horizons.

In panel B we repeat our analysis using measures of commodity-specific risk factors, as measured by individual commodity implied volatility. In contrast to measures of financial market risk, commodity-specific risks matter in ways that make economic sense.[23] The interactive dummy on own commodity volatility is positive and significant in the *t+1* regressions and positive band marginally significant for predicting the return impact at in week *t+2*. The estimated dummy

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[22] Unreported results show that if we include the *contemporaneous* change in the VIX in our return regressions, we replicate the significantly negative coefficient reported in CKX but find that including changes in the VIX does not affect the significance of position changes or smoothed hedging pressure. Moreover, including changes in the VIX does not *predict* futures returns.

[23] We collect near the money call and put options prices with 1 to 2 months remaining to expiration, to compute the implied volatility for a given commodity. For each week, we take the average of the daily implied volatility for all the trading days in that week to obtain the weekly implied volatility for a given commodity. Similar to the VIX we create an interactive dummy that isolates the returns impact of a position change when implied volatility is above its sample median. We construct implied volatilities for the 22 commodities that have options traded on the corresponding futures. We take the average of the implied volatilities of the commodity futures options whose delta's absolute value is between 0.375 to 0.625. The commodities in our sample that do not have options data are platinum, palladium, and Minneapolis wheat. Lean hogs options start trading after 1996. Therefore, we exclude these four commodities from the implied volatility analysis.

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).

In sum 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. The price of liquidity provision instead varies with commodity-specific volatility. This is consistent with the central premise that commercials traders who provide liquidity need to manage their risk exposure to the underlying commodity market through their proprietary trading department or by adjusting their hedging positions related to their commercial operations.

6.2 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 is not easily observed by non-commercial investors. In this section we present several additional pieces of empirical evidence that favours 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 4 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.[24]

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.[25] 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 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.[26]

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

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[24] Kaniel, Saar, and Titman (2008) find 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, he provides (consumes) liquidity. Hence, the negative contemporaneous relationship between the position change of the commercial traders and the contemporaneous futures returns documented in Tables 2 and 4 indicates that they are liquidity providers.

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

[26] Hedgers 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 – hedgers 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.

context of our study, when speculators trade in the same direction over several consecutive weeks, the commercials will be pushed farther 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 hedgers, or following weeks during which speculators 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 11 show that, consistent with our predictions, the coefficients on the dummy variables are significantly positive in each of the three scenarios. The first specification shows that following large losses of the commercials, the cost of liquidity consumption for speculators significantly increases. The regression coefficients indicate that a typical net purchase by the commercials, which is equal to 3.39% of the open interest, would result in an expected price increase of 8.2 basis points in the next week. But in weeks following a large capital loss of hedgers, 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 b_1 and b_2 are similar in magnitude, which suggests that the return impact of a speculative position adjustment also about doubles when net positions of the commercial traders have changed in the same direction in each of the prior four weeks.[27]

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.

6.3 Insights from the DCOT Data.

Our analysis thus far has focused on the COT data from the CFTC. The advantage of this data is its long history, but the disadvantage is its high level of aggregation of positions of potentially potential dissimilar traders. The convention that has been widely used in the literature, is to designate the commercial traders (as defined by the COT reports) as hedgers and non-commercial traders as speculators. There are valid concerns about the accuracy of this classification.[28] First, the distinction between hedging and speculation is not clear. If for example, commercial "hedgers" use private information to selectively hedge, their positions can have a speculative as well as a hedging component. Second, misclassification can occur: an example 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 position of the end investor is speculative in nature.[29]

The Disaggregate Commitment of Trader (DCOT) data, which is published by CFTC since

[27] In the right half of Table 5, 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.
[28] See Houthakker (1957), Rockwell (1967), Chang (1985), Bessembinder (1992), DeRoon et al. (2000), Asness et al (2013).
[29] Cheng, Kirilenko and Xiong (2015) contains a detailed discussion of trader misclassification based on a comparison of CTFT reports to the LTRS database of trader positions that is maintained internally by the CFTC.

