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

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First Draft: August 15, 2013
This version: December 4, 2016

**Abstract**

This paper studies the dynamic interaction between the net positions of hedgers and speculators and risk premiums in commodity futures markets. Short-term position changes are mainly driven by the trading demands of impatient speculators, while long-term variation is primarily driven by the hedging demands from commercial hedgers. Variation in hedging pressure - the central variable in tests of the theory of normal backwardation- reflects both the liquidity demands of speculators and the demand for price insurance of hedgers. We provide empirical evidence that these two components influence expected futures returns with opposite signs.

Keywords: Commodity futures, liquidity provision, return predictability, theory of normal backwardation, hedging pressure, risk premium

* We have benefited from comments and suggestions from Hendrik Bessembinder, Geetesh Bhardwaj, Ing-haw Cheng, Gary Gorton, Ravi Jagannathan, Pete Kyle, Peng Liu, Anna Pavlova, Neil Pearson, Tarun Ramadorai, Matthew Spiegel, Dimitry Vayanos, and seminar participants at 2013 NBER Meetings on the Economics of Commodity Markets, 2015 Western Finance Association Annual Conference, 2015 China International Conference in Finance, First Commodity Conference, Leibnitz University Hannover, the CFTC, the City University of Hong Kong, CKGSB, Notre Dame, Hong Kong Polytech University, JP Morgan Commodity Centre at University of Colorado Denver, Shanghai JiaoTong University, Shanghai University of Finance and Economics, SKKU Graduate School of Business (Seoul), and Yale University.

## 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 with 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 this view of insurance provision is not controversial per se, at the same time there are several reasons to believe that speculators have motives to trade that are independent from accommodating commercial hedging demands. First, the positions of hedgers and speculators observed in data published by the Commodity Futures Trading Commission (CFTC) exhibit large variation over short time periods (weekly horizon), and while hedgers are on average net short in most commodity futures markets, there are frequent episodes where the net balance of their positions is long. This is unlikely to be entirely driven by changes in the hedging plans of commercial producers, which are by nature more stable over time. [1] Second, speculators are in aggregate short-term trend followers. For example, Commodity Trading Advisors, which represent an important source of speculative capital in futures markets, have been shown to actively pursue momentum style investment strategies.[2]

[1] Cheng and Xiong (2014) observe that hedgers trade a large amount relative to their fundamental hedging demand.

[2] Several papers have studied the trading behavior of hedge funds, which have become a major source of speculative capital over recent decades. Fung and Hsieh (1997, 2001) analyze trend following strategies by hedge funds. More recently, Bhardwaj, Gorton, and Rouwenhorst (2014) show that the

It seems unlikely that these investment styles simply originate from passively meeting hedging demands by commercial market participants. Third, the empirical support for the relation between hedging pressure and the expected futures risk premium as predicted by the theory of normal backwardation is mixed (see Rouwenhorst and Tang (2012)).

In this study, we examine futures returns around the weekly position changes reported by the CFTC, and provide evidence that active trading decisions by speculators influence the price setting in commodity futures markets independently from the demand for insurance by hedgers. Our empirical strategy follows Kaniel, Saar, and Titman (2008) by testing for the predictability of short-term returns following position changes of traders, and uses 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 are most heavily bought by speculators earn significantly lower returns than commodities that are sold by them. And commodities that are most heavily purchased by hedgers subsequently outperform those that are sold by them. These findings parallel the prediction from the microstructure theory literature on liquidity provision (e.g., Grossman and Miller (1988)

returns of Commodity Trading Advisors correlate with simple momentum and carry strategies in stocks, currencies, and commodities. 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.

[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.

and Campbell, Grossman, and Wang (1993)). According to these models, liquidity providers (or market makers) tend to trade against the market trend as contrarians, while impatient traders (e.g., momentum followers) consume liquidity and need to offer a price concession to encourage risk-averse market makers taking the other side of their trades. Put into the context of commodity futures markets, hedgers trade as contrarians and earn a compensation for liquidity provision by accepting a price concession offered by impatient momentum traders (i.e., speculators) who demand immediacy.

The short-term underperformance of commodity futures sold by hedgers is opposite to the prediction of Keynes' theory of normal backwardation, which associates an increase in 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 speculators, and longer-term component that is driven by changes in hedging demands of commercial market participants. We hypothesize that the latter is relatively stable over short horizons due to the slow evolution of underlying production decisions in physical markets. We provide empirical evidence to support these conjectures. A main finding of our paper is that the expected excess return to a commodity futures contract embeds two return premiums related to position changes: one premium paid by hedgers to speculators for obtaining price insurance associated with, and one premium paid by speculators to hedgers for accommodating their short-term liquidity needs. The opposite sign of these two premiums implies that cost of short-term liquidity consumption paid by speculators partially erodes the insurance premium they receive from hedgers for providing price insurance. Our analysis suggests that a large portion of the premium that speculators earn from providing price insurance is returned to hedgers by demanding liquidity.

Our findings contribute to the literature on commodity futures in the following ways. First, the notion that short-term speculative traders are consuming liquidity runs counter to the traditional view of speculators as providers of liquidity in futures markets.[4] Second, the relative impatience of speculative trading provides a new explanation for the question of why hedgers appear to trade so much (Cheng and Xiong (2014)): they are induced by speculators and are compensated for providing short-term liquidity to them. Third, our findings explain why regression tests of Keynes' theory of normal backwardation often fail to find a strong link between hedging pressure and expected futures returns (see Rouwenhorst and Tang (2012)).[5] Variation in hedging pressure embeds two components that predict futures returns with opposite signs. Failure to control for liquidity provision introduces a bias that attenuates the estimated influence of insurance demand on future excess returns. Finally, the presence of two premiums can explain why empirical estimates of speculative profits in commodity future markets have been low:[6] the profits earned by speculators for providing insurance are diminished by the compensation paid for their desire to obtain short-term liquidity.

[4] See for example Keynes (1930), Blau (1944) and Gray (1967). There is a large literature on the effect of speculators on the level and volatility of prices reviewed in Gray and Rutledge (1971).

[5] Gray and Rutledge (1971) also review the early literature on the ability of speculators to forecast prices. Chang (1985) and Bessembinder (1992) observe that positions of traders can predict futures returns to some extent. Rouwenhorst and Tang (2012) find that these findings become weaker in a more recent data sample. See also Basu and Miffre (2013) and Szymanowska et al. (2014) for recent studies on hedging pressure.

[6] See for example Working (1931), Rockwell (1967), and Hartzmark (1987) who do not detect profits to speculators in commodity futures markets. See also Keim (2003) who reports similar findings in US equity markets.

Our study also contributes to the broader literature on demand-based asset pricing, which argues that the changes in demand for an asset can have a significant impact on its expected return. In option markets, recent 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. Our study links variation in long-term hedging pressure – net selling by commercial hedgers – to variation in excess futures returns.

The outline of the paper is as follows. Section 2 summarizes our data and presents some stylized facts about the CFTC positions reports, trading behaviour, and futures returns. Section 3 presents our empirical findings on short-term liquidity provision. Section 4 re-examines the theory of normal backwardation and tests the predictive power of long-term hedging pressure for expected returns after controlling for short-term fluctuations in hedging pressure that are related to liquidity provision. We conduct a variety of robustness checks on our results in Section 5. Section 6 concludes our paper.

## 2. Data and Summary Statistics

We use publicly available data provided by the Commodity Futures Trading Commission (CFTC) to study the trading behavior of various types of investors 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. 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 1994/01/02 to 2014/11/01. 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). There is a long tradition in the literature to view commercials as hedgers, and non-commercials as speculators.[7] While our classification of hedgers and speculators follows the tradition of the literature, we acknowledge the imperfection of this classification method. In Section 5, we conduct a robustness 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 commercials 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 hedgers 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 $t$:

[7] For example, see Houthakker (1957), Rockwell (1967), Chang (1985), Bessembinder (1992), DeRoon et al. (2000).

[8] Cheng et al. (2014) 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.

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

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 week:

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

Assuming constant open interest, the trading measure for hedgers in commodity *i* is 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 hedgers is calculated as:

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

Futures price data are obtained from Pinnacle Corp. We construct weekly excess returns (Tuesday-Tuesday) to match the measurement of the positions by the CFTC. We compute excess returns using the front-month (nearest-to-maturity) contract and roll positions on the 7th 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:

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

[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.

[10] If the 7th 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.

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 data and trading measures for each of the 26 commodities listed in column 1. Columns 2 to 3 show that the average excess return has been positive in 18 out of 26 markets, and has averaged 4.0% per annum across commodities, with an average annualized standard deviation of 28.1%. Column 4 shows that average hedging pressure was positive for all commodities, except feeder cattle. The large average standard deviation of 17.1% across commodities implies that the balance of hedging demands is not always on the short side of the market. The average frequency of hedgers being net short was 71.3% across markets, indicating that net long positions by hedgers are not uncommon. The volatility of hedging pressure is further 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 hedgers and speculators, which average about 3% of the total open interest.[11] The final three columns of Table 1 depict the propensity to trade for both speculators and hedgers, which is analogous to the portfolio turnover rate in the stock market. Columns 9 and 10 show that the propensity to trade is almost twice as high for speculators (9.38% per week) as it is for hedgers (5.40% per week). Column 11 shows that this difference is statistically significant.

These summary statistics motivate the following empirical observations. First, the average net short positions of hedgers and the positive average risk premium to long

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

futures positions are consistent with Keynes' theory of normal backwardation. Figure 2 shows that the slope coefficient of cross-sectional regression of the average risk premium on the average hedging pressure is significantly positive, with a *t*-statistic of 2.53. Second, there is large weekly variation in hedging pressure. Cheng and Xiong (2014) have questioned whether the variation in net short positions of commercial participants in agricultural futures markets can be explained by their attempts to hedge price and output risk. Moreover, there is little predictability of futures excess returns using hedging pressure at short-term horizons. The average slope coefficient of a weekly Fama-MacBeth cross-sectional regression of weekly excess futures returns on prior week hedging pressure in the previous week is insignificantly different from zero with a *t*-statistic of -0.43.[12] Thus, while there is a long-term correlation between average hedging pressure and average returns, there is no short-term predictability. Third, the high propensity to trade by speculators opens the possibility that much of the 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 immediacy by speculators to the extent that they follow investment styles that are independent from these hedging plans.

## 3. Liquidity Provision in Commodity Futures Markets

In this section we characterize the trading behaviour of various commodity market

[12] Table 6 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.

participants, and infer the direction of liquidity provision from the predictable component of futures prices following their trades.

