The Role of Hedgers and Speculators in Liquidity Provision to Commodity Futures Markets

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Abstract

This paper studies the dynamic relation between position changes and short-horizon returns in commodity futures markets. In contrast to the Keynesian view that speculators provide liquidity to hedgers, we find evidence that hedgers provide short-term liquidity to speculators. Speculators follow momentum strategies and trade more impatiently than hedgers, who trade as contrarians. Commodity futures prices predictably increase (decrease) following hedgers' buying (selling) activity. This predictability is stronger when hedgers face more binding funding constraints and higher inventory pressure. These findings are consistent with the view that hedgers receive compensation for providing liquidity to speculators.

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1. Introduction

Liquidity provision is a key aspect of well-functioning capital markets, and economists and policy makers are keenly interested in understanding the role of various market participants in contributing to the overall liquidity of the market. This is particularly true for commodity futures markets where, ever since Congress passed the Onions Futures Act of 1958 to ban the trading of onion futures in the U.S., there has been an ongoing debate concerning the role of speculative capital. Milton Friedman (1960) argued that speculators in commodity futures markets ultimately perform the important function of providing liquidity for hedgers. This premise also underlies the classical theory of normal backwardation, originated from Keynes (1923) and Hicks (1939), which describes the function of commodity futures markets as to allow commercial producers to hedge their underlying long position in the physical commodity. Risk-averse speculators accommodate this hedging demand by taking an opposite position in futures for which, according to the theory, they receive compensation in the form of a risk premium. In current policy discussions about commodity markets, the belief that speculators provide liquidity is often used as the primary justification for their presence. For example, in a public hearing on the Dodd-Frank Act, the U.S. Senator of Michigan State Carl Levin (2011) states that "Speculators, who by definition don't plan to use the commodities they trade, but profit from the changing prices, are needed only insofar as they supply the liquidity needed for producers and users to hedge their risks."

Much of the early empirical academic literature on commodity futures markets has attempted to measure or test for the risk premium in futures prices (Working (1949), Telser (1958), and Dusak (1973)) or to calculate the compensation for providing liquidity to hedgers by measuring the profitability of speculators (Rockwell (1967), Chang (1985), and Harzmark (1987)). But as of today, there is no general consensus in the literature about the presence of risk premiums or the contribution of speculative capital to overall market liquidity. There is some evidence to support that the long side of commodity futures positions has on average received a positive risk premium over the past half century (Bodie and Rosanski (1980), Gorton and Rouwenhorst (2006)). And, broadly consistent with the notion of normal backwardation, there is also evidence that speculative positions were on average net long in most commodity futures markets during this period. Yet it has proven to be difficult to establish a strong link between variation in speculative positions, and the overall profits earned by speculators (see Rouwenhorst and Tang (2012) for a review of the evidence).

In this paper we step back from the "low frequency" question of the risk premium earned by speculators for allowing hedgers to obtain price insurance. Instead we focus on high frequency (weekly) changes in speculative and hedging positions, and examine the question of liquidity provision at this shorter horizon. We will examine whether observed short-term position changes are predominantly driven by either shocks to hedging demands of commercial traders or by the desire of speculators to adjust their portfolios. Our empirical strategy is similar to Kaniel, Saar, and Titman (2008) who study the response of equity prices following heavy selling by institutional investors. If one subset of investors demands liquidity for immediacy, this is likely to show up in the form of predictable returns following the trade. In the context of commodity futures markets, we will examine short-term price adjustments following position changes by commercial hedgers and non-commercial speculators, and use such return predictability to make inferences about liquidity provision in these markets.

Using publicly available data on aggregate positions published by the CFTC, we document that speculators are in aggregate momentum traders, purchasing when prices rise and selling in declining markets, while hedgers trade like contrarians. We also find that speculative traders are more impatient; their trading propensity is on average twice as large as hedgers.

The main finding of our paper is that commodity futures prices predictably change following position adjustments by hedgers and speculators. During the week following a trade, commodities that are most heavily bought by speculators temporarily earn lower returns than commodities that are heavily sold by speculators. And commodities which are purchased by hedgers subsequently outperform those that are sold by them. To quantify these effects: a “typical” purchase by speculators leads to a price reversal of 16 basis points during the week following the position change. A long-short investment strategy that buys the top half (quintile) of commodities most heavily purchased by hedgers and sells the bottom half (quintile) earns on an average excess return of 43 (67) basis points in the twenty days following the position change. These findings are consistent with the view that hedgers provide short-term liquidity to commodity futures markets and speculators are consumers of liquidity, and are opposite to the commonly held view that speculators are the providers of liquidity.

Our findings parallel predictions from the microstructure theory literature (Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993)), where liquidity providers (or market makers) tend to trade against the market trend as contrarians, since they need to maintain the continuity of the security price and accommodate the order flow imbalances on the market, while momentum followers usually consume liquidity from the market.[1] Impatient investors who require immediacy need to offer price concessions to encourage risk-averse market makers taking the other side of their trades. Hence, the contrarian trading by market makers earns a compensation for providing liquidity by exploiting subsequent price reversals.

We attempt to rule out alternative explanations for the returns earned by hedgers, such as private information, and provide additional support for the liquidity provision hypothesis. For example, consistent with the models of Xiong (2001) and Brunnermeier and Pedersen (2009), we find that after hedgers experience losses they become more reluctant to provide liquidity and demand a higher premium to do so. Furthermore, similar to the role of order imbalance documented by Chordia, Roll, and Subrahmanyam (2002) for liquidity in the stock market, we show that hedgers' willingness to provide liquidity depends on the direction of past position changes. Other factors that contribute to the cost of liquidity provision are the proportion of hedgers and speculators in the market, and the balance between long and short positions among hedgers and speculators.