January 2006, provides a more detailed breakdown of trader categories. While the data history is relatively short, it offers an opportunity to more narrowly characterize 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, consists of market participants that are thought to have a clear hedging motive, whereas money managers are generally considered to be "speculators". 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.[30]

We use the producer's category to construct an alternative, more focused proxy for "hedging" pressure, and compute the net trading by (Q), and smoothed hedging pressure ($\overline{HP}$) as before. Hedging pressure (HP) and trading (Q) under the alternate (DCOT) definition of "hedgers" are highly correlated with their counterparts calculated using the COT data. For the period that the samples overlap, the average correlation is 0.79 for HP and 0.90 for Q respectively.

Table 12 reports the results of re-estimating the futures return prediction regression using the DCOT classifications. We obtain results that closely resemble our findings using the COT data (Table 7), when we established the presence of two premiums associated with position changes. The commodity futures that are heavily bought (sold) by producers, on average earn higher (lower) returns in the following week. And smoothed hedging pressure is positively related to future expected returns.

These findings confirm that producers are short-term liquidity providers. A natural follow-up question is which type of traders the producers primarily provide liquidity to? Since the DCOT

[30] Cheng, Kirilenko, and Xiong (2015) shows that their findings based on the DCOT data are similar to those based a more detailed, proprietary dataset of trader positions maintained internally by CFTC.

reports provide a more detailed breakdown of the speculative category, it allows us to more narrowly isolate the demand for liquidity. We estimate a Fama-MacBeth regression as described by equation (5) for each trader category, and provide the coefficient estimates in the Appendix Table A3. Inspecting the average slope coefficients for Q across various trader categories, we find that money managers, which include CTAs and hedge funds, stands out as the major consumer of liquidity, based on the size and statistical significance of their coefficient on position changes.[31] The DCOT data confirm our conclusions based on the COT data, and suggest that, at least in the most recent period since 2006, the liquidity provision channel primarily operates between money managers as consumers, and physical commodity market participants as suppliers of liquidity.[32]

7. Conclusion

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 relative underperformance of the commodities that are bought them following their trading, and outperformance of the commodities they sell. We show that the cost to non-commercials for obtaining liquidity increases when commercials face more binding capital constraints or when the volatility in commodity futures markets is expected to be high.

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

[31] The insignificance of the coefficient estimate on the swap dealers' Q measure suggests that they are unlikely to be the main liquidity consumers.

[32] We also conducted our analysis for the smaller set of commodities reported in the Commitment of Index Traders (CIT) report of the CFTC. Our previous finding that commercials (non-commercials) are providers (consumers) of liquidity remains robust in the CIT data, and there is no significant evidence about whether that index traders are providers or consumers of liquidity on the commodity futures market. Our finding regarding the impact of CIT index traders is consistent with Sanders and Irwin (2016).

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 potentially explain why prior research has documented that the profits from speculative activity have been low.

The presence of liquidity provision and its associated premium helps to explain the apparent puzzle why commercials willingly take the opposite side of 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 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.

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Figure 1: Hedging Pressure 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 2017/12/30. The hedging pressure is defined as the net short position of commercial traders divided by total open interest.