### *3.1 How do Hedgers and Speculators Trade?*

For each of the three trader categories identified by the CFTC, we run weekly Fama-MacBeth cross-sectional regressions of their trading measure $Q$ on contemporaneous futures excess returns, or on past excess 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 the changes of both speculative and hedging positions are significantly related to contemporaneous and lagged commodity futures returns, but their correlations with returns have opposite signs: speculators increase positions in commodities that exhibit relative price strength, whereas hedgers buy commodity futures that experience price declines or for which prices have fallen in the prior week. In other words, speculators are *momentum traders* and hedgers are *contrarians*. The smaller traders in the non-reportable category act like speculators. 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 Rouwenhorst and Tang (2012).

### *3.2 Regression Test of Return Predictability and Liquidity Provision*

The strong correlation between positions changes and returns does not identify which group of traders 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 both univariate Fama-MacBeth regressions of commodity futures excess returns in week $t$+1 on position changes in week $t$, as well as multivariate regressions that include a set of controls that have been suggested in the literature to capture variation in expected futures returns:[14]

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

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 speculators are net long and -1 when speculators are net short.

Table 3 shows that commodities that are bought by hedgers in week $t$ deliver significantly higher returns in week $t+1$ than commodities sold by them ($t$-statistic = 4.84). The estimated return impact becomes larger if we include controls for expected

[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 $\frac{ln(F_i(t,T_1))-ln(F_i(t,T_2))}{T_2-T_1}$, 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 $i$.

returns in our regression ($t$-statistic = 6.55). On the other hand, commodities that are bought by speculators witness a significant predictable price decline in the week subsequent to trading.

To gauge the economic significance of the effect of investors' position changes on subsequent futures returns, consider the return impact of an average position change by hedgers, which is equal to 3.5% of total open interest (reported in Table 1). The cross-sectional slope of 4.77% indicates that this changes the expected return in the subsequent week by 4.77%*3.5% = 0.168%, or by 9.1% annualized. A parallel calculation for a typical speculative position change gives a similar return impact of 5.56%*3.0%=0.167% in the subsequent week. Position changes by small traders as a group do not seem to significantly impact subsequent returns, which suggests that the return predictability is a transfer among the reportable (large) players in commodity futures markets. For this reason, we will suppress the results for non-reportables in the remainder of our paper. Also, for sake of brevity we will report results for one side of the market (i.e, hedgers or speculators), as the results closely mirror each other.

### *3.3 Portfolio Sorts on Hedgers' Position Changes*

As an alternative non-parametric test, we construct portfolios by sorting commodities according to past position changes, and compare their post-ranking returns. 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 commercial positions (i.e., hedgers' $Q$). We form five equally-weighted "quintile" portfolios, containing 5, 5, 6, 5, and 5 commodity futures respectively, and calculate the excess returns of these five portfolios during the 40-trading-day period following the portfolio construction. Because the CFTC report is released after the market close on the Friday following the Tuesday measurement of positions, we separately report the excess 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 hedgers, who most intensively buy commodities that have fallen in price during the prior two weeks (prior return of -3.09%), and most intensively sell winners (prior return of 3.68%). The third column shows that during the 4 days after portfolio formation, commodities in the top quintile (largest $Q$) earn on average 0.20% compared to -0.01 % for commodities in the bottom quintile portfolio (smallest $Q$). The return difference of 0.21% is significant, with a $t$-statistic of 3.04.[16] The next columns shows that a positive excess return spread persists during days 5-20 following the release of the CFTC report: 0.30% during days 5-10 ($t$ = 3.62) and 0.15% ($t$ = 1.23) during days 11-20. These numbers are economically large: a spread of 67 basis points during the four weeks (1-20 days) following a position change translates to an annualized excess return of about 9% per year. This is about twice the unconditional risk premium earned on an equally-weighted

[16] When estimating the $t$-statistics for the return difference between the commodity futures portfolios with the highest and lowest past hedgers trading measure $Q$, we use the Newey-West adjustment with four lags to adjust heteroskedasticity and serial correlation.

portfolio across all commodities reported in Table 1. By this measure the liquidity cost of rebalancing the extreme quintile portfolios exceeds the premium earned by taking a passive long position in an equally-weighted commodity futures market portfolio.

Panel B tracks the position changes by hedgers in the quintile portfolios during the weeks following portfolio formation. Induced by the momentum trading of speculators, hedgers 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 hedgers begin to buy back the commodities they sold before, and sell out of the positions that they bought before. The last column of panel B shows that over the 8 week period following portfolio ranking hedgers partially reverse the previous transactions during the week of the ranking.

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. Hedgers follow contrarian strategies to accommodate the pressure from speculators' momentum trading. They take long (short) positions when the selling (buying) pressure from speculators pushes commodity futures price down (up). Microstructure models suggest that traders who demand immediacy (e.g., speculators) need to offer price concession to attract liquidity-supplying orders from other risk-averse investors (e.g., hedgers). The price concession offered by speculators to hedgers explains why we observe that commodity futures prices increase after speculators sell and hedgers buy, and decline after speculators buy and hedgers sell.

Our empirical finding suggests that speculators in commodity markets consume liquidity and their short-term loss can be understood as the cost of demanding immediacy. We show in Table 1 that speculators have a higher propensity to trade than hedgers, partly because their momentum strategies require more frequent trading compared to the implementation of hedging plans by hedgers that are by nature more stable over time. Following short-term price trends consumes liquidity, and speculators have to pay a cost to hedgers so that they can accommodate the trading demands from speculators.

### *3.4 Liquidity versus Private Information*

An alternative explanation for our finding that position changes predict futures returns is that hedgers 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 hedgers access to information about fundamentals that is not easily observed by non-commercial investors. In this section we present several pieces of empirical evidence that favours our interpretation of liquidity provision.

The first is the direction of trading by hedgers in the week prior to the positions report. In the quintile sorts of Table 4 we document that the prices of commodities in the quintile that are bought most heavily by hedgers on average underperform the quintile that are sold most heavily by hedgers by 6.77% during the two weeks prior to the positions report, followed by a partial reversal of 0.61% during the next 40 trading days, leaving (on net) a permanent component to the price change of 6.16%. If hedgers possess 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 hedgers (quintile 5) should simultaneously increase, and the commodities sold by hedgers (quintile 1) should witness a contemporaneous price drop. Instead we find that hedgers 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.[17] Vayanos and Wang (2012) argue that if an investor's position change co-moves negatively (positively) with prices changes, he provides (consumes) liquidity. As we showed in Tables 2 and 4, the negative (positive) contemporaneous relationship between the position change of hedgers (speculators) and the contemporaneous futures returns indicates that hedgers (speculators) are liquidity providers (consumers).

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

*Capital Loss*: Recent theoretical models suggest that a deterioration of the wealth or the collateral base of market makers can hinder their liquidity provision.[18] By analogy, when hedgers have suffered a severe loss on their futures positions, they have to finance

[17] 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 consistent with the hypothesis that individual investors provide liquidity to the stock market (see their page 298).
[18] See Xiong (2001), Kyle and Xiong (2001), Vayanos (2004), and Brunnermeier and Pedersen (2009).

this loss by posting additional collateral. As a result, their willingness to provide liquidity could be negatively impacted after suffering a loss on their hedges, and therefore speculators need to offer a larger price concession to attract the reluctant hedgers to absorb their immediacy demand.[19]

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

*Amihud illiquidity*: Our final piece of empirical evidence is to compare the compensation for liquidity provision across commodities with different levels of illiquidity. Naturally, we expect such compensation to be larger for the less liquid commodities. To proxy for commodity market liquidity, we follow Marshall, Nguyen, and Visaltanachoti (2012) and use Amihud's (2002) illiquidity measure.[20]

Our hypothesis here is that the futures return predictability based on position changes

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[19] 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.

[20] For each commodity in a given week, we compute its Amihud illiquidity measure as the average of the daily ratio of the absolute value of its daily return divided by its dollar trading volume in the same day for all the trading days in the week. Then we take a past 52-week average of the weekly Amihud measure estimated above from week $t$-51 to $t$, and define a dummy variable Dm(Illiquidity), which equals to one for those commodities whose past 52-week average Amihud ratio is in the highest (most illiquid) quartile in a given week $t$.

should be stronger following a capital loss for hedgers, following weeks during which speculators repeatedly trade in the same direction, and in commodity futures markets that are more illiquid. We test for these hypothesis by conducting the following panel regression:

$$R_{i,t+1} = b_0 + b_1 Q_{i,t} + b_2 D(\cdot)_{i,t} Q_{i,t} + controls + \varepsilon_{i,t+1} \qquad (6)$$

*D* is a dummy that takes on the value of 1 when we predict the cost of liquidity to be high: following large losses by hedgers, when hedgers' positions have changed in the same directions in the prior 4 weeks, or when a commodity is illiquid. The other variables are defined in a same way as equation (5).

The panel estimation results in Table 5 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 hedgers, the cost of liquidity consumption for speculators significantly increases. The regression coefficients indicate a net purchase by hedgers equal to 3.5% of the open interest would result in an expected price increase of 8.9 basis points in the next week. But in weeks following a large capital loss of hedgers, the return impact of this same position change more than doubles to 21.2 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 hedgers is low, and it is unclear why hedgers would earn higher returns when their information becomes less precise.

The second specification shows that coefficients for $b_1$ and $b_2$ are similar in magnitude, which suggests that the return impact of a speculative position adjustment is about twice as large when net positions of hedgers have changed in the same direction in each of the prior 4 weeks.

The coefficient estimate of the dummy variable in the third regression specification is significantly positive for hedgers. It suggests that there is a larger return impact associated with position changes for illiquid commodity futures than for liquid commodity futures. Consistent with our hypothesis of liquidity provision, our findings here imply that the cost of liquidity is indeed higher in less liquid commodity futures markets.

In brief, our analysis here indicates that hedgers demand a higher liquidity premium from speculators in the presence of more binding capital constraints, larger concerns about order imbalances, and in more illiquid futures markets. These observations are consistent with our liquidity provision story and more difficult to reconcile with the private information hypothesis.

## 4. The Theory of Normal Backwardation Revisited

The conclusion from the previous section is that short-term fluctuations in hedging pressure are primarily driven by the liquidity demands of speculators, and represent a factor in the determination of futures prices that is separate from commercial hedging demands. This factor has not been considered in regression tests of the theory of normal backwardation, which has interpreted movements in hedging pressure as being motivated by the demand for price insurance by 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 it stems from demand for price insurance by hedgers or from demand for liquidity by speculators. In this section we attempt to separate these two effects.

While the demand for immediacy by speculators influences futures prices at short-term horizons (i.e., weekly frequency), we hypothesize that the demand for insurance by hedgers 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 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.