[1] More recent studies, such as Kaniel, Saar, and Titman (2008) and Comerton-Forde et al. (2010), provide empirical support to this theoretical claim using data on the U.S. stock market.

Our paper contributes to several strands of literature. First, a growing set of papers that examine the role of speculators in commodity markets, and how trading by speculators can influence prices; a question which has received much attention with the recent rise in investor interest in commodities (Tang and Xiong (2012), Singleton (2011), Kaufmann (2011) and Cheng, Kirilenko, and Xiong (2012)).[2] Second, we expand the literature on short-term reversals related to market making and liquidity provision to commodity futures markets (e.g., Conrad, Hameed, and Niden (1994), Avramov, Chordia, and Goyal (2006), Kaniel, Saar, and Titman (2008)). Finally, our paper can contribute to the literature on risk premiums in commodity futures markets by suggesting a partial explanation for why speculators seemingly have failed to earn a profit from providing hedgers protection against price risk over longer horizons despite the fact that the long side of commodity futures contracts has received a risk premium: by demanding short-term liquidity to rebalance their portfolios towards winners and away from losers, speculators in effect rebate to the hedgers a part of the premium that they were originally offered for longer-term insurance provision.

The remainder of the paper is organized as follows. Section 2 describes the data and provides basic summary statistics about the frequency and size of position changes in commodity futures markets. In Section 3 we characterize the trading behavior of hedgers and speculators and present the central result of the paper concerning the return predictability based on past trading behavior. Section 4 explores

[2] Other examples include Hamilton (2009) and Fattouh, Kilian and Mahadeva (2012) who do not find evidence that speculation drove up oil prices during the 2003 to 2008 period. Pirrong (2010) and Buyuksahin and Harris (2011) further argue that that speculators in general contributes to a more well-functioning commodity future market.

the factors that affect the compensation for liquidity provision. Section 5 conducts several robustness checks on our results by considering different datasets and methods to calculate futures returns. Section 6 concludes our paper.

2. Data and Summary Statistics

We use publicly available data provided by Commodity Futures Trading Commission (CFTC) to study the trading behavior of various types of investors in commodity futures markets. More specifically, we obtain our data from the weekly Commitment of Trader (COT) reports on aggregate long and short positions of commodity futures market participants, classified by trader type: commercials, non-commercials, or non-reportables. Every Tuesday beginning in 1993, the CFTC collects information about the trading positions in all exchange-traded futures on US-based exchanges, and publishes the position breakdown on the subsequent Friday. Our data sample covers 26 commodities that are traded on four North American exchanges (NYMEX, NYBOT, CBOT and CME) for the period from 1994/01/02 to 2012/06/29.[3]

The classification of traders as either commercial or non-commercial is coarse, and there exists considerable heterogeneity among market participants within these categories. (see for example Ederington and Lee (2002)). We follow the empirical literature which has traditionally associated commercials with hedgers and non-commercials with speculators (Houthakker (1957), Rockwell (1967), Chang

[3] The CFTC dataset originally have 28 commodities, we do not include pork belly and RBOB since pork belly has stopped trading, and RBOB only starts trading from the year of 2006.

(1985), Bessembinder (1992), Hong and Yogo (2012), Acharya, Lochstoer and Ramordai (2013)).[4] We check the robustness of our results using the positions data from the Disaggregate Commitment of Trader (DCOT) and Commodity Index Trader (CIT) reports. The time period covered by these databases is shorter (2006-2012) than the COT report, but the former has the advantage of a finer partitioning of speculative positions. The DCOT report distinguishes between producers / merchant / processor / user, swap dealers, money managers, and other reportables. The weekly CIT supplement tracks the allocations of index traders to 12 agricultural commodities[5] and covers the subset of swap dealer positions which offset index investments by their clients, as well as direct futures investments by index funds.

Our futures price data is obtained from Pinnacle Corp. and constructed to match the CFTC positions data for the 26 commodities in our sample for the period from 1994/01/02 to 2012/06/29. For each commodity, we follow Gorton and Rouwenhorst (2006) and Erb and Harvey (2006) in constructing weekly excess returns (Tuesday to Tuesday) using the front-month (nearest-to-maturity) contract. On the 7th calendar day of its maturity month we roll into the next-to-maturity contract. If 7th is not a business day, the next business day is used as our roll date. Our contract selection strategy generally takes positions in the most liquid portion of the futures curve.[6] In the later section of this paper, we also use returns based on longer maturity contracts as a

[4] The CFTC classifies a trader as commercial "if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3(z), 17 CFR 1.3(z)".
[5] These include corn, soybeans, Chicago wheat, Kansas wheat, soybean oil, coffee, cotton, sugar, cocoa, feeder cattle, lean hogs, and live cattle.
[6] Popular commodity indexes follow similar strategy to ensure sufficient liquidity for each component contract in the index. For example, SP-GSCI index is rolled from the fifth to ninth business day of each maturity month with 20% rolled during each day of the five-day roll period.

robustness check. The excess return $R_{i,t}$ on commodity *i* at the end of week *t* is defined as:

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

where $F_i(t,T)$ is the futures price at time *t* for commodity *i* of a futures contract maturing on date *T*. In addition to the returns we calculate the annualized (log) basis $B_{i,t}$ as follows:

$$B_{i,t} = \frac{logF_i(t,T2) - logF_i(t,T1)}{T2 - T1} \tag{2}$$

where $T1$ is the maturity of the front-month contract and $T2$ is that of the second-month contract. The basis will be used as one of the controls in our empirical work.