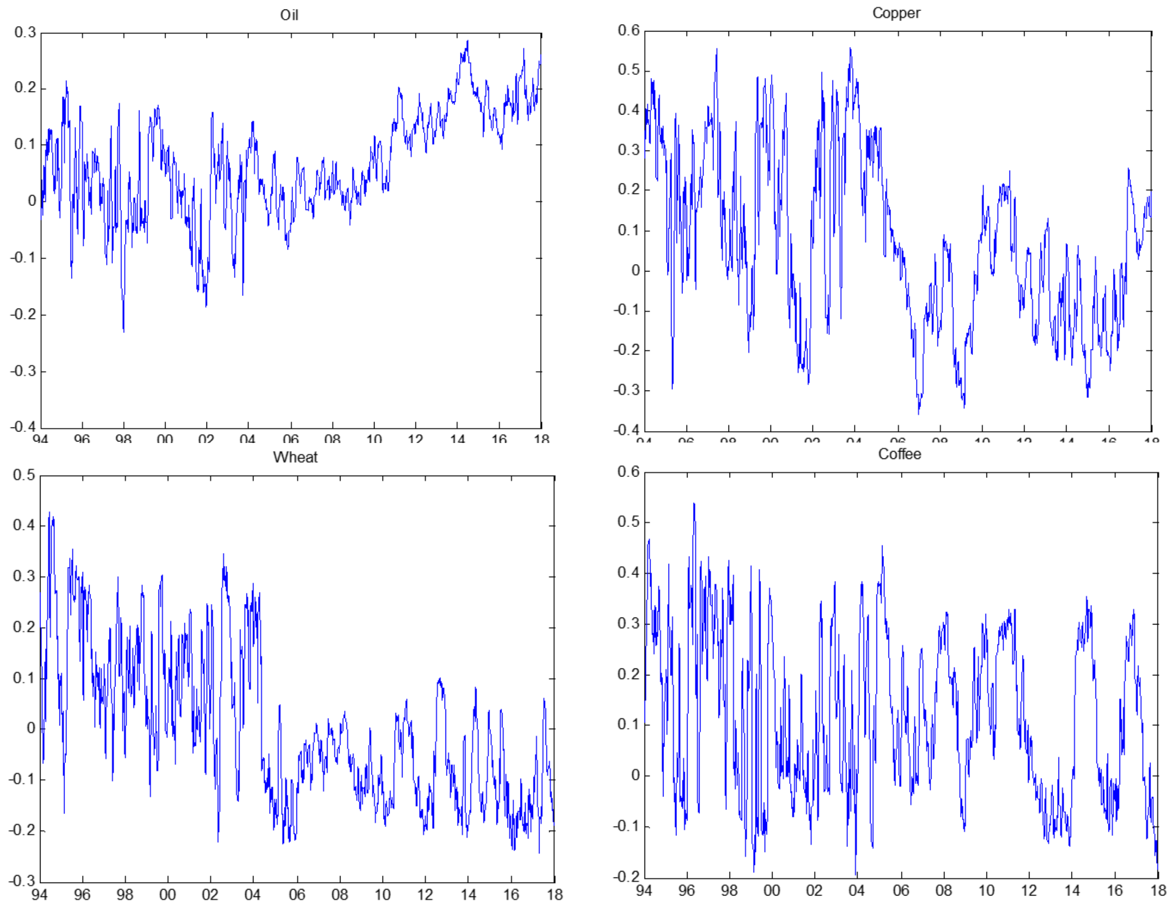

Figure 2: Average Futures Excess Returns and Average Hedging Pressure

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%.