### *4.1 Fama-MacBeth Regression Results for Smoothed Hedging Pressure*

Table 6 revisits 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 ($t = -0.43$).

Next, we replace *HP* by $\overline{HP}$, which is calculated as a trailing 52-week moving average of hedging pressure.[21] 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 6 shows that the average slope coefficient on smoothed hedging pressure is positive and statistically significant ($t$ = 3.35), 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.

Our decomposition of variation in hedging pressure helps to explain why simple predictive regressions of excess returns on lagged hedging pressure fail to detect a significant influence (Rouwenhorst and Tang, 2012). Depending on the source of variation in hedging pressure, there are opposite effects on the 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 speculators it lowers the risk premium.

[21] We have experimented with a variety of methods to smooth hedging pressure, including the application of a Hodrick-Prescott filter. Unreported results show that our findings are robust across methods, and not sensitive to the choice of the length of the moving average window.

*4.2 Portfolio Sorting Results for Smoothed Hedging Pressure*

Panel A of Table 7 summarizes the performance of two-way sorted portfolios, constructed by first ranking commodities on smoothed hedging pressure $\overline{HP}$, and then according to prior week net hedger 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 short-term trading is higher for commodities with high hedging pressure. Our conjecture for this observation is that a higher hedging pressure is the result of stronger hedging demand for futures, and therefore hedgers may be more reluctant to deviate from their hedging positions to accommodate the short-term trading needs of speculators. 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.

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. The return difference between high and low $\overline{HP}$ portfolios are statistically significant and economically important. For example, during the first twenty days following portfolio formation when the CFTC positions information is in the public domain, high

$\overline{HP}$ portfolios that experience high hedger buying (High $Q$) outperform low $\overline{HP}$ portfolios that experience high hedger buying by on average 105 bp, or more than 12% annualized.

Panel B of Table 7 shows the associated trading measures for the double sorted portfolios. The high $Q$ portfolios experience a brief net buying following the portfolio ranking, but witness net selling subsequently. The reverse is true for low $Q$ portfolios, which initially experience continuation of selling followed by subsequent buybacks.

Overall the documented return and trading patterns are consistent with mean reversion of temporary deviations of hedging positions from target levels, induced by liquidity provision to speculative traders. Commodities that have poor returns are subsequently sold by speculators and bought by hedgers, thereby reducing its hedging pressure. 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 hedgers for their liquidity provision. Similarly, commodities that have good returns are subsequently bought by speculators and sold by hedgers. 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. We show that is important to distinguish between variation in the net position of hedgers (often called "hedging pressure") that is driven by the insurance demands of hedgers, and variation in the net position 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. Robustness tests

### *5.1 Liquidity Provision and Convective Risk Flows*

In a recent study, Cheng, Kirilenko, and Xiong (2015) (CKX hereafter) examine the response of commodity futures prices to shocks to the risk-absorbing capacity of financial traders during the recent financial crisis. With an increase in overall risk during a crisis, speculators experience a reduction in risk appetite. This causes speculators to cut down their risky positions in commodity futures, and hedgers facilitate this by reducing their net short positions accordingly. In their empirical work they document a contemporaneous correlation between changes in the VIX (proxy for risk appetite of financial traders), trader positions, and commodity futures returns. The CKX study of the financial crises shares resemblance to our paper in that it studies the price impact of speculator-induced trading that is absorbed by hedgers. To assess whether our study identifies a channel whereby speculative trading impacts prices that is different from the CKX paper, we conduct the following additional empirical tests.

First, we examine whether our results survive when we control for changes in the VIX in our regressions. More specifically, we estimate the following panel regression:

$$R_{i,t+1} = b_1 Q_{i,t} + b_2 \Delta\overline{HP}_{i,t} + b_3 \Delta VIX_{t+1} + b_4 \Delta VIX_t + controls + u_i + \varepsilon_{i,t+1} \quad (7)$$

The first specification in Table 8 excludes the VIX terms to show that our estimated coefficients in the panel regression qualitatively match our Fama-MacBeth estimates in Table 5. In the next regression we show that the coefficient on contemporaneous changes in the VIX is negative and statistically significant. This mirrors the findings of CKX. The final regression shows that the coefficient of lagged changes in the VIX is small and not significantly different from zero. Most importantly, we highlight that the inclusion of changes in the VIX does not alter the coefficients of either short-term trading $Q$ or smoothed hedging pressure $\overline{HP}$. Hence, we conclude that the impact of short-term liquidity provision and the role of long-term hedging pressure found in our study are separate from the influence of the shocks to intermediary risk-taking capacity as reported by CKX.

Second, CKX find that a sudden increase of the VIX during the financial crisis was *contemporaneously* accompanied by a decrease of speculative long positions and a drop of commodity futures prices. They do not examine the effect of an increase of the VIX on expected risk premiums. We document that the position change of hedgers or speculators can *predict* the return of commodity futures, controlling for contemporaneous or lagged change of VIX.

Third, CKX report that the negative correlation between commodity returns and the change in the VIX is only present during the post-crisis period, whereas it is insignificant in the pre-crisis period. By contrast, a sub-period analysis of Table 3 shows that our predictability results are present and significant in both halves of our sample, albeit some slightly stronger in the more recent part (see the Appendix Table A1). Therefore, our findings are not confined to the recent post-crisis period and can be attributed to a more general aspect of price formation in futures markets.

Overall, these three findings indicate that our results capture a channel through which speculative positions affect futures prices in a way that is fundamentally different from Cheng, Kirilenko, and Xiong (2015).

*5.2 DCOT data*

In our analysis thus far, we have followed a convention that has been widely used in the literature, which designates the commercial traders (as defined by the COT reports) as hedgers and non-commercial traders as speculators.[22] There are valid concerns about the accuracy of this classification. For example, a long futures positions by a financial intermediary to hedge an over-the-counter commodity index swap with an institutional investor would normally be classified as a commercial position, although the underlying position of the end investor is speculative in nature.[23] In this section, we briefly discuss some recent empirical studies based on the COT data, and conclude that despite its shortcomings, the data are informative and therefore useful for our analysis. Our conclusion is supported by the results of additional tests using the DCOT

[22] See Houthakker (1957), Rockwell (1967), Chang (1985), Bessembinder (1992), DeRoon et al. (2000), etc.

[23] Cheng, Kirilenko and Xiong (2014) 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.

dataset which employs finer breakdown of the speculator category.

First, although it may be a somewhat coarse method to associate COT commercial traders with hedgers, this classification scheme remains effective in general, both in our study as well as elsewhere in the literature. The premise of the Keynesian theory of normal backwardation is that the aggregate hedging demand for futures is net short, and the prediction that hedgers are expected to pay a premium to speculators as a compensation for their insurance service is broadly supported by the data. In Table 1 we documented that the commercials have short positions in commodity futures market more than 70% of the time, and that their net short position is on average, across time and commodities, 14% of the total open interest. Moreover, our study shows that non-commercials earn a risk premium that varies with low frequency movements in hedging pressure as measured by the net short positions by commercials. In light of concerns about misclassification, these results are surprisingly robust. This finding mirrors CKX (2015) who report that their conclusions using the DCOT positions are qualitatively similar to those based a more detailed, proprietary dataset of trader positions that is maintained internally by the CFTC. Furthermore, Hong and Yogo (2012) find that higher aggregate market-wide hedging demand, measured as the average imbalance between the short and long positions of COT commercial traders, can marginally predict higher commodity futures market returns. Acharya, Lochstoer, and Ramadorai (2013) find that, consistent with their model predictions, COT commercials in energy futures increase their net short positions when listed energy firms face an increased risk of default. Therefore, the observation that all these empirical findings are consistent with the corresponding theory predictions implies that despite the misclassification concern, the COT data still provides a reasonable measure for the hedgers' hedging demand.

Second, we check the robustness of our results using the Disaggregate Commitment of Trader (DCOT) data, which is published by CFTC since January 2006. The weekly DCOT data classifies commodity futures traders into five groups: producers/merchant/processor/user, money managers, swap dealers, other reportable, and 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.

Using the producers category in the DCOT reports as our alternative proxy for hedgers, we compute the net trading by hedgers ($Q$), and smoothed hedging pressure ($\overline{HP}$) as before. Table 9 report the results of re-estimating equation (5) using the DCOT classifications. We obtain results that closely resemble our findings using the COT data (Table 6), 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, as predicted by the theory of normal backwardation.

These findings confirm that producers (hedgers) are short-term liquidity providers.

Which traders do producers provide liquidity to? Because the DCOT 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. The regression coefficient estimates are provided in the Appendix Table A2, and can be compared to the estimates based on the courser classifications reported in Table 3. Inspecting the average slope coefficients for $Q$ across various trader categories, we find that producers are the only category with a positive sign. All other trader categories have negative point estimates, which indicates that they are all short-term consumers of liquidity. The category of money managers, which includes CTAs and hedge funds, stands out. Based on the size and statistical significance of its coefficient on $Q$ it appears to be the major liquidity consumer, and not the swap dealers which would include financial intermediaries that provide institutional investors with commodity index exposure through swaps.[24]

Overall, we find that our empirical results obtained from the DCOT data closely resemble those based on the COT data. It suggests that our empirical finding are robust to concerns about potential COT data misclassification.

## 6. A Concise Model

We construct a concise model to better illustrate the economic intuition of our main empirical findings. In this model we show that the futures price change can be positively

[24] 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 hedgers (speculators) are providers (consumers) of liquidity remains robust in the CIT data, and there is no significant evidence about whether that index traders are provider 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).

(negatively) predicted by the short-term trading of the hedger (the speculator), and the insurance premium predicted by the normal backwardation theory can be more precisely measured by controlling for the short-term fluctuation in the hedger's position. The implication of the model is consistent with empirical results in this paper. For the brevity of the paper, the model and its proof are included in the Appendixes B and C respectively.

## 7. Conclusion

In this paper, we show that the traditional view of commodity futures markets, which emphasizes how speculative capital provides "liquidity" to hedgers, is incomplete because it abstracts from speculative motives to trade that are independent of meeting the demand for price insurance of hedgers. Speculators are short-term momentum traders and have a higher propensity to trade than hedgers. In this process, hedgers provide liquidity to speculators, and earn a compensation by benefiting from a reversal in prices following their trading activity. These findings parallel the results of Kaniel, Saar, and Titman (2008) for US equity markets, where individuals provide liquidity to institutions that demand immediacy in their trade execution. We further show that the cost to speculators for demanding liquidity from hedgers increases when hedgers face more binding capital constraints or when the positions of hedgers become more skewed.