The summary statistics of weekly futures excess returns and basis for the 26 commodity futures in our sample are provided in Panel A of Table 1, and match the stylized facts reported in the literature for this time period (see Rouwenhorst and Tang (2012) for a review). The average annualized excess return of all commodities has been positive 4.2% per year, with the Energy and Metals sectors outperforming the agricultural sectors (Grains, Soft, and Livestock). The long side of the market has on average received a risk premium over our nearly 20-year sample in 18 of the 26 commodities. Meanwhile, most commodity futures curves have on average been in contango, as indicated by the positive basis which has averaged 4.9% across all commodities.

Based on the COT dataset, we denote $SL_{i,t}$, $SS_{i,t}$, $HL_{i,t}$, $HS_{i,t}$ and $OI_{i,t}$ as the number of contracts in speculator's long, speculator's short, hedger's long, and hedger's short positions and the open interest, respectively, for commodity *i* in week *t*. We define hedging pressure for commodity *i*, $N_{i,t}$, as the net short (short minus long) position of hedgers divided by total open interest:.

$$N_{i,t} = \frac{HS_{i,t} - HL_{i,t}}{OI_{i,t}} \tag{3}$$

Panel B of Table 1 summarizes the statistical properties of *N* for our sample commodities. The third columns shows that for most commodities (25 out of 26), hedgers are on average short during our sample period from 1994 to 2012. The last row shows that the proportion of months that hedgers are net short averages 72% over time and across commodities. These stylized facts are well-known in the literature. There is considerable variation in short hedging over time, as well as across commodities. For Livestock, the proportion of short hedging never exceeds 61%, whereas short hedging exceeds 68% for all Metals. The weekly standard deviation of hedging pressure is given in the fourth column and averages 17% across commodities. A two standard deviation interval around the average hedging pressure of 14% implies a wide range of -3% to 31% in the hedger's net short positions. Considering the magnitude of these weekly changes, it seems unlikely that these position changes merely reflect resizing of hedges in response to changes in underlying production plans of commodity producers and consumers. Absent a fundamental model of hedging, it is difficult to gauge whether trading is excessive. But on the other hand, the narrative underlying the theory of Normal Backwardation where hedgers obtain price protection for their input demand or output of a commodity, would suggest more stability in hedging positions than found in the data. Figure 1 illustrates the time series fluctuation of hedging pressure for four commodities (oil, copper, coffee, and wheat) in a vivid manner and suggests that commercial participants must trade for reasons other than pure hedging as well.

We use the CFTC data to infer "net trading activity," defined as the change of the net long position of different participants in commodity *i* from week *t*-1 to week *t*, normalized by that commodity future's total open interest:

$$Q_{i,t} = \frac{netlong\ position_{\ i,t} - netlong\ position_{i,t-1}}{OI_{i,t-1}}. \tag{4}$$

Because short and long positions are always evenly matched, the net long positions (and hence the change in positions) add up to zero for each commodity when summed across speculative, hedging and non-reportable positions.

Panel C of Table 1 presents the summary statistics of our weekly trading measure for different futures investor groups. On average across commodities, hedgers trade 3.6% of the total open interest and speculators trade 3.1%. As a group, small traders are the least active.

We calculate a measure of the propensity of hedgers (and speculators) to trade commodity *i* based on the weekly change in gross positions, as a fraction of beginning of week gross positions. For hedgers and speculators, these measures are defined as:

$$PY_{i,t}^{Hedger} = \frac{abs(HL_{i,t} - HL_{i,t-1}) + abs(HS_{i,t} - HS_{i,t-1})}{HL_{i,t-1} + HS_{i,t-1}} \tag{5}$$

$$PY_{i,t}^{Spec} = \frac{abs(SL_{i,t} - SL_{i,t-1}) + abs(SS_{i,t} - SS_{i,t-1})}{SL_{i,t-1} + SS_{i,t-1}} \tag{6}$$

We evaluate whether the propensity to trade by hedgers differs from speculators by a *t*-test on the time series average of $DiffPY_{i,t} = PY_{i,t}^{Spec} - PY_{i,t}^{Hedge}$. Panel D of Table 1 gives summarized the average propensity by commodity and test for equality of propensities. Panel D shows that the propensity to adjust speculative positions exceeds the hedger's propensity in 25 of 26 markets. Speculators are less patient than hedgers, and are more prone to adjust their position. The microstructure literature (e.g., Amihud and Mendelson (1986)) would suggest that market participants with more patience are more likely to be liquidity providers.