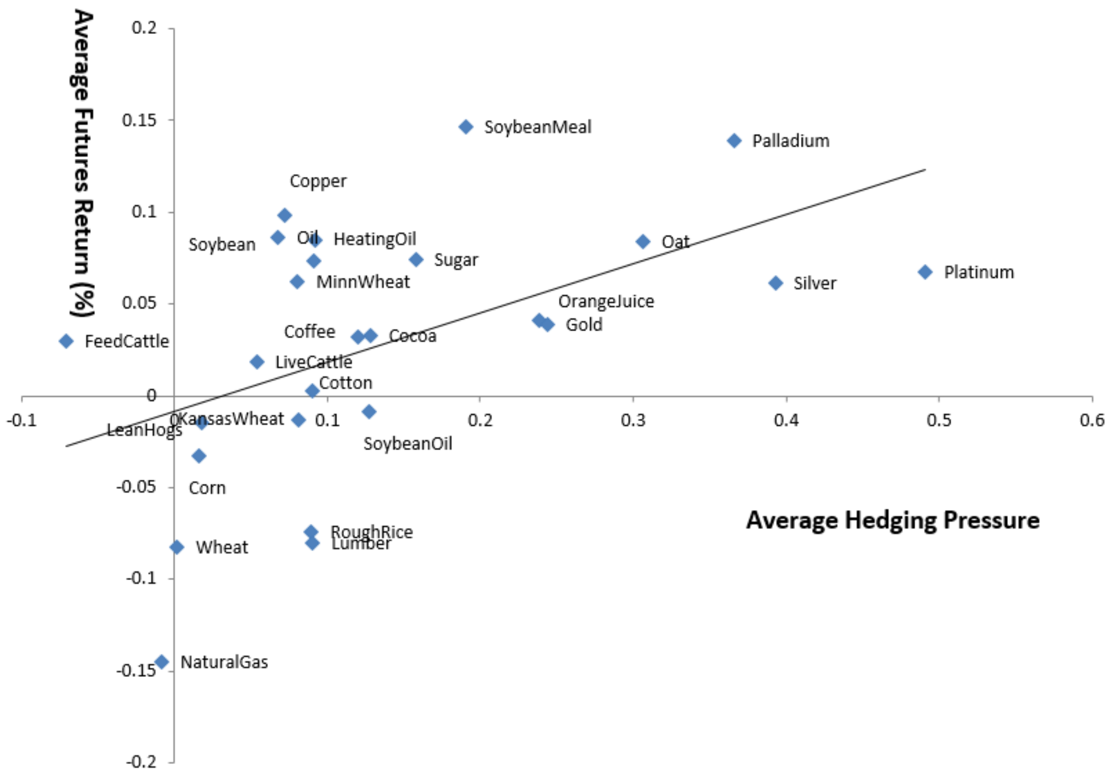

Figure 3: Cumulative Return Impact of Liquidity- and Momentum-driven Position Changes

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

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

with n ∈ $\{1, \dots \dots, 26\}$. $CumulR_{i,t+n}$ 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* 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*.