Commodity futures prices embed two premiums related to position (changes): one for providing price insurance to hedgers, and one for providing liquidity to speculators. The opposite nature of these premiums can explain why previous regression tests of the theory of normal backwardation 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 to speculative activity has been low.

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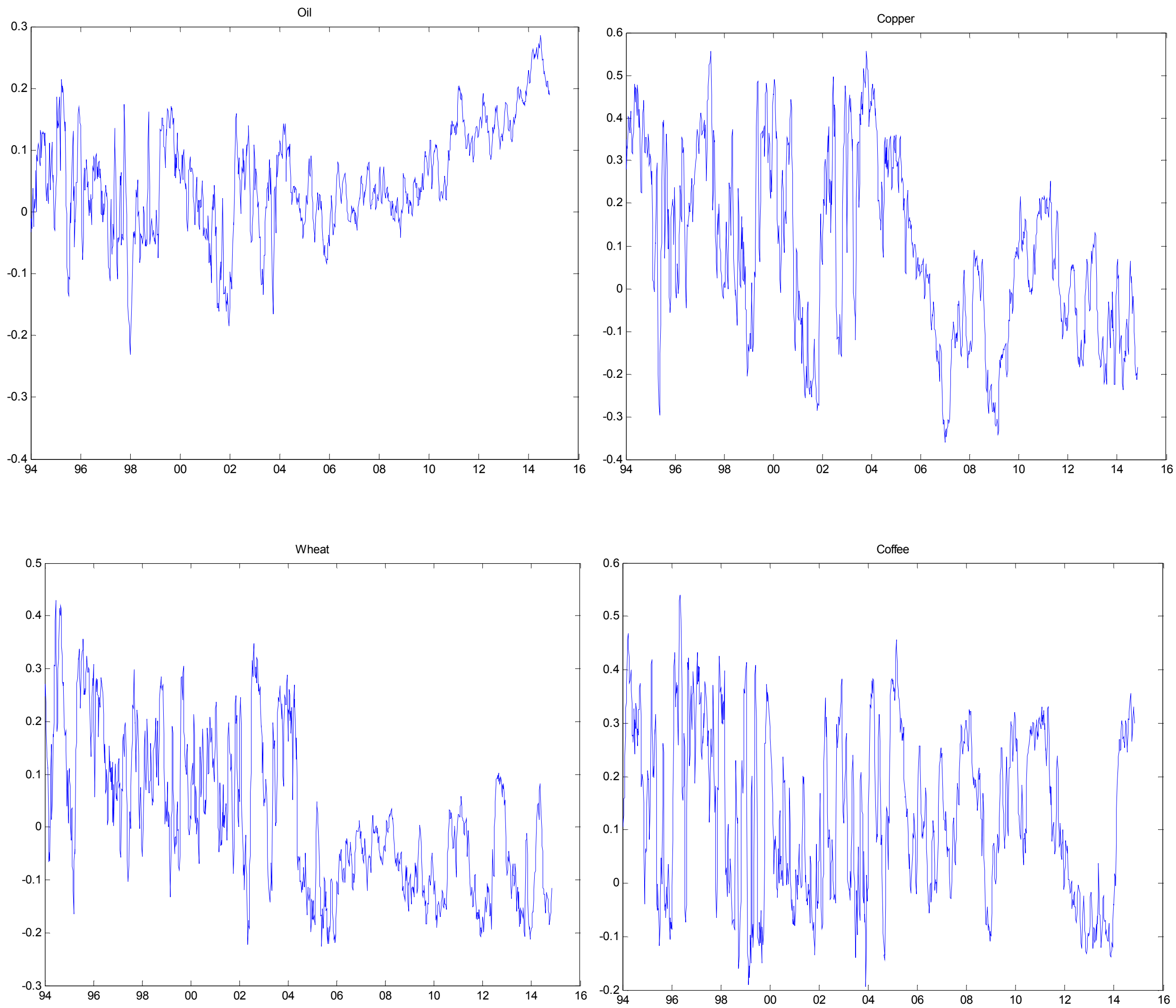
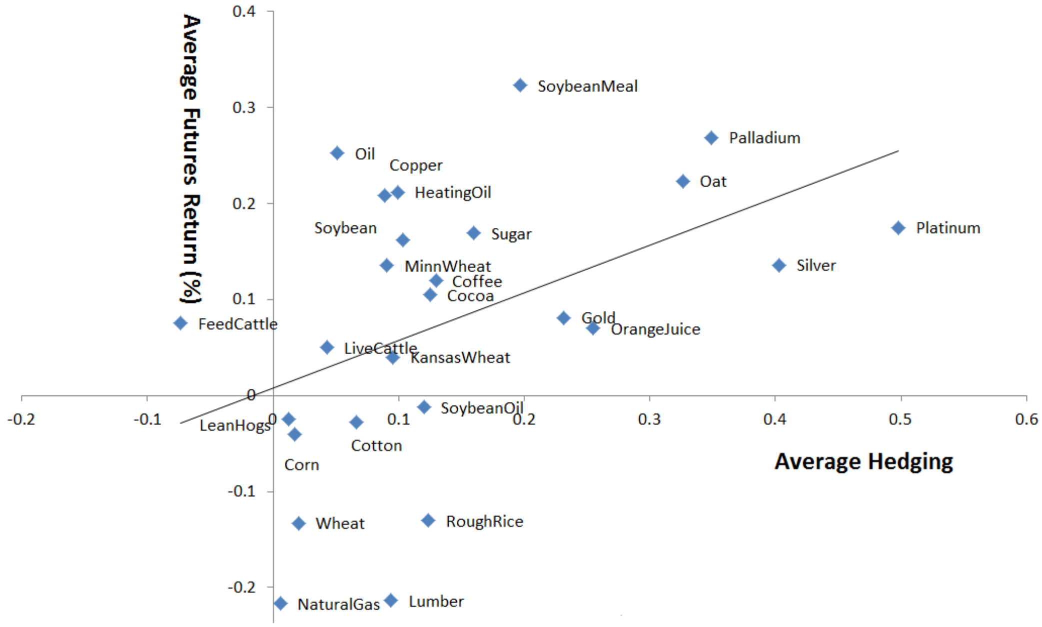
Figure 1: Hedging Pressures of Four Commodities




The figure shows the time series of hedging pressure for oil, copper, coffee, and wheat over the period from 1994/01/02 to 2014/11/01. The hedging pressure is defined as the hedgers' net short position (short minus long position) divided by the total open interest.

Figure 2: Average Futures Excess Returns and Average Hedging Pressure




The figure provides a scatter plot of the average excess futures return and average hedging pressure for the 26 sample commodities between 1994 and 2014. The cross-sectional regression line has a slope coefficient of 0.50 with *t*-statistic of 2.53 and an $R^2$ of 21%.

## 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 October 2014. 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 7th day of the month or the next day if the 7th 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 its total open interest, i.e., $HP_{i,t} = (HedgerShort_{i,t} - HedgerLong_{i,t})/OpenInterest_{i,t}$. The probability of short hedging, Prob(HP>0), is defined as the fraction of weeks when hedgers 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 hedgers and speculators. Finally, we examine the difference of the propensity of adjusting portfolio positions between speculators and hedgers. Denote SL, SS, HL and HS as the size of speculator's long, speculator's short, hedger's long, hedger's short positions, respectively, we define the propensity to trade as, $PT_{i,t}^{Hedger} = \frac{abs(HL_{i,t}-HL_{i,t-1})+abs(HS_{i,t}-HS_{i,t-1})}{HL_{i,t-1}+HS_{i,t-1}}$ ; $PT_{i,t}^{Spec} = \frac{abs(SL_{i,t}-SL_{i,t-1})+abs(SS_{i,t}-SS_{i,t-1})}{SL_{i,t-1}+SS_{i,t-1}}$. The *t*-statistic for the difference between hedgers and speculative propensity to trade is calculated by using Newy-West standard errors with 4 lags.

| Commodity | Annualized % Excess Return | | Hedging Pressure (*HP*) % | | | Average Absolute Value of Net Trading ($\lvert Q \rvert$) % | | Average Propensity to Trade *(PT)* % | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Standard Dev | Mean | Standard Dev. | Prob (HP>0) | Hedgers | Specs | Specs | Hedgers | Difference | (t-statistic) |
| Oil | 13.1 | 32.6 | 5.13 | 8.72 | 73.66 | 1.83 | 1.48 | 6.61 | 3.28 | 3.32 | (13.05) |
| Heating Oil | 11.0 | 31.2 | 9.89 | 8.82 | 85.73 | 2.66 | 1.94 | 10.03 | 4.30 | 5.73 | (12.57) |
| Natural Gas | -11.3 | 46.9 | 0.60 | 11.36 | 51.01 | 1.70 | 1.44 | 7.47 | 3.65 | 3.83 | (8.04) |
| Platinum | 9.1 | 22.0 | 49.77 | 23.44 | 95.30 | 6.26 | 5.43 | 11.25 | 7.42 | 3.82 | (17.60) |
| Palladium | 14.0 | 34.7 | 34.88 | 34.05 | 77.99 | 4.46 | 3.56 | 10.10 | 5.90 | 4.21 | (18.89) |
| Silver | 7.1 | 29.2 | 40.27 | 16.68 | 100.00 | 3.75 | 3.45 | 7.27 | 5.67 | 1.59 | (17.57) |
| Copper | 10.8 | 25.2 | 8.88 | 21.27 | 63.17 | 4.16 | 3.31 | 10.51 | 5.48 | 5.02 | (14.83) |
| Gold | 4.2 | 16.6 | 23.16 | 28.12 | 76.61 | 5.06 | 4.13 | 8.26 | 6.03 | 2.23 | (17.32) |
| Wheat | -6.9 | 28.8 | 2.02 | 14.49 | 49.36 | 3.09 | 2.68 | 6.88 | 4.89 | 1.99 | (10.36) |
| KC Wheat | 2.1 | 27.2 | 9.54 | 13.54 | 75.23 | 2.92 | 2.37 | 9.94 | 4.74 | 5.20 | (12.10) |
| Minn Wheat | 7.1 | 26.5 | 9.08 | 12.45 | 76.52 | 2.93 | 2.20 | 17.31 | 5.89 | 11.42 | (14.89) |
| Corn | -2.1 | 27.3 | 1.70 | 13.62 | 55.71 | 2.41 | 2.23 | 6.52 | 3.52 | 3.00 | (10.10) |
| Oat | 11.6 | 34.4 | 32.61 | 16.84 | 95.12 | 4.17 | 3.01 | 12.62 | 6.24 | 6.38 | (14.73) |
| Soybean | 8.4 | 23.8 | 10.31 | 16.61 | 72.93 | 2.83 | 2.64 | 7.11 | 4.56 | 2.56 | (15.66) |
| Soybean Oil | -0.6 | 23.8 | 12.02 | 17.71 | 69.80 | 4.01 | 3.07 | 8.18 | 5.15 | 3.03 | (-0.61) |
| Soybean Meal | 16.8 | 27.6 | 19.70 | 15.23 | 85.64 | 3.59 | 2.77 | 8.57 | 4.80 | 3.77 | (17.19) |
| Rough Rice | -6.8 | 25.8 | 12.34 | 22.53 | 68.97 | 3.87 | 2.87 | 11.30 | 6.15 | 5.14 | (11.95) |
| Cotton | -1.4 | 29.4 | 6.67 | 22.06 | 62.15 | 4.50 | 3.88 | 9.69 | 5.12 | 4.57 | (15.26) |
| Orange Juice | 3.6 | 31.7 | 25.5 | 22.34 | 85.64 | 4.80 | 4.00 | 10.07 | 6.02 | 4.05 | (11.08) |
| Lumber | -11.1 | 31.5 | 9.37 | 18.8 | 64.46 | 4.41 | 4.35 | 12.65 | 12.92 | -0.27 | (7.17) |
| Cocoa | 5.5 | 30.5 | 12.53 | 16.88 | 74.49 | 2.86 | 2.47 | 8.76 | 3.37 | 5.39 | (8.85) |
| Sugar | 8.8 | 32.0 | 15.97 | 17.89 | 78.08 | 3.83 | 2.72 | 9.81 | 4.50 | 5.32 | (15.22) |
| Coffee | 6.2 | 38.2 | 12.96 | 15.68 | 72.74 | 3.97 | 3.53 | 9.68 | 5.16 | 4.53 | (9.22) |
| Lean Hogs | -1.3 | 24.9 | 1.24 | 13.74 | 56.26 | 2.64 | 2.80 | 7.98 | 4.98 | 3.00 | (13.43) |
| Live Cattle | 2.6 | 15.2 | 4.29 | 10.38 | 62.15 | 1.83 | 2.24 | 6.18 | 3.30 | 2.88 | (17.80) |
| Feeder Cattle | 3.9 | 14.2 | -7.39 | 10.93 | 24.59 | 2.23 | 3.29 | 9.13 | 7.38 | 1.75 | (6.89) |
| Average | 4.0 | 28.1 | 13.96 | 17.08 | 71.28 | 3.49 | 3.00 | 9.38 | 5.40 | 3.98 | (12.74) |