3. Liquidity Provision in Commodity Futures Markets

The summary statistics of the CFTC reports reveal substantial weekly variation in the futures positions of commodity market participants. In this section we analyze how changes in these positions co-vary with returns, both contemporaneously as well as in a predictive sense. First we examine whether trading of various market participants can be classified as following a particular style, in particular whether they behave like contrarians or resemble momentum traders. The market microstructure literature suggests that contrarian traders are typically liquidity providers and traders who follow momentum strategies are liquidity consumers. For example, Campbell, Grossman, and Wang (1993) argue that when investors desire to sell a stock for exogenous reasons, market makers absorb the selling pressure and the related price movement by buying the stock at a discounted price in the expectation of receiving a higher expected return. Empirical support for this hypothesis is given by, Comerton-Forde et al. (2010), who find that NYSE specialists tend to buy the stocks they are making the market for more aggressively and accumulate larger inventory long positions when stock market declines. Previewing our findings, we find that hedgers trade as contrarians at the weekly horizon, decreasing net long positions (increasing shorts) during weeks when prices increase. Speculators are short-term momentum traders, increasing net long positions in a rising markets. Next, we examine what happens to futures prices following these trades by hedgers and speculators. We find a predictable component to futures prices where prices of commodities that have been subject to more intense speculator buying decline relative to prices of commodities that have been sold by them. This is consistent with liquidity provision by hedgers to speculators.

3.1 Trading Behavior of Hedgers and Speculators

To characterize the trading behavior of investors we run a cross sectional regression of our trading measure $Q_{i,t}$ (the weekly change of net long positions scaled by open interest) on the contemporaneous commodity futures excess return $R_{i,t}$:

$$Q_{i,t} = a_0 + a_1 R_{i,t} + \varepsilon_{i,t} \tag{7}$$

We employ a Fama-Macbeth framework and report the time-series average of the cross-sectional regression coefficient estimates in Panel A of Table 2. The first columns of Panel A show that the full sample estimate for a_1 is negative for hedgers and positive for both speculators and small traders. Commodities with high returns relative to their peers simultaneously experience larger increases in long positions from speculators and small investors than commodities with low relative returns. The next columns show that the results are qualitatively similar in the subsamples, but quantitatively stronger in the first half of our sample. Despite the increase in the size of the speculative positions over time in many commodity markets, the co-movement of these positions with returns has diminished. In general our findings are consistent with the early findings in the literature Houthakker (1957), and resemble the findings of Rouwenhorst and Tang (2012) obtained using a time-series regression approach.

Next, we examine how various types of commodity futures market participants adjust their positions in response to past returns and position changes using a similar Fama-Macbeth regression:

$$Q_{i,t} = a_0 + a_1 R_{i,t-1} + a_2 Q_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

and report the results in Panel B of Table 2. The table shows that position changes are predictable using past position changes and depend on past returns with in a direction that is similar to the contemporaneous regressions in Panel A. Both speculative and hedging positions depend positively on past position changes, but have opposite signs to past returns: speculative positions changes depend positively on both past speculative changes and past returns, whereas hedging position respond negatively to past returns.

The conclusion from Table 2 is that there exists a very strong correlation between price changes and position changes. Speculators and small traders increase positions in commodities that exhibit relative price strength whereas hedgers do the opposite; they shift positions towards commodities for which prices have gone down (or increased the least) and add to short positions for those commodities that experience relative price increases. In other words, speculators and small traders are *momentum* traders and hedgers are *contrarian* traders.

3.2 Regression Test of Return Predictability and Liquidity Provision

The fact that hedgers in commodity futures markets are contrarian traders and appear to trade more patiently than speculators suggests that they are more likely to be the liquidity providers in commodity futures markets, and speculators demanders of liquidity. We propose to infer who provides liquidity from the relationship between trading activity and subsequent futures returns. This approach is inspired by models from microstructure theory (e.g. Grossman and Miller (1988), and Campbell, Grossman, and Wang (1993)) which suggest that impatient investors who require immediacy need to offer price concessions to encourage risk-averse market makers to take the other side of their trades. One prediction from this line of theoretical models is that market makers typically trade against price trends, and earn compensation for providing liquidity by benefiting from subsequent price reversals. These predictions have found broad empirical support for equity markets (Conrad, Hameed, and Niden (1994), Avramov, Chordia, and Goyal (2006), and Kaniel, Saar, and Titman (2008)).

Our empirical strategy parallels this approach for commodity futures markets. We examine whether the futures excess returns can be predicted by prior position changes and infer the provision of liquidity to that side of the market which benefits from the trades. We propose two tests. In this section of the paper we show the results of a predictive regression of futures excess returns on past position changes and controls. In the next section we present the results of a simple portfolio sort, whereby we sort commodity futures in portfolio based on the size of past position changes.

We regress next week excess returns on current position changes and controls that proxy for variation in expected excess returns:

$$R_{i,t+1} = b_0 + b_1 Q_{i,t} + b_2 B_{i,t} + b_3 S_{i,t} \hat{v}_{i,t} + b_4 R_{i,t} + \varepsilon_{i,t+1} \tag{9}$$

Where, $Q_{i,t}$ is our trading measure at the end of week *t*, $B_{i,t}$ is the log futures bases at time *t* (as defined in equation (2), $\hat{v}_{i,t}$ is the annualized standard deviation of the residuals from the regression of 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.

A few observations about the control variables in equation (9): inclusion of 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) that idiosyncratic risk is priced due to the presence of non-marketable risks (presented by volatility of error term in the CAPM) and hedging demands (presented by speculators net long position).

Our lagged return variable captures short-term momentum, as documented by Pirrong (2005), Erb and Harvey (2006), and Miffre and Rallis (2007). Because commodity futures momentum documented in these papers operates generally at lower frequencies (1 month to 1 year) than the weekly observation interval of our study, the importance of this control remains an empirical matter.