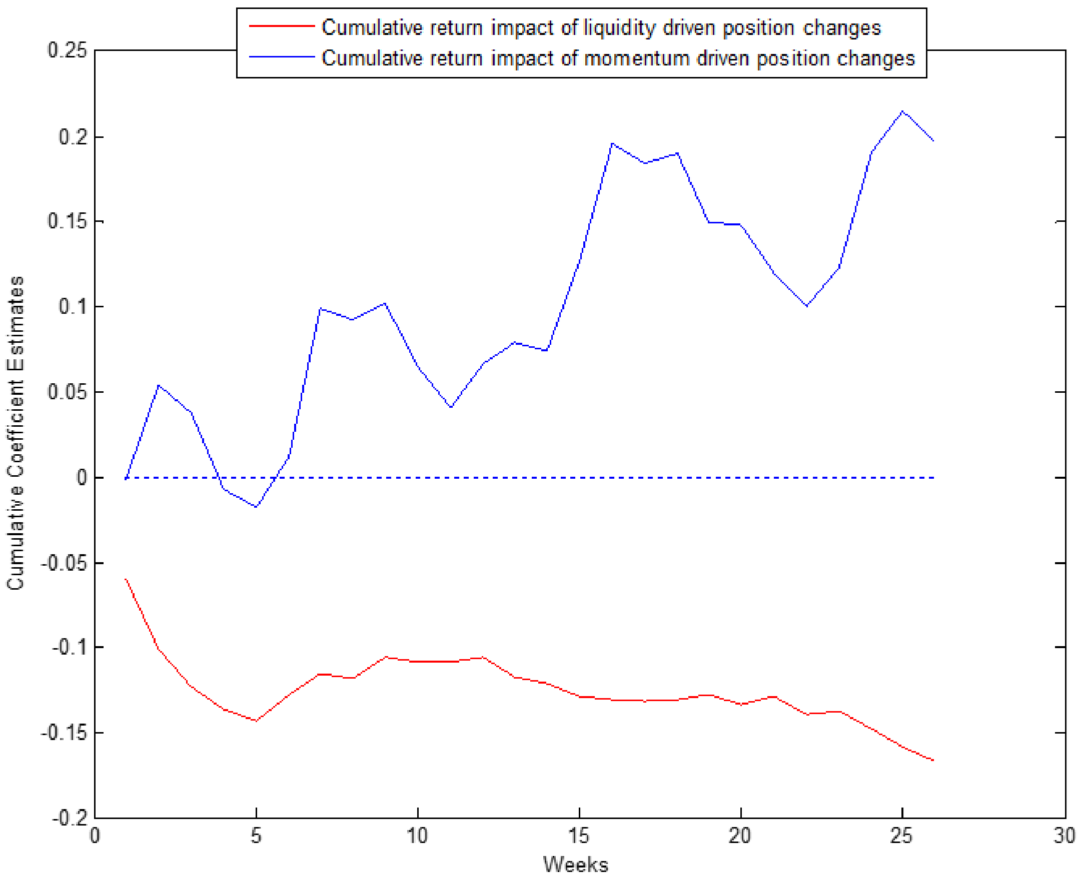

Table 1: Summary Statistics

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. 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. The front-month contract is rolled on the 7^th^day of the month or the next day if the 7^th^ is not a business day. 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., $HP_{i,t} = (HS_{i,t} - HL_{i,t})/OI_{i,t}$. 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. The net trading measure, Q, which is defined as the weekly change of the net long position normalized by open interest. $Q_{i,t} = (net\ long\ position_{i,t} - net\ long\ position_{i,t-1})/ OpenInterest_{i,t-1}$. We report the time-series average of the *absolute value* of the trading measure for the commercial and non-commercial traders. Finally, we examine the difference of the propensity of adjusting portfolio positions between the non-commercial and commercial traders. We denote SL, SS, HL, and HS as the size of the non-commercials' long position, the non-commercials' short position, the commercials' long position, and the commercials' short positon respectively, and then define the propensity to trade as$PT_{i,t}^{Hedger} = \frac{abs(HL_{i,t}-HL_{i,t-1})+abs(HS_{i,t}-HS_{i,t-1})}{HL_{i,t-1}+HS_{i,t-1}}$ and $PT_{i,t}^{Spec} = \frac{abs(SL_{i,t}-SL_{i,t-1})+abs(SS_{i,t}-SS_{i,t-1})}{SL_{i,t-1}+SS_{i,t-1}}$. 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.

Commodity	Annualized % Excess Return		Hedging Pressure (*HP*)%			Average Absolute Value of Net Position Change (|*Q*|) %		Average Propensity to Trade *(PT)* %			
	Mean	Standard Dev	Mean	Standard Dev.	Prob (HP>0)	Commercials	Non-Commercials	Non-Commercials	Commercials	Difference	(t-stat)
Oil	8.65	33.44	6.78	9.26	77.14	1.72	1.42	6.07	3.20	2.87	11.49
Heating Oil	8.51	31.49	9.19	8.87	83.69	2.49	1.81	9.24	4.18	5.06	14.37
Natural Gas	-14.50	45.57	-0.83	11.64	46.52	1.62	1.38	6.80	3.69	3.11	8.90
Platinum	6.72	21.85	49.11	22.47	95.92	5.94	5.19	10.46	7.15	3.31	10.66
Palladium	13.88	33.69	36.57	32.78	80.90	4.42	3.60	9.56	5.91	3.65	7.05
Silver	6.16	28.51	39.29	16.48	100.00	3.68	3.43	7.09	5.49	1.61	10.11
Copper	9.80	24.51	7.20	21.06	60.43	3.97	3.23	9.95	5.39	4.57	15.31
Gold	3.86	16.24	24.38	26.91	79.70	4.93	4.09	7.98	5.97	2.01	9.28
Wheat	-8.27	28.70	0.17	14.53	43.88	3.03	2.67	6.59	4.95	1.64	11.01
KC Wheat	-1.32	27.41	8.13	13.78	70.50	2.83	2.37	9.29	4.61	4.69	12.66
Minn Wheat	6.21	26.15	8.06	12.35	72.82	2.83	2.18	15.93	5.61	10.31	8.29
Corn	-3.24	26.41	1.63	12.91	55.32	2.37	2.24	6.22	3.51	2.71	17.37
Oat	8.37	33.68	30.63	18.11	93.45	4.02	2.98	12.02	6.35	5.67	17.46
Soybean	7.36	23.07	9.08	16.35	70.10	2.78	2.62	6.88	4.48	2.40	18.13
Soybean Oil	-0.84	23.32	12.69	17.03	73.14	3.89	3.02	7.78	5.01	2.77	15.11
Soybean Meal	14.67	26.85	19.07	14.86	85.61	3.45	2.68	8.08	4.59	3.49	17.79
Rough Rice	-7.40	25.47	8.93	23.92	63.47	3.75	2.86	10.96	5.93	5.03	11.54
Cotton	0.23	28.43	9.06	22.24	65.55	4.42	3.81	9.20	5.02	4.18	15.03
Orange Juice	4.08	32.51	23.89	23.35	83.85	4.86	4.06	10.17	6.06	4.11	17.32
Lumber	-8.02	31.01	9.05	20.01	63.71	4.56	4.46	12.20	12.94	-0.73	-1.79
Cocoa	3.26	29.59	12.80	16.64	74.66	2.77	2.42	8.33	3.40	4.94	17.38
Sugar	7.45	31.78	15.78	17.71	77.62	3.62	2.60	9.09	4.31	4.78	12.06
Coffee	3.21	37.38	12.04	15.68	70.02	3.79	3.42	9.19	4.94	4.25	16.15
Lean Hogs	-1.48	25.63	1.77	13.24	57.79	2.54	2.69	7.49	4.84	2.65	13.02
Live Cattle	1.82	15.71	5.37	10.98	64.99	1.79	2.17	5.93	3.22	2.70	18.44
Feeder Cattle	2.96	15.08	-7.08	10.59	25.98	2.11	3.09	8.54	7.04	1.50	6.59
Average	2.77	27.83	13.57	17.07	70.65	3.39	2.94	8.89	5.30	3.59	12.72