## Table 2: Weekly Position Changes, Contemporaneous and Lagged Returns

The table reports the average slope coefficients and R-square of weekly Fama-McBeth cross-sectional regressions of the net position change (scaled by open interest) $Q_t$ in week $t$, on an intercept, the contemporaneous futures excess return ($R_t$) or the lagged return ($R_{t-1}$) and the lagged position change ($Q_{t-1}$). Separate regressions are run for each of three trader types using CFTC COT classifications: hedgers (commercials), speculators (non-commercials) and others (non-reportables). The table reports the time-series average of the weekly cross-sectional slope coefficients and the average R-square. The *t*-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags.

| | Hedgers | | Speculators | | Others | |
|---|---|---|---|---|---|---|
| $R_t$ | -0.66 | | 0.52 | | 0.14 | |
| | (-34.45） | | (32.44) | | (20.16) | |
| $R_{t-1}$ | | -0.20 | | 0.22 | | 0.02 |
| | | (-16.35) | | (20.00) | | (3.89) |
| $Q_{t-1}$ | | 0.17 | | 0.14 | | -0.02 |
| | | (17.30) | | (15.46) | | (-1.93) |
| $R^2$ | 24.25% | 16.67% | 20.64% | 16.76% | 10.4% | 12.62% |

## Table 3: Weekly Return Predictability Following Position Changes: Regression Approach

The table reports the average slope coefficients and R-square of weekly Fama-McBeth cross-sectional regressions of the excess return ($R_{t+1}$) in week $t+1$ on an intercept, the net position change (scaled by open interest) $Q_t$ in week $t$, both with and without a set of controls for expected returns. The controls are the log futures basis ($B_t$), excess returns ($R_t$), and $S_t\hat{v}_t$ 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 speculators are net long and -1 when speculators are net short. Separate regressions are run for each of three trader types using CFTC COT classifications: hedgers (commercials), speculators (non-commercials) and others (non-reportables). The table reports the time-series average of the weekly cross-sectional slope coefficients and the average R-square. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags.

| Coefficient Estimates ($\times \mathbf{100}$) | Hedgers | | Speculators | | Others | |
|---|---|---|---|---|---|---|
| $Q_t$ | 3.13 | 4.77 | -4.04 | -5.56 | -1.15 | -2.16 |
| | (4.84) | (6.55) | (-5.99) | (-7.43) | (-0.79) | (-1.45) |
| $B_t$ | | -0.47 | | -0.46 | | -0.48 |
| | | (-2.54) | | (-2.50) | | (-2.55) |
| $S_t\hat{v}_t$ | | -0.04 | | -0.01 | | -0.04 |
| | | (-0.29) | | (-0.06) | | (-0.29) |
| $R_t$ | | 4.43 | | 4.38 | | 2.02 |
| | | (3.91) | | (3.95) | | (2.00) |
| $R^2$ | 4.76% | 25.21% | 4.55% | 25.08% | 2.46% | 24.94% |

## Table 4: Return Predictability Following Position Changes: Portfolio Sorting Approach

On Tuesday of each week, commodities are ranked based on the change in net hedger positions *Q*. We sort commodities into five "quintile" portfolios containing 5, 5, 6, 5, 5 commodities each, respectively. The table reports the average excess returns (Panel A) and average position changes (Panel B) of hedgers (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 4 lags.

### Panel A: Average Excess Returns (in %)

| | -10 to 0 days | 1-4 days | 5-10 days | 11-20 days | 21-40 days | 1-40 days |
|---|---|---|---|---|---|---|
| Portfolio 1 (smallest Q) | 3.68 | -0.01 | -0.08 | 0.15 | 0.50 | 0.55 |
| Portfolio 2 | 1.61 | 0.03 | 0.04 | 0.14 | 0.25 | 0.48 |
| Portfolio 3 | 0.09 | 0.10 | 0.08 | 0.18 | 0.23 | 0.59 |
| Portfolio 4 | -1.40 | 0.19 | 0.12 | 0.14 | 0.30 | 0.75 |
| Portfolio 5 (largest Q) | -3.09 | 0.20 | 0.21 | 0.29 | 0.43 | 1.16 |
| Portfolio 5 − Portfolio 1 | -6.77 | 0.21 | 0.30 | 0.15 | -0.07 | 0.61 |
| (*t*-statistics) | | (3.04) | (3.62) | (1.23) | (-0.39) | (2.28) |

### Panel B: Average Position Changes of Hedgers (in %)

| | -2 to 0 week | 1 week | 2 week | 3-4 weeks | 5-8 weeks | 1-8 weeks |
|---|---|---|---|---|---|---|
| Portfolio 1 (smallest Q) | -7.85 | -1.52 | -0.20 | 0.51 | 0.88 | -0.33 |
| Portfolio 2 | -2.43 | -0.55 | -0.24 | 0.08 | 0.19 | -0.52 |
| Portfolio 3 | 0.20 | -0.05 | -0.01 | 0.03 | 0.05 | 0.01 |
| Portfolio 4 | 2.60 | 0.47 | 0.03 | -0.43 | -0.53 | -0.46 |
| Portfolio 5 (largest Q) | 7.73 | 1.40 | 0.06 | -0.91 | -1.81 | -1.28 |
| Portfolio 5 − Portfolio 1 | 15.58 | 2.92 | 0.26 | -1.43 | -2.69 | -0.94 |
| (*t*-statistics) | | (24.32) | (2.17) | (-7.24) | (-8.53) | (-2.37) |

# Table 5: Factors Affecting Liquidity Provision

This table examines weekly return predictability in commodity futures markets by estimating panel regressions of weekly returns on past position changes of commercial hedgers. The dependent variable is the excess return ($R_{t+1}$) in week $t+1$, and the independent variables are an intercept, the weekly position $Q_t$ in week $t$ for hedgers, a dummy $D(\cdot)_t$ that is 1 when the cost of liquidity provision is expected to be high, and a set of controls for expected returns. The control variables are the same as in Table 3. The table reports the result of a panel regression using data for all 26 commodities with each commodity returns having a fixed effect, the t-statistics is adjusted by the Newey-West method with 4 lags. As follows, we explain the dummy variables in more details.

Capital Loss: We first calculate capital loss *D*(*CapitalLoss*) for hedgers in week *t* as $CapitalLoss_t = HP_{i,t-1} \cdot R_{i,t}$, where $HP_{i,t-1}$ is the hedging pressure (i.e., the net short position of hedgers) for commodity $i$ in week $t$-1. The dummy variable $D(Capital\ Loss)$ takes on the value 1 when the capital lost in past 4 weeks is in the highest quartile of all sample observations of a certain commodity, and zero otherwise.

Order Imbalance: $D(OrderImbalance)$ is set equal to one when hedger's net trading (*Q*) is in the same direction (either buying or selling) in 4 continuous weeks from *t-3* to *t*, and zero otherwise.

Illiquidity: For each commodity in a given week, we compute its Amihud illiquidity measure as the average of the daily ratio of the absolute value of its daily return divided by its dollar trading volume in the same day for all the trading days in the week, and then take a past 52-week average of the weekly Amihud measure from week *t*-51 to *t*. We define a dummy variable *Dm(Illiquidity)* to be one for those commodities whose past 52-week average Amihud ratio is in the highest (most illiquid) quartile among all commodities in that week, and zero otherwise. When calculating the Amihud measure in the illiquidity test, we use the volume data from CRB dataset, which starts at January 2001. This time is also the starting point of the illiquidity regression.

| Coefficient Estimates ($\times \mathbf{100}$) | Capital Loss | Order Imbalance | Illiquidity |
|---|---|---|---|
| $Q_t$ | 2.55 | 2.70 | 1.89 |
| | (5.07) | (5.24) | (2.12) |
| $Q_t \times D(Capital\ Loss)_t$ | 3.50 | | |
| | (2.82) | | |
| $Q_t \times D(Order\ Imbalance)_t$ | | 2.35 | |
| | | (2.04) | |
| $Q_t \times D(Illiquidity)_t$ | | | 3.17 |
| | | | (2.35) |
| Controls | yes | yes | yes |
| $R^2$ | 0.30% | 0.28% | 0.33% |

## Table 6: Futures Return Predictability and Hedging Pressure

The table reports the average slope coefficients and R-square of weekly Fama-McBeth cross-sectional regressions of the excess return ($R_{t+1}$) in week $t+1$ on an intercept, lagged hedging pressure $HP_t$ smoothed lagged hedging pressure $\overline{HP}_t$, lagged net position changes of hedgers $Q_t$ and a set of controls for expected returns. The controls are the log futures basis ($B_t$), excess returns ($R_t$), and $S_t \hat{v}_t$ 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 speculators are net long and -1 when speculators are net short. The table reports the time-series average of the weekly cross-sectional slope coefficients and the average R-square. The *t*-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags.