The results are summarized in Table 3, which reports the average of the Fama-Macbeth cross-sectional slope coefficients and *t*-statistics. The first panel shows that the prices of commodities that experience buying by hedgers experience significantly higher subsequent returns than commodities that experience hedger selling. By contrast, commodities that experience speculator buying experience predictable price declines in the subsequent week. Small speculators as a group do not seem to impact returns subsequent to their position changes. To gauge the economic significance of the effect of position changes on subsequent returns, consider the typical position change by hedgers of 3.6% (the average across all commodities documented in Table 1, Panel C). The cross-sectional slope of 4.58% indicates that this changes the expected return in the subsequent week by 4.58% * 3.6% = 0.165%, or by 8.6% on an annualized basis. A parallel calculation of the return impact of a typical speculative position change gives a return impact of 5.36% * 3.1% = 0.166%, or 8.6% per annum.

The return impact is a transfer among the reportable (large) players in commodity futures markets, and the small non-reportable positions do not have a significant impact on prices. As shown in the right two panels of Table 3, it is noteworthy that the point estimates of slope coefficients are larger during the second half of our sample, which is when speculative markets participation in commodity markets was largest.

Combining our empirical results regarding the interaction of trading behavior and returns, a clearer picture starts to emerge about liquidity provision in commodity markets. By following contrarian strategies to accommodate momentum trading by speculators, hedgers benefit from short-term reversals in commodity prices that are most heavily bought by speculators. This is consistent with the view that speculators in commodity markets consume liquidity and that their short-term loss can be understood as the cost of demanding immediacy associated with return chasing. At first glance it would seem that many hedgers would happily accommodate speculators' buying activity as prices rise, and not requiring additional compensation especially if this would mean an opportunity to lock in higher prices of physical long positions that are yet to be hedged. But we showed that the speculators have a higher propensity to trade than hedgers, perhaps because momentum strategies require immediacy whereas hedging plans are more stable over time. Following short-term price trends consumes liquidity, and speculators have to pay a cost to the hedgers so that they can accommodate the trading demands from speculators.

Some of our findings closely mirror those of Kaniel, Saar, and Titman (2008) who show that in the stock market, individual investors tend to be contrarian and provide liquidity to institutional investors who are momentum traders. Our study shares their view that trading by money managers and institutions (which make up the speculative category) consumes liquidity in the commodity futures market. By contrast, where it comes to the provision of liquidity, small traders play no role in commodity futures markets, where hedgers accommodate the liquidity demands of investors.

3.3 Portfolio Sorting and Returns to Liquidity Provision

For our second test of the impact of position changes on expected returns we sort commodity futures into portfolios based on ranking by past traders' position changes, and compare their returns following the ranking. More precisely, at the end of Tuesday of each week, the measurement day of the CFTC positions report, we rank the 26 commodity futures in ascending order based on the prior week change in hedgers' (or speculative) net long positions. We form two equally-weighted portfolios of 13 futures positions, and calculate the excess returns of these two portfolios during the 20 day period following the ranking. Because the CFTC report is released at the end of the Friday following the Tuesday measurement date, we separately calculate the returns during days 1-4 when the report is not yet public and days 5-20 when the information contained in the report is in the public domain.

Panel A of Table 4 summarized the excess returns for the portfolios formed by ranking based on changes in hedgers positions. The third column shows that during the 20 days post formation, the portfolio of futures with highest past hedger buying earns on average 0.612% whereas the portfolio of futures with the least hedger buying earns 0.182%. The return difference of 0.431% (*t*-statistic = 4.16) is highly significant. The next two columns show that about half of the 20 day excess return accrues during the days that precede the release of the CFTC report, and the remainder during the 16 days post release. Inspection of the returns during days -10 to -1 prior to portfolio formation confirms our previous findings about position changes by hedgers. The commodities that rank in the top half of hedger buying have underperformed commodities in the bottom half of the ranking by 1.50% in the ten days prior to ranking. Hedgers act as contrarians increase their net long positions (decrease short positions) in commodities with poor relative performance, and increase short in commodities that exhibit relative price strength. Panel B shows the mirror image for position changes by speculators. Speculators follow momentum strategies and buy commodities with high relative strength, and a long-short strategy on position changes earns negative performance of -0.29% during the 20 days subsequent to ranking.

The bottom portion of each panel in Table 4, illustrates that it is possible to obtain a larger spread of the returns if we group the commodities in quintiles instead of halves. Comparing the 20-day excess returns on portfolios comprising the top and bottom quintiles of hedger buying gives a spread of 0.667% (*t*-statistic = 4.02); sorting on speculator position changes yields a spread of -0.654% (*t*-statistic = -4.15). In both instances substantial portions of the excess return accrues during the days following the release of the CFTC report (0.433% versus -0.345%), both of which are significantly different from zero at the 5% level.

These results closely mirror our Fama-Macbeth regression results from the previous section, and are consistent with the view that hedgers provide short-term liquidity to speculators in commodity futures markets. Quantitatively, the compensation that hedgers receive through price reversals is comparable to the premium for liquidity provision in equity markets. For example, Kaniel, Saar, and Titman (2008) document that stocks that are most bought by individual investors (who tend to be liquidity providers in stock market) subsequently outperform stocks that they most heavily sell by around 0.38% during the following week.

3.4 Liquidity Provision Versus Private Information

An alternative explanation for our finding that position changes predict returns is that hedgers exploit private information about the fundamental information of commodities. This informational advantage could be the by-product of their activities in the underlying physical commodities markets that allows hedgers access to information about fundamentals that is not easily observed by non-commercial players.[7]

The trading behavior of hedgers which we documented in Table 2 and 4 makes the hypothesis of liquidity provision more likely than the private information explanation. While private information about the direction of a future price change predicts buying before a price increase, and selling ahead of a price drop, it seems unlikely that the nature of the private information is such that the hedger's buying occurs during a week where prices fall (presumably on bad news) and the return earned is comprised of a rebound of prices that recovers only a fraction of these losses over the subsequent 20-day period.