Table 2: 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 3: 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 4: 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 day	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 week	1 week	2week	3-4 weeks	5-8 weeks	1-8weeks
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 5: Time-Series Return Predictability

In Panel A we conduct time-series regression 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 3. 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 components, following the method of Moskowitz, Ooi, and Pedersen (2012).

Panel A: Time-series Regressions

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

Panel B: Return Decompositions

Cross-sectional strategy return: R^{XSLIQ}				Time-series strategy return: R^{TSLIQ}		
Auto	Cross	Mean level	Total	Auto	Mean squared	Total
0.69%	-0.08%	0.00%	0.61%	0.71%	-0.01%	0.71%

Table 6: Return Predictability: Major and Minor Commodities

In this table we conduct the 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 3, for the sub-sample of major and minor commodities separately. We divide the 26 sample commodities into two equal halves, according to the average number of total traders as reported in 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)	Dependent Variable: $R_{i,t+1}$				Dependent Variable: $R_{i,t+2}$			
	Major		Minor		Major		Minor	
	Commercials	Non-Commercials	Commercials	Non-Commercials	Commercials	Non-Commercials	Commercials	Non-Commercials
$Q_{i,t}$	4.79	-4.92	5.16	-5.44	2.02	-2.28	4.68	-5.23
	(*3.77*)	(-*3.54*)	(*5.28*)	(-*5.31*)	(*1.55*)	(-*1.55*)	(*4.61*)	(-*4.85*)
$B_{i,t}$	-0.28	-0.24	-0.80	-0.98	-0.22	-0.22	-0.92	-0.93
	(-*1.29*)	(-*1.14*)	(-*2.14*)	(-*2.65*)	(-*1.03*)	(-*1.04*)	(-*2.62*)	(-*2.60*)
$S_{i,t}\hat{v}_{i,t}$	-0.21	-0.22	0.17	0.07	0.09	0.10	-0.01	0.03
	(-*1.00*)	(-*1.03*)	(*0.72*)	(*0.28*)	(*0.44*)	(*0.49*)	(-*0.05*)	(*0.12*)
$R_{i,t}$	4.55	4.40	5.05	4.32	2.79	1.97	1.58	1.19
	(*2.69*)	(*2.65*)	(*3.33*)	(*2.89*)	(*1.76*)	(*1.25*)	(*0.95*)	(*0.74*)
R^2	43.82%	43.98%	39.51%	39.73%	42.93%	42.92%	40.08%	40.01%

Table 7: 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 $HP_{i,t}$, smoothed lagged hedging pressure $\overline{HP}_{i,t}$, lagged net position changes of hedgers $Q_{i,t}$ and the same set of control variables as in Table 3. 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 8: 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 9: Returns Following Momentum-driven versus Non-Momentum Position Changes

We first 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 the 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 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 3. 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%	35.61%

Table 10: Profit Attribution of Commercial Traders

In this table we decompose the profits and losses of commercial traders, expressed as a % of their net positions, into three components: hedging pressure, momentum trading, and liquidity provision. “Hedging Demand” is calculated as the 52-week moving average of past hedging pressure. The deviation between actual hedging pressure and smoother hedging pressure is decomposed into a component that can be predicted based on past returns and a residual. The former is labeled “Momentum Trading”, and the latter “Liquidity Provision”. The first column “Commercials” measures the average profit or loss as a fraction of their net position in each commodity. The next two columns give a breakout of offsetting gains or losses to the traders taking the opposite side of the commercial positions (Non-Commercials and Non-Reportables).