Dependent Variable: $R_{t+1}$

| Coefficient Estimates ($\times \mathbf{100}$) | (1) | (2) | (3) |
|---|---|---|---|
| $HP_t$ | -0.07 | | |
| | (-0.43) | | |
| $\overline{HP_t}$ | | 0.54 | 0.49 |
| | | (3.35) | (2.80) |
| $Q_t$ | | | 4.88 |
| | | | (6.20) |
| Controls | yes | yes | yes |
| $R^2$ | 25.67% | 25.54% | 29.60% |

## Table 7: 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 hedgers' 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 hedger's $Q$ assigning 6 to Low $Q$ and 7 to the High $Q$ cohort. Panel A reports the average excess returns on the double sorted portfolios, and Panel B reports the average position changes of hedgers (normalized by the open interest of the ranking day) in the days and weeks subsequent to the sorting. Because the CFTC measures positions on Tuesdays and publishes the positions after the market close on Friday, we separately calculate the average 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 4 lags.

### Panel A: Average Excess Returns (in %)

| | Low $Q$ | High $Q$ | H – L $Q$ | *t*-stat |
|---|---|---|---|---|
| *Days 1-4* | | | | |
| Low $\overline{HP}$ | -0.10 | 0.13 | 0.23 | (3.90) |
| High $\overline{HP}$ | 0.09 | 0.26 | 0.17 | (2.66) |
| H – L $\overline{HP}$ | 0.19 | 0.13 | | |
| (*t*-statistics) | (2.80) | (2.10) | | |
| *Days 5-20* | | | | |
| Low $\overline{HP}$ | -0.04 | -0.10 | -0.07 | (-0.48) |
| High $\overline{HP}$ | 0.31 | 0.82 | 0.51 | (3.89) |
| H – L $\overline{HP}$ | 0.34 | 0.92 | | |
| (*t*-statistics) | (1.76) | (5.48) | | |
| *Days 21-40* | | | | |
| Low $\overline{\mathrm{HP}}$ | -0.06 | -0.09 | -0.03 | (-0.17) |
| High $\overline{\mathrm{HP}}$ | 0.79 | 0.73 | -0.06 | (-0.39) |
| H – L $\overline{\mathrm{HP}}$ | 0.85 | 0.82 | | |
| (*t*-statistics) | (4.09) | (3.77) | | |
| *Days 1-40* | | | | |
| Low $\overline{HP}$ | -0.18 | -0.05 | 0.13 | (0.57) |
| High $\overline{HP}$ | 1.18 | 1.80 | 0.62 | (2.90) |
| H – L $\overline{HP}$ | 1.36 | 1.85 | | |
| (*t*-statistics) | (3.87) | (5.50) | | |

Panel B: Average Position Changes of Hedgers (in %)

| | Low $Q$ | High $Q$ | H – L $Q$ | $t$-stat |
|---|---|---|---|---|
| | *1 Week* | | | |
| Low $\overline{HP}$ | -0.88 | 0.34 | 1.22 | (15.85) |
| High $\overline{HP}$ | -0.84 | 0.95 | 1.79 | (17.57) |
| H – L $\overline{HP}$ | 0.04 | 0.60 | | |
| ($t$-statistics) | (0.34) | (7.24) | | |
| | *2-4 weeks* | | | |
| Low $\overline{HP}$ | -0.53 | -0.75 | -0.21 | (-1.29) |
| High $\overline{HP}$ | 0.79 | -0.24 | -1.03 | (-5.06) |
| H – L $\overline{HP}$ | 1.32 | 0.51 | | |
| ($t$-statistics) | (5.13) | (2.34) | | |
| | *5-8 weeks* | | | |
| Low $\overline{HP}$ | -0.09 | -1.26 | -1.16 | (-6.14) |
| High $\overline{HP}$ | 0.88 | -0.28 | -1.16 | (-4.43) |
| H – L $\overline{HP}$ | 0.97 | 0.98 | | |
| ($t$-statistics) | (3.28) | (3.40) | | |
| | *Week 1-8* | | | |
| Low $\overline{HP}$ | -1.50 | -1.66 | -0.16 | (-0.64) |
| High $\overline{HP}$ | 0.83 | 0.43 | -0.40 | (-1.16) |
| H – L $\overline{HP}$ | 2.33 | 2.09 | | |
| ($t$-statistics) | (5.11) | (5.16) | | |

## Table 8: Liquidity and Convective Risk Flows

The table reports the slope coefficients and R-square of a panel regression of the excess return ($R_{t+1}$) in week $t+1$ on an intercept, lagged hedging pressure $HP_t$ smoothed lagged hedging pressure $\overline{HP}_t$, and lagged net position changes of hedgers $Q_t$, the contemporaneous and lagged change of the *VIX*, and a set of controls for expected returns. The controls are the log futures basis ($B_t$), excess returns ($R_t$), and $S_t\hat{v}_t$ 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 speculators are net long and -1 when speculators are net short. The *t*-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags.

| Coefficient Estimates (× 100) | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| $\overline{HP}$ | 0.44 | 0.45 | 0.44 |
| | (2.25) | (2.35) | (2.25) |
| $Q_{i,t}$ | 3.03 | 3.01 | 3.05 |
| | (6.30) | (6.26) | (6.34) |
| $dVIX_{t+1}$ | | -0.19 | |
| | | (-16.80) | |
| $dVIX_t$ | | | 0.01 |
| | | | (1.18) |
| Controls | yes | yes | yes |
| $R^2$ | 0.29% | 1.98% | 0.30% |

## Table 9: Hedging Pressure and Liquidity Provision: DCOT Data

The table examines the robustness of our results using the Disaggregate Commitment of Traders (DCOT) dataset. DCOT data is from 2006/01/03 to 2014/11/01 at the weekly frequency. The DCOT report classifies traders into producers and merchant users, swap dealers, managed money, other reportables, and non-reportables, for the same set of commodities as in COT database. The table reports the time-series average of slope coefficients and R-square of weekly Fama-McBeth cross-sectional regressions of the excess return ($R_{t+1}$) in week $t+1$ on an intercept, lagged hedging smoothed pressure $\overline{HP}_t$, and lagged net position changes of hedgers $Q_t$ with and without a set of controls for expected returns. The controls are the log futures basis ($B_t$), excess returns ($R_t$), and $S_t\hat{v}_t$ 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 speculators are net long and -1 when speculators are net short. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags.

| Coefficient Estimates ($\times\mathbf{100}$) | DCOT data Without controls | DCOT data With controls |
|---|---|---|
| $\overline{HP}_{i,t}$ | 0.85 | 0.58 |
| | (2.64) | (1.61) |
| $Q_t$ | 5.40 | 8.59 |
| | (3.69) | (5.32) |
| Controls | no | yes |
| $R^2$ | 10.37% | 29.41% |

## Appendix A: Appendix Tables

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

The table reports the average slope coefficients and R-square of weekly Fama-McBeth cross-sectional regressions of the excess return ($R_{t+1}$) in week $t+1$ on an intercept, the net position change (scaled by open interest) $Q_t$ in week $t$, with a set of controls for expected returns. The controls are the log futures basis ($B_t$), excess returns ($R_t$), and $S_t\hat{v}_t$ 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 speculators are net long and -1 when speculators are net short. Separate regressions are run for hedgers and speculators. The table reports the time-series average of the weekly cross-sectional slope coefficients and the average R-square. The *t*-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags. In panel A, we divide the sample period into two equal sub-sample periods: from 1994/1/2 to 2003/12/31, and from 2004/1/2 to 2014/11/1. In panel B, we separate the sample to before and after the financial crisis (2008/9/15).

Panel A: Two Equal-half Sub-periods

| | 1994/01/02 – 2003/12/31 | | 2004/01/02 – 2014/11/01 | |
|---|---|---|---|---|
| Coefficient Estimates ($\times$ 100) | Hedgers | Speculators | Hedgers | Speculators |
| $Q_{i,t}$ | 4.07 | -4.28 | 5.43 | -6.73 |
| | (5.23) | (-4.96) | (4.52) | (-5.68) |
| $B_{i,t}$ | -0.37 | -0.38 | -0.57 | -0.54 |
| | (-1.53) | (-1.57) | (-2.03) | (-1.94) |
| $S_{i,t}\hat{v}_{i,t}$ | -0.16 | -0.12 | 0.08 | 0.10 |
| | (-0.94) | (-0.73) | (0.41) | (0.54) |
| $R_{i,t}$ | 6.00 | 5.75 | 2.97 | 3.11 |
| | (3.73) | (3.59) | (1.89) | (2.04) |
| $R^2$ | 12.0% | 12.0% | 10.0% | 9.7% |

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

| | 1994/01/02 - 2008/09/15 | | 2008/09/16 - 2014/11/01 | |
|---|---|---|---|---|
| Coefficient Estimates ($\times$ 100) | Hedgers | Speculators | Hedgers | Speculators |
| $Q_{i,t}$ | 3.66 | -4.37 | 8.17 | -9.18 |
| | (4.67) | (-5.57) | (4.69) | (-4.80) |
| $B_{i,t}$ | -0.40 | -0.39 | -0.69 | -0.67 |
| | (-2.11) | (-2.04) | (-1.81) | (-1.74) |
| $S_{i,t}\hat{v}_{i,t}$ | -0.03 | 0.00 | -0.04 | -0.04 |
| | (-0.23) | (0.03) | (-0.16) | (-0.15) |
| $R_{i,t}$ | 5.30 | 5.25 | 1.76 | 1.72 |
| | (4.03) | (4.03) | (0.87) | (0.87) |
| $R^2$ | 11.4% | 11.3% | 9.5% | 9.3% |