[7] By contrast, using the CFTC data on equity futures Schwarz (2012) documents that speculators are better informed than hedgers.

This is further illustrated in Figure 2 which plots the cumulative market-adjusted excess returns of the portfolios constructed by sorting commodity futures based on past position changes by hedgers. While we track the cumulative holding period returns up to two months (45 business days), but it is apparent from the figure that the excess returns stabilize after 20 business days (4 weeks) following the hedgers' position changes.

In the next section, we will further explore the liquidity provision hypothesis to provide additional detail on the interaction between position changes and prices in commodity futures markets.

4. Factors Influencing the Compensation for Liquidity Provision

In this section, we study in more details about how hedgers provide liquidity to commodity futures markets, and how speculators consume liquidity in these markets.

4.1 Factors Affecting Liquidity Provision by Hedgers

In this section we introduce a number of proxies that measure the willingness of hedgers to provide liquidity. These measures are inspired by and adapted from the market microstructure literature, and correspond to market maker's capital constraint and order imbalance. Recent microstructure models suggest that a deterioration of the wealth or the collateral base of market makers can hinder their liquidity provision, as illustrated by Xiong (2001), Brunnermeier and Pedersen (2009). By analogy, because hedgers have to finance losses on their futures positions by posting additional collateral, their willingness to provide liquidity could be negatively impacted after suffering a loss on their hedges even if this loss is matched by an unrealized gain on the value of their physical output or inventories. We calculate a standardized measure of capital loss for hedgers in week *t* by multiplying $N_{i,t-1}$ and $R_{i,t}$, where $N_{i,t-1}$ is hedgers' hedging pressure (or net short position) for i^{th} commodity at week t-1. Then we introduce a dummy variable,$Dm(CapitalLoss)$, which is set to one for the decile containing the 10% all observations when hedgers experience their largest capital loss and zero otherwise.

Our second proxy of the willingness on behalf of hedgers to provide liquidity is motivated by Chordia, Roll, and Subrahmanyam (2002) who show that excess order imbalance can exacerbate market maker's inventory concerns and reduce liquidity in the stock market. In our context, when hedgers are asked to absorb liquidity demands from speculators in a way that would require them to repeatedly trade in the same direction, this would affect their willingness to absorb additional trades in that direction going forward. To capture this idea, we introduce a dummy variable, $Dm(OrderImbalance)$, that is set to be one when hedgers (as liquidity providers) trade in the same direction in both the previous week (*t*-1) and the current week (*t*). The prediction is that present a concern of "order imbalance," hedgers will be less willing to provide liquidity in commodity futures market. Therefore, the futures price increases (decreases) after hedgers' net buying (selling) activity should become stronger in this scenario.

We estimate the dummies using the following panel regression:

$$R_{i,t+1} = b_1 Q_{i,t}^{hedger} + b_2 Dm(\cdot) Q_{i,t}^{hedger} + controls + u_i + \varepsilon_{i,t+1} \quad (10)$$

where the control variables used are the same as in equation (9), and u_i is a vector of commodity fixed effects. In this section we use a panel regression instead of the Fama-Macbeth methodology for the following two reasons: first, we want to address how the price of liquidity changes over time given different conditions of hedgers' (or speculators') characteristics; second, since we only have 26 sample commodities, it is possible that in a given week there is not enough cross-sectional variation in the dummy variable to allow its estimation. Our *t*-statistics are calculated using Newey-West standard errors with four lags to adjust for heteroskedasticity and serial correlation.

Our estimates of the dummy variables are summarized in Table 5. The second column in the table shows that following large losses by hedgers, the compensation for providing liquidity increases (*t*-statistic = 2.01). The regression coefficients indicate a net purchase by hedgers equal to 3.6% of the open interest would result in an expected price increase of 9.6 basis points in the next week. But in weeks following a large capital loss, the impact of this same position change on returns would more than double to 22.1 basis points. The notion that hedgers as liquidity providers in commodity futures market are unwilling to provide liquidity when they have less capital available to them is consistent with what Hameed, Kang, and Viswanathan (2010) document for the stock market.

The third column of Table 5 shows a similarly significant impact of "order flow" imbalance on expected returns. The price impact of a given size trade more than doubles when hedgers experience position changes in the same direction for two weeks in a row.

The findings in this section are broadly consistent with the hypothesis that hedgers receive a compensation for providing liquidity in commodity futures markets. When we condition on information that would likely negatively impact their willingness to accommodate speculators we find that the compensation for a given size position change increases substantially.

4.2 When Do Speculators Consume Liquidity?

If hedgers demand a higher compensation for liquidity provision when they are capital constrained or when they face an "order imbalance," speculators might prefer to trade at times when there is more speculative capital in the market that is willing to take the other side of their trades. A cost-minimizing strategy for liquidity-demanding speculators would be to trade when other speculators with opposite trading demands are present. This would allow for their trading orders to be matched with each other, similar to a situation where a large fund family can pair trading demands from its fund managers internally before submitting the net order to outside open markets. A larger proportion of speculators in commodity futures markets is likely to make this task easier thereby potentially reducing the price of liquidity. Our first prediction is therefore that an increase of the fraction of speculators in the market has a negative influence on the price of liquidity provision.