	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%

Table 11: Factors Affecting Liquidity Provision

In Panel A, we measure the incremental impact of a position change by defining dummy variables $D(VIX)_t$ and $D(CVol)_{i,t}$ that take on the value 1 when either the VIX is above its full sample median, or when the implied volatility of that individual is above it 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:

$$R_{i,t+1} = b_0 + b_1\overline{HP}_{i,t} + b_2 Q_{i,t} + b_3 Q_{i,t} D()_t + controls + \varepsilon_{i,t+1}$$

Variables are defined in the same as in Table 7. 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	2.66	3.16	2.41	1.79	1.75
	(*5.76*)	(*4.71*)	(*4.32*)	(*3.39*)	(*3.10*)	(*2.44*)
$Q_{i,t} \times D(VIX)_t)$	-0.73		-0.99	0.26		0.08
	(*-0.82*)		(*-1.11*)	(*0.29*)		(*0.09*)
$Q_{i,t} \times D(CVol)_{i,t}$		2.39	2.50		1.81	1.80
		(*2.54*)	(*2.65*)		(*1.97*)	(*1.95*)
$\overline{HP}_{i,t}$	0.44	0.42	0.42	0.41	0.40	0.40
	(*2.28*)	(*2.19*)	(*2.17*)	(*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 12: Hedging Pressure and Liquidity Provision: DCOT Data

The table examines the robustness of our results based on the Commitment of Traders (COT) Report to using positions data from the Disaggregate Commitment of Traders (DCOT) Report for the period that both datasets overlap. The weekly DCOT data is available from January 2006 to December 2016, and classifies traders into the categories of producers/merchant/processor/user, swap dealers, managed money, other reportables, and non-reportables. Hedging pressure is calculated as the net short positions of the producers-merchant-processor-user category scaled by open interest. 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 the same set of control variables as in Table 3. 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%

Appendix Tables

Table A1: Weekly Return Predictability Following Position Changes: Sub-period Results

The table reports the subsample results for Table 3. In Panel A, we divide the sample period into two sub-sample periods before and after the financialization of commodity futures markets, that is, from 1994/1/2 to 2003/12/31, and from 2004/1/2 to 2017/12/30. In Panel B, we separate the sample before and after the financial crisis (2008/9/15).

Panel A: Two Half Sub-periods

LHS: $R_{i,t+1}$	Pre-Financialization		Post-Financialization	
Coefficient Estimates (×100)	Commercials	Non-Commercials	Commercials	Non-Commercials
$Q_{i,t}$	4.07	-4.28	4.96	-5.93
	(*5.23*)	(*-4.96*)	(*4.71*)	(*-5.58*)
$B_{i,t}$	-0.36	-0.38	-0.55	-0.54
	(*-1.53*)	(*-1.57*)	(*-2.24*)	(*-2.22*)
$S_{i,t}\hat{v}_{i,t}$	-0.16	-0.12	0.03	0.06
	(*-0.94*)	(*-0.73*)	(*0.20*)	(*0.38*)
$R_{i,t}$	6.00	5.75	3.45	3.51
	(*3.73*)	(*3.59*)	(*2.55*)	(*2.64*)
R^2	26.10%	26.04%	24.89%	24.73%
LHS: $R_{i,t+2}$	Pre-Financialization		Post-Financialization	
Coefficient Estimates (×100)	Commercials	Non-Commercials	Commercials	Non-Commercials
$Q_{i,t}$	2.32	-1.71	3.62	-4.77
	(*3.02*)	(*-2.09*)	(*3.32*)	(*-3.88*)
$B_{i,t}$	-0.19	-0.18	-0.34	-0.34
	(*-0.83*)	(*-0.81*)	(*-1.41*)	(*-1.40*)
$S_{i,t}\hat{v}_{i,t}$	-0.13	-0.12	-0.01	-0.01
	(*-0.74*)	(*-0.66*)	(*-0.05*)	(*-0.09*)
$R_{i,t}$	1.47	0.36	2.35	2.44
	(*0.82*)	(*0.20*)	(*1.75*)	(*1.83*)
R^2	26.34%	26.19%	24.05%	24.04%