Table A2:
Weekly Return Predictability Following Position Changes: DCOT Dataset

The table reports the average slope coefficients and R-square of weekly Fama-McBeth cross-sectional regressions of the excess return ($R_{t+1}$) in week $t+1$ on an intercept, the net position change (scaled by open interest) $Q_t$ in week $t$, with a set of controls for expected returns. The controls are the log futures basis ($B_t$), excess returns ($R_t$), and $S_t \hat{v}_t$ 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 speculators are net long and -1 when speculators are net short. Separate regressions are run for each of the trader types using CFTC DCOT classifications: producers and merchant users, swap dealers, managed money, other reportables, and non-reportables,. The table reports the time-series average of the weekly cross-sectional slope coefficients and the average R-square. The $t$-statistics in parentheses below the coefficients are adjusted using the Newey-West method with 4 lags.

| Coefficient Estimates ($\times$ 100) | Producer | Money Manager | Swap Dealer | Other Reportable | Small Investor |
|---|---|---|---|---|---|
| $Q_{i,t}$ | 8.83 | -6.91 | -2.88 | -1.56 | -1.47 |
| | (5.73) | (-3.97) | (-0.81) | (-0.48) | (-0.43) |
| $B_{i,t}$ | -0.72 | -0.79 | -0.80 | -0.76 | -0.77 |
| | (-2.17) | (-2.35) | (-2.41) | (-2.31) | (-2.29) |
| $S_{i,t}\hat{v}_{i,t}$ | -0.05 | -0.12 | -0.07 | -0.08 | -0.05 |
| | (-0.22) | (-0.47) | (-0.28) | (-0.34) | (-0.21) |
| $R_{i,t}$ | 3.84 | 3.47 | 0.52 | 0.66 | 0.92 |
| | (2.12) | (1.80) | (0.32) | (0.39) | (0.55) |
| $R^2$ | 10.5% | 10.7% | 9.5% | 9.8% | 9.6% |

## Appendix B: A Concise Model

In this section we present a concise model to better illustrate the economic intuition of our main empirical findings.

*B.1 Model Setup*

In the model, there are one representative producer (i.e., hedger) and one representative speculator, both with mean-variance utility. Information is symmetric for all investors in the economy. There are three time periods: $t \in \{0,1,2\}$. The producer starts producing the physical commodity at time 0, and output is realized at time 2. The production amount *G* is scheduled in advance and cannot be changed once it is set at time 0.[25] Commodity futures contracts are traded at times 0 and 1 at prices $F_0$ and $F_1$, and mature at time 2 with $F_2 = S_2$, where $S_2$ is the commodity spot price at time 2.

The producer chooses her position in futures, $h_{p,t}$, at time 0 and 1 to maximize her terminal utility of wealth:

$$\max_{h_{p,t}} \mathrm{E}_t\left[\mathrm{W}_{p,2}\right] - \frac{\gamma_p}{2} Var_t[\mathrm{W}_{p,2}] \ ,$$

$$\text{with } \mathrm{W}_{p,2} = S_2 G + \sum_{i=0}^{1} h_{p,i}(F_{i+1} - F_i) \qquad \text{(B.1)}$$

where $t \in \{0,1\}$, $\mathrm{W}_{p,2}$ is producer's wealth at time 2, and $\gamma_p$ is her coefficient of risk aversion.

We denote the speculator's position in commodity futures at time 0 and 1 by $h_{s,t}$, with $t \in \{0,1\}$. At time 1, the speculator is endowed with $u_1$ units of an asset with payoff $S_2 + \eta_2$ at time 2. The value of the asset is correlated with the commodity price.

[25] For parsimonious reason, we assume the producer cannot hold inventory. The main implication from our model does not change if we relax this constraint.

An example of such asset can be the equity shares of a firm for which the commodity is an input or output, an investment in an emerging country whose economic performance depends on the commodity price, or an asset that is correlated with inflation. $\eta_2$ is a random zero mean quantity that is independent of other variables. $u_1$ is a Gaussian random variable realized at time 1 with mean zero and variance $\sigma_u^2$, and is also independent with other variables.

Thus, for $t \in \{0,1\}$ the speculator's optimization procedure can be described as

$$\max_{h_{s,t}} \mathrm{E}_t\left[\mathrm{W}_{s,2}\right] - \frac{\gamma_s}{2} Var_t[\mathrm{W}_{s,2}] \ ,$$

$$\text{with } \mathrm{W}_{s,2} = \sum_{i=t}^{1} h_{s,i}(F_{i+1} - F_i) + u_1(S_2 + \eta_2) \qquad \text{(B.2)}$$

where $\mathrm{W}_{S,2}$ is speculator's terminal wealth at time 2 and $\gamma_s$ is his risk aversion coefficient.

The demand for the physical commodity at time 2 is $Q_2 = l(k_2 - S_2)$, where $k_2$ is a stochastic variable representing a fundamental demand shock at time 2 and $l$ is a constant. We assume that $k_t$ follows a random walk, with starting value $k_0$ and an incremental innovation drawn from a normal distribution with mean zero and standard deviation σ for each time period. Thus, $k_2$ can be considered as the demand shock realized at time 2, and $k_0$ and $k_1$ can be interpreted as the investors' expectation of this demand shock at time 0 and 1 respectively. Equating demand and supply to clear the spot market at time 2, we have $l(k_2 - S_2) = G$, which implies a spot price of:

$$S_2 = k_2 - G/l \ . \qquad \text{(B.3)}$$

*B.2 Model Solution*

As shown in Appendix C, the solution of the model provides

$$h_{s,0} = [\frac{\gamma_p \sigma^2}{(\gamma_p+\gamma_s)(\sigma^2+b^2\sigma_u^2)} + \frac{\gamma_p^2\gamma_s^2\sigma^4\sigma_u^2(\gamma_p-\gamma_s)}{(\gamma_p+\gamma_s)^3(\sigma^2+b^2\sigma_u^2)} - \frac{\gamma_p\ \gamma_s^2\sigma^2\sigma_u^2}{(\sigma^2+b^2\sigma_u^2)(\gamma_p+\gamma_s)^2 l}]G \tag{B.4a}$$

$$h_{p,0} = -h_{s,0} \tag{B.4b}$$

$$E_0[F_1 - F_0] = \frac{\gamma_p\gamma_s\sigma^2 G}{\gamma_p+\gamma_s} + \frac{\gamma_p^2\gamma_s^2\sigma^2 G\sigma_u^2}{(\gamma_p+\gamma_s)^2 l}\ . \tag{B.5}$$

$$h_{s,1} = \frac{\gamma_p G}{\gamma_s+\gamma_p} - \frac{\gamma_s u_1}{\gamma_s+\gamma_p} \tag{B.6a}$$

$$h_{p,1} = -h_{s,1} \tag{B.6b}$$

$$E_1[S_2 - F_1] = \frac{\gamma_p\gamma_s\sigma^2}{\gamma_p+\gamma_s}G + \frac{\gamma_p\gamma_s\sigma^2}{\gamma_p+\gamma_s}u_1. \tag{B.7}$$

where $b = \frac{\gamma_p\gamma_s\sigma^2}{\gamma_p+\gamma_s}$.

*B.3 Model implications*

*Futures Price Changes and Holdings*:

The futures price change from time 0 to 1 can be written as:

$$\Delta F_1 = F_1 - F_0 = k_1 - k_0 - \sigma^2\gamma_p\Delta h_p + C$$

$$=k_1 - k_0 + \sigma^2\gamma_p\Delta h_s + C \tag{B.8}$$

where $C = \frac{\gamma_p\gamma_s\sigma^2 G}{\gamma_p+\gamma_s} + \frac{\gamma_p^2\gamma_s^2\sigma^2\sigma_u^2 G}{(\gamma_p+\gamma_s)^2 l} - \frac{b^2\sigma_u^2\gamma_s\gamma_p\sigma^2 G}{(\gamma_p+\gamma_s)(\sigma^2+b^2\sigma_u^2)} - \frac{b^2\sigma_u^2 G}{(\sigma^2+b^2\sigma_u^2)l}$ is a constant.

Therefore, the futures price change is not only determined by the fundamental demand shock $(k_1 - k_0)$, but is also related to the position change of the producer or speculator. More specifically, the futures price change is positively correlated with the speculator's position change ($\Delta h_s$) and negatively correlated with the producer's position change ($\Delta h_p$) in the same time period. This suggests that the speculator trades in the same direction as the futures price change, while the producer trades in the opposite direction of the contemporaneous futures price change. This implication is consistent with what we have observed in Table 2, where the position change of speculators (hedgers) is positively (negatively) correlated with the contemporaneous futures price change.

*A Tale of Two Premiums:*

As shown in equation (B.7), the risk premium embedded in the commodity futures price consists of two components: the first part, $\frac{\gamma_p \gamma_s \sigma^2}{\gamma_p + \gamma_s} G$, is the risk premium corresponding to the producer's hedging demands and can be interpreted as a hedging premium; the second part, $\frac{\gamma_p \gamma_s \sigma^2}{\gamma_p + \gamma_s} u_1$, stems from the trading demands of speculators and can be interpreted as a liquidity premium.

To better understand the model's predictions, we assume without loss of generality, $\sigma_u^2$=0 in this sub-section. This implies $h_{s,0} = -h_{p,0} = \frac{\gamma_p G}{\gamma_s + \gamma_p}$. Starting with the simple case when $u_1$ is zero, we find that $h_{p,1} = h_{p,0}$ and $h_{s,1} = h_{s,0}$. In this situation, there is no need for the speculator or the producer to trade at time 1 since their positions have already been optimized based on their utility preference at time 0. Moreover, the expected futures risk premium at time 1 will be $\frac{\gamma_p \gamma_s \sigma^2}{\gamma_p + \gamma_s} G$, which is essentially an insurance premium offered by the producer for her hedging demand.

When $u_1$ is not zero, the speculator needs to redo his utility maximization at time 1 to determine his new optimal futures position. As shown by (B.6a), the speculator's optimal position at time 1 will be different from his existing futures position established at time 0 by $\frac{-\gamma_s u_1}{\gamma_s + \gamma_p}$. Therefore, a trading need arises for the speculator. For example, when $u_1$ is negative, the speculator needs to buy in the futures market ($h_{s,1} - h_{s,0} > 0$), and his purchase will push the futures price to a level higher than the case without speculator's trading needs. The futures risk premium will be reduced since the extra price the speculator pays for his demand of immediacy erodes the hedging premium he receives from the producer. Similarly, when $u_1$ is positive, the speculator sells in futures market and futures risk premium increases by extra amount that the speculator pays for demand of liquidity. Hence, $\frac{\gamma_p \gamma_s \sigma^2}{\gamma_p+\gamma_s} u_1$ thus represents liquidity premium that comes from the speculators' trading demand.