Our second hypothesis considers the net position of speculators and the direction of trading as a factor in the price of liquidity. Although speculators in aggregate are momentum traders and consume liquidity, there will likely be a fraction of speculators whose trading deviates from the average and may compete with hedgers for the business of providing liquidity to other liquidity-demanding speculators. If this proportion of speculators who can act as liquidity providers is high, the stronger will be the competition that hedgers face and hence the lower the price of liquidity will be. More specifically, speculators demand to increase net positions at a time when most speculative positions are long, the probability of obtaining liquidity from other speculators will be lower than at a time when the aggregate size of speculative short positions is large. Our prediction is therefore that the cost of liquidity is higher when speculators trade in the same direction as the position imbalance: increase long positions at a time when net speculative positions are predominately long or sell when speculative positions are predominantly short.

For our first hypothesis, we calculate two versions of the speculative ratio F. The first scales the total number of speculative positions by the total number of positions held by hedgers:

$$F^1_{i,t-1} = (SL_{i,t-1} + SS_{i,t-1})/(HL_{i,t-1} + HS_{i,t-1}). \tag{11}$$

Our second measure is similar, but focuses on the "balanced portion" of the speculative and hedging positions:

$$F^2_{i,t-1} = min\left(SL_{i,t-1}, SS_{i,t-1}\right)/\ min\quad\left(HL_{i,t-1}, HS_{i,t-1}\right) \tag{12}$$

To test whether the cost of liquidity provision depends on the speculative ratio, we sort our sample observations for commodity *i* in two halves based to the level of $F_{i,t-1}$. We define a dummy variable *Dm*(*FRatio*·)$_{i,t}$, which is equal to one when $F_{i,t-1}$ is below or equal its median value for commodity *i*, and zero otherwise. Our conjecture is that the sign of b_2 is negative in the following panel regression:

$$R_{i,t+1} = b_0 + b_1 Q_{i,t}^{Spec} + b_2 Dm(FRatio\ \cdot)_{i,t} \cdot Q_{i,t}^{Spec} + controls + \varepsilon_{i,t+1} \qquad (13)$$

where the controls are defined as in previous tables. The coefficient estimates are reported in the first column of Table 6, and as expected, the sign of b_2 is significantly negative. The estimated coefficients for b_1 and b_2 are similar in magnitude, which suggests that the return impact of a speculative position adjustment is twice as large when the speculative ratio is low (below the median) compared to when it is high (above the median). The results for the "balanced" speculative ratio in column 2 are qualitatively similar, with a slightly higher coefficient (-3.74, *t*-stat = -3.03) on the marginal influence of low speculative activity on the cost of liquidity provision.

For our second hypothesis, we construct a conditional variable that interacts the direction of trading with the beginning of week net position of speculators. The net long position of speculators (*SpecPosition*) for commodity *i* at the end of week *t*-1, normalized by the total open interest at the end of week *t*-1 is:

$$SpecPosition_{i,t-1} = (SL_{i,t-1} - SS_{i,t-1})/OI_{i,t-1}. \qquad (14)$$

We introduce a dummy variable $Dm(SpecPosition)_{i,t}$, for week *t* based on the value of $SpecPosition_{i,t-1}$. When speculators are buying in week *t* ($Q_{i,t}^{spec} > 0$), the dummy variable is set to be one if the value of $SpecPosition_{i,t-1}$ is positive and in the highest 20% quintile for commodity i, and zero otherwise; when speculators are selling in week t ($Q_{i,t}^{spec} < 0$), the dummy variable is equal to one if the value of $SpecPosition_{i,t-1}$ is negative and in the lowest 20% quintile for commodity i, and zero otherwise. Hence the dummy variable $Dm(SpecPosition)_{i,t}$ is intended to isolate weeks when the position changes amplify the net positions in place at the beginning of the week.

We amend regression equation (13) with $Dm(SpecPosition)$ replacing $Dm(FRatio)$ and summarize the coefficient estimates in the third column of Table 6. The coefficient for $Dm(SpecPosition)$ is -4.63 (t-statistic = -2.67) which is significantly differently different from zero. It has the negative sign predicted by our hypothesis that liquidity-demanding speculators pay a higher price of liquidity when they add to a large existing net long (short) position that was previously accumulated by other speculators. For example, at the median level of net speculative positions, a position change equal to 3.1% of the total open interest impacts returns in the following week by 9.2 basis points, or at an annualized rate of 4.9%. But if speculators choose to add 3.1% to net long positions when speculative positions are in the top quintile, or add to shorts when in the bottom quintile, the average incremental impact on returns is 14.2 basis points per week, or 7.7% annualized, for a total impact of 23.4. bp or 14.6% annualized.

In the final column of Table 6, we separately estimate a separate dummy coefficient for the top and the bottom quintiles of the distribution of the speculative positions, and find that the effects of position changes on the cost of liquidity are similar in both tails. The conclusion from Table 6 is that when the number of speculators in the market is low, or their net positions deviate from the average of their historical distributions, speculators likely have to rely on hedgers to meet their liquidity demands, and the cost of liquidity provision significantly increases.

5. Robustness Tests

In this section, we perform two robustness checks. First, we examine the sensitivity of our results to different trader classifications obtained from two alternate databases published by the CFTC. The second robustness check is to examine whether our conclusion of liquidity provision is sensitive to the location on the futures curve where we choose to measure the price impact of position changes.