Panel B: Sub-periods before and after the Recent Financial Crisis

LHS: $R_{i,t+1}$	Pre-Crisis		Post-Crisis	
Coefficient Estimates (×100)	Commercials	Non-Commercials	Commercials	Non-Commercials
$Q_{i,t}$	3.66	-4.37	6.34	-6.89
	(*4.67*)	(*-5.57*)	(*4.70*)	(*-4.70*)
$B_{i,t}$	-0.40	-0.39	-0.61	-0.62
	(*-2.11*)	(*-2.04*)	(*-2.00*)	(*-2.03*)
$S_{i,t}\hat{v}_{i,t}$	-0.03	0.00	-0.07	-0.05
	(*-0.23*)	(*0.03*)	(*-0.38*)	(*-0.28*)
$R_{i,t}$	5.30	5.25	3.02	2.93
	(*4.03*)	(*4.03*)	(*1.74*)	(*1.70*)
R^2	25.59%	25.46%	24.99%	24.88%

LHS: $R_{i,t+2}$	Pre-Crisis		Post-Crisis	
Coefficient Estimates (×100)	Commercials	Non-Commercials	Commercials	Non-Commercials
$Q_{i,t}$	2.39	-2.79	4.39	-4.82
	(*2.95*)	(*-3.07*)	(*3.18*)	(*-3.19*)
$B_{i,t}$	-0.24	-0.23	-0.35	-0.37
	(*-1.32*)	(*-1.24*)	(*-1.20*)	(*-1.26*)
$S_{i,t}\hat{v}_{i,t}$	-0.07	-0.06	-0.03	-0.06
	(*-0.51*)	(*-0.40*)	(*-0.17*)	(*-0.31*)
$R_{i,t}$	1.88	1.44	2.17	1.80
	(*1.36*)	(*1.07*)	(*1.24*)	(*1.05*)
R^2	25.09%	25.03%	24.86%	24.76%

Table A2: Time-Series Predictability: Major and Minor Commodities

The table reports a robustness check for Table 5 panel A. We separately check for time-series predictability in the sub-samples of major and minor commodities as defined in Table 6.

Panel A: Major commodities

Dependent Variable: $R_{i,t+1}$	Commercials				Non-Commercials			
	Q_t	B_t	$S_t\hat{v}_t$	R_t	Q_t	B_t	$S_t\hat{v}_t$	R_t
Mean	2.65	-0.06	0.04	0.62	-3.14	-0.05	0.05	0.73
(*t-statistics*)	(*1.98*)	(-*0.25*)	(*0.26*)	(*0.59*)	(-*2.39*)	(-*0.20*)	(*0.31*)	(*0.73*)
Median	1.47	0.02	-0.01	0.81	-2.01	0.03	-0.02	1.28

Dependent Variable: $R_{i,t+2}$	Commercials				Non-Commercials			
	Q_t	B_t	$S_t\hat{v}_t$	R_t	Q_t	B_t	$S_t\hat{v}_t$	R_t
Mean	1.34	-0.19	-0.04	0.76	-0.33	-0.20	-0.04	0.16
(*t-statistics*)	(*1.04*)	(-*0.53*)	(-*0.24*)	(*0.43*)	(-*0.18*)	(-*0.55*)	(-*0.25*)	(*0.09*)
Median	0.77	0.18	-0.04	0.62	-0.47	0.17	-0.05	1.17

Panel B: Minor commodities

Dependent Variable: $R_{i,t+1}$	Commercials				Non-Commercials			
	Q_t	B_t	$S_t\hat{v}_t$	R_t	Q_t	B_t	$S_t\hat{v}_t$	R_t
Mean	5.24	-0.52	-0.20	3.33	-6.25	-0.50	-0.17	2.76
(*t-statistics*)	(*4.38*)	(-*1.05*)	(-*1.39*)	(*3.10*)	(-*4.16*)	(-*1.03*)	(-*1.19*)	(*2.76*)
Median	4.52	-0.59	-0.11	3.86	-4.50	-0.57	-0.02	4.07

Dependent Variable: $R_{i,t+2}$	Commercials				Non-Commercials			
	Q_t	B_t	$S_t\hat{v}_t$	R_t	Q_t	B_t	$S_t\hat{v}_t$	R_t
Mean	2.54	-0.63	-0.09	1.27	-3.31	-0.64	-0.06	0.88
(*t-statistics*)	(*2.44*)	(-*1.45*)	(-*0.74*)	(*0.84*)	(-*3.05*)	(-*1.45*)	(-*0.55*)	(*0.61*)
Median	1.73	-0.51	0.00	2.14	-2.93	-0.50	0.01	0.30

Table A3: 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 3. 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 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%