In brief, according to our model, the risk premium in the futures market consists of both the hedging premium stemmed from the producer's hedging demand and the liquidity premium that arises from the trading needs of speculators. This is consistent with our empirical results. For example, in Table 6 and 7, we preform regression and double-sorting tests, and find that both premiums significantly exist in commodity futures markets.

Next we illustrate the liquidity premiums and hedging premiums in more detail.

*Liquidity Premium*: From equation (C.17a), the liquidity premium $\frac{\gamma_p \gamma_s \sigma^2}{\gamma_p+\gamma_s} u_1$ can be written as:

$$\frac{\gamma_p \gamma_s \sigma^2}{\gamma_p+\gamma_s} u_1 = \sigma^2 \gamma_p \Delta h_p - B = -\sigma^2 \gamma_p \Delta h_s - B \tag{B.9}$$

where $B = \frac{b^2 \sigma_u^2 \gamma_s \gamma_p \sigma^2 G}{(\gamma_p+\gamma_s)(\sigma^2+b^2\sigma_u^2)} + \frac{b^2 \sigma_u^2 G}{(\sigma^2+b^2\sigma_u^2) l}$ is a constant.

Therefore, the liquidity premium is determined by the position change of the speculator (negative relationship) or of the producer (positive relationship). For example, if the speculator were to sell at time 1, the futures price will be pushed down. (See also equation B.8.) In this situation, the speculator offer a price concession (sell at a lower price level), to provide an incentive for the producer to deviate from her optimal hedging position established previously and to accommodate the speculator's trading desire. As a result, the premium embedded in futures that are sold by the speculator (or bought by the producer) will increase. Similarly, the premium embedded in futures that are bought by the speculator (or sold by the producer) will decrease. This return predictability can be interpreted as a liquidity premium, which the speculator pays to the producer to obtain immediacy for his trading demand. This supports our empirical findings in Table 3 and 4 in that the position changes of hedgers (speculators) can positively (negatively) predict next-week futures returns.

Furthermore, as shown in (B.9), the liquidity premium increases in the risk aversion coefficient $\gamma_p$ of producers. When the producer is more risk averse, she would ask for a higher risk premium to absorb the speculator's demand for immediacy. This is consistent with what we observe in Table 5, where hedgers with more binding capital constraints or with higher position imbalance tend to ask for higher liquidity premiums.

*Hedging premium*: As shown in (B.6a) and (B.6b), the producer's position contains a hedging component, $-\frac{\gamma_p G}{\gamma_s+\gamma_p}$, and a liquidity component, $\frac{\gamma_s u_1}{\gamma_s+\gamma_p}$, hence producer's position can be influenced by the short-term trading demands of the speculator. In empirical tests of the influence of hedging pressure on the risk premium (for example based on the theory of normal backwardation) this may lead to an attenuation of the results. It is important to control for the component in the producer's position that is related to speculative trading to isolate the impact of the demand for price insurance on the risk premium. Hence, it is important to control the short-term fluctuation in the hedger's position to obtain a more precise measure of the hedging premium as predicted by the normal backwardation theory.

More precisely, according to our model, from the equation (B.6a) and (B.6b) we have

$$E_0[h_{p,1}] = -\frac{\gamma_p}{\gamma_s+\gamma_p} G \tag{B.10}$$

Equation (B.10) indicates that taking the expectation of the producer's position yields a more accurate measure of her hedging needs, since the short-term trading shock $u_1$ is a zero-mean stochastic variable that will be canceled out by taking expectations. In empirical applications, this can be done by taking a long-term average of hedgers' position. As shown in Table 6, smoothed (averaged) hedging pressure can predict futures excess returns, whereas unsmoothed hedging pressure fails to do so.

## Appendix C: Model Solution

*C.1 Market clearing at time 1*:

At time 1, given that the distribution of $k_2$ conditional on investors' information set is a normally distributed $N(k_1, \sigma)$, we have

$$E_1(S_2) = k_1 - G/l \ , \quad \text{(C.1a)}$$

$$Var_1(S_2) = \sigma^2 \ . \quad \text{(C.1b)}$$

In the futures market, substituting in the expression of $W_{p,2}$, we see that the producer solves the optimality problem

$$\max_{h_{p,1}} E_1[S_2 G + h_{p,1}(S_2 - F_1)] - \frac{\gamma_p}{2} Var_1[S_2 G + h_{p,1}(S_2 - F_1)] \quad \text{(C.2)}$$

Taking the first order condition with respect to the futures position $h_{p,1}$ we get,

$$h_{p,1} = \frac{E_1[S_2 - F_1]}{\gamma_p \sigma^2} - G \quad \text{(C.3)}$$

The speculator needs to maximize his utility function as

$$\max_{h_{s,1}} E_1[h_{s,1}(S_2 - F_1) + u_1(S_2 + \eta_2)] - \frac{\gamma_s}{2} Var_1[h_{s,1}(S_2 - F_1) + u_1(S_2 + \eta_2)].$$

(C.4)

The optimization procedure leads to

$$h_{s,1} = \frac{E_1[S_2 - F_1]}{\gamma_s \sigma^2} - u_1 \ . \quad \text{(C.5)}$$

The market clearing condition is

$$h_{p,1} + h_{s,1} = 0 \ . \quad \text{(C.6)}$$

The clearing of the futures market at time 1 suggests that

$$E_1[S_2 - F_1] = \frac{\gamma_p \gamma_s \sigma^2}{\gamma_p + \gamma_s} G + \frac{\gamma_p \gamma_s \sigma^2}{\gamma_p + \gamma_s} u_1 \ , \quad \text{(C.7)}$$

which leads to

$$F_1 = k_1 - \frac{G}{l} - \frac{\gamma_p \gamma_s \sigma^2 G}{\gamma_p + \gamma_s} - \frac{\gamma_p \gamma_s \sigma^2 u_1}{\gamma_p + \gamma_s} \ . \quad \text{(C.8)}$$

The futures positions of the producer and speculator at time 1 are

$$h_{p,1} = -\frac{\gamma_p G}{\gamma_s + \gamma_p} + \frac{\gamma_s u_1}{\gamma_s + \gamma_p} \ , \quad \text{(C.9a)}$$

$$h_{s,1} = \frac{\gamma_p G}{\gamma_s + \gamma_p} - \frac{\gamma_s u_1}{\gamma_s + \gamma_p} \ . \quad \text{(C.9b)}$$

*C.2 Market clearing at time 0*:

In the futures market, the producer's optimization at time 0 can be solved as

$$\max_{h_{p,0}} E_0[S_2 G + h_{p,1}(S_2 - F_1) + h_{p,0}(F_1 - F_0)]$$

$$-\frac{\gamma_p}{2}Var_0\left[S_2G+h_{p,1}(S_2-F_1)+h_{p,0}(F_1-F_0)\right] \ . \tag{C.10}$$

Taking the first order condition of equation (C.10) with respect to the producer's futures position $h_{p,0}$, we have

$$h_{p,0}=\frac{E_0[F_1-F_0]-\gamma_pA-\sigma^2\gamma_pG}{\gamma_p(\sigma^2+b^2\sigma_u^2)} \tag{C.11}$$

where we define $b=\frac{\gamma_p\gamma_s\sigma^2}{\gamma_p+\gamma_s}$, $\mathrm{A}=\frac{\gamma_p^2\gamma_s^2\sigma^4(\gamma_p-\gamma_s)G\sigma_u^2}{(\gamma_p+\gamma_s)^3}$ .

Similarly, the speculator solves

$$max_{h_{s,0}}\mathrm{E}_0\left[h_{s,0}(F_1-F_0)+h_{s,1}(S_2-F_1)+u_1(S_2+\eta_2)\right]-\frac{\gamma_S}{2}Var_0[h_{s,0}(F_1-F_0)+h_{s,1}(S_2-F_1)+u_1(S_2+\eta_2)] \tag{C.12}$$

we can solve the speculator's optimization at time 0 and derive his futures position $h_{s,0}$ as

$$h_{s,0}=\frac{E_0[F_1-F_0]+\gamma_s(A-\frac{G}{l}b\sigma_u^2)}{\gamma_s(\sigma^2+b^2\sigma_u^2)} \ . \tag{C.13}$$

The clearing of the commodity futures market at time 0 implies that

$$E_0[F_1-F_0]=\frac{\gamma_p\gamma_s\sigma^2G}{\gamma_p+\gamma_s}+\frac{\gamma_p^2\gamma_s^2\sigma^2G\sigma_u^2}{(\gamma_p+\gamma_s)^2l} \ , \tag{C.14}$$

This leads to

$$F_0=k_0-\frac{G}{l}-\frac{2\gamma_p\gamma_s\sigma^2G}{\gamma_p+\gamma_s}-\frac{\gamma_p^2\gamma_s^2\sigma^2G\sigma_u^2}{(\gamma_p+\gamma_s)^2l} \ . \tag{C.15}$$

And the futures positions of the producer and speculator at time 0 are

$$h_{s,0}=[\frac{\gamma_p\sigma^2}{(\gamma_p+\gamma_s)(\sigma^2+b^2\sigma_u^2)}+\frac{\gamma_p^2\gamma_s^2\sigma^4\sigma_u^2(\gamma_p-\gamma_s)}{(\gamma_p+\gamma_s)^3(\sigma^2+b^2\sigma_u^2)}-\frac{\gamma_p\ \gamma_s^2\sigma^2\sigma_u^2}{(\sigma^2+b^2\sigma_u^2)(\gamma_p+\gamma_s)^2l}]G \ , \tag{C.16a}$$

$$h_{p,0}=-h_{s,0} \ . \tag{C.16b}$$

Also, it is easy to show

$$\Delta h_s=h_{s,1}-h_{s,0}=[\frac{b^2\sigma_u^2\gamma_s}{(\gamma_p+\gamma_s)(\sigma^2+b^2\sigma_u^2)}+\frac{\gamma_p\ \gamma_s^2\sigma^2\sigma_u^2}{(\sigma^2+b^2\sigma_u^2)(\gamma_p+\gamma_s)^2l}]G-\frac{\gamma_su_1}{\gamma_s+\gamma_p} \ , \tag{C.17a}$$

$$\Delta h_p=h_{p,1}-h_{p,0}=-\Delta h_s \ . \tag{C.17b}$$

and

$$\Delta F_1=F_1-F_0=k_1-k_0+\frac{\gamma_p\gamma_s\sigma^2G}{\gamma_p+\gamma_s}+\frac{\gamma_p^2\gamma_s^2\sigma^2G\sigma_u^2}{(\gamma_p+\gamma_s)^2l}-\frac{\gamma_p\gamma_s\sigma^2u_1}{\gamma_p+\gamma_s}. \tag{C.18}$$