5.1 DCOT and CIT Datasets

Starting from January 2006, the CFTC publishes two additional ways to break down positions in commodity futures markets. The weekly Disaggregate Commitment of Traders reports (DCOT) classifies traders of all 26 sample commodities into five groups: producers/merchant/processor/user, money managers, swap dealers, other reportable, and non-reportable (or small investors). The first group which we for brevity will refer to as producers consists of market participants that are thought to have a hedging motive, whereas money managers are generally considered to be speculators. In addition we collect data from the weekly CFTC Commodity Index

Trader (CIT) Report, which for 12 agricultural commodities classifies the positions of commodity index traders separate from the commercials (hedgers), non-commercials (speculators), and non-reportable traders (small investors). The position of commodity index traders has been at the center of an intense political debate on the role of speculative capital into commodity futures markets. We calculate our trading measure *Q* for each of these groups of market participants, and run a Fama-Macbeth regression as described by equation (9) in Section 3.2. The regression estimates for the DCOT data are given in Panel A of Table 7; the CIT results are in Panel B.

Consistent with our previous results, we find that the trading activity of producers can forecast subsequent commodity future returns with a statistically significant positive sign. The regression coefficient indicates that if the producer group buys (sells) 2.5% of the total open interest of a given type of commodity future in the market, the price of this commodity future is expected to increase (decrease) by 0.21% relative to a commodity that experienced no inflows in the prior week – or at an annualized return rate of 11.1% per year.[8] Likewise, position changes by money managers have a statistically significant negative influence on subsequent returns. As before traders in the hedger category serve as liquidity providers to the futures market, while money managers, the main category of speculators, consume liquidity instead. The coefficient on position changes is smaller for swap dealers, other reportable, and small traders, and insignificantly different from zero in all three cases.

The main interest and focus of the CIT data is to study influence of position

[8] The average absolute amount of the trading measure *Q* by producers/merchant/processor/users is 2.5%.

changes by index traders. The fourth column of Panel B shows that position changes by the index traders exert a large influence on prices, but at the same time that this influence cannot be estimated very accurately. Although the signs of the slope coefficients are the same, the *t*-statistics in panel B of Table 7 are all small relative to the sub-sample results of Table 3. This is likely caused by the much smaller cross-section of commodities in the CIT database. However, the general pattern of liquidity provision by hedgers and liquidity consumption by speculators is consistent across all three datasets.

5.2 Longer-dated Futures Returns

For the empirical analysis of this paper, we have constructed commodity futures excess returns using prices from the closest-to-maturity contracts. The positions data from the CFTC do not separately break down position changes for individual contracts and the positions of hedgers and speculators may not be evenly distributed across the maturity spectrum. In this section, we check the robustness of our return predictability regression results reported in section 3.2 and construct the excess returns using contracts that are always one contract further out on the curve than the closest to maturity contract used in our baseline specification. The trading measure Q is still constructed from the COT dataset. We run the Fama-Macbeth regression as described by equation (9), with all other control variables are constructed in a same manner. The regression coefficient estimates are presented in Table 8. While the point estimates for the influence of position changes are slightly lower than in Table 3, they remain statistically significant with the same sign in the full sample, as well as the sub-samples.

In brief, our conclusion that hedgers are liquidity providers in commodity futures markets and that speculators consume liquidity is robust across the various publicly available CFTC datasets and alternative methods for calculating returns.

6. Conclusion

In this paper, we examine liquidity provision in commodity futures markets. The traditional view, held by many academics and practitioners, is that speculative capital provides liquidity to hedgers who use futures markets to purchase protection against price risk. While this view is not necessarily incorrect, it is incomplete because it does not describe the demand and supply of liquidity associated with considerable volatility of short-term position changes in commodity futures markets.

We show that speculators are short-term momentum traders and that their propensity to trade is higher than for hedgers, who trade like contrarians. In this process, the hedgers are providing liquidity to speculators, and earn a compensation for liquidity provision by benefiting from a reversal in prices following their trading. These findings parallel the results of Kaniel, Saar and Titman (2008) for US equity markets, where individuals provide liquidity to institutions that demand immediacy of execution.

We further show that the cost to speculators from demanding liquidity from hedgers increases when hedgers become more collateral constrained or when positions of hedgers become more imbalanced. The increased cost reflects hedgers' reluctance to providing liquidity under such circumstances, which is consistent with microstructure models. We also show that the cost of liquidity speculators pay increases when there are fewer speculators relative to hedgers in the market or when speculators demand to hold more extreme positions. Our explanation is that under these conditions, it is more difficult for speculators to settle their trades with other speculators, and therefore hedgers enjoy more monopoly power and can extract higher economic rent from liquidity demanding speculators.

References

Acharya, Viral, Lochstoer, Lars and Ramadorai, Tarun, 2013, Limits to arbitrage and hedging: Evidence from commodity markets, *Journal of Financial Economics*, 109, 441 – 465.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Avramov, Doron, Tarun Chordia, and Amit Goyal, 2006, Liquidity and autocorrelation of individual stock returns, *Journal of Finance* 61, 2365–2394.

Buyuksahin, Bahattin and Jeffrey H. Harris, 2011, Do Speculators Drive Crude Oil Futures Prices? *The Energy Journal*, 32, 167-202.

Bessembinder Hank. 1992. Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies*, 4:637 – 67.

Bodie, Zvi and Rosanski Victor 1980. Risk and Return in Commodity Futures. *Financial Analysts Journal*,36: 27-39.

Brennan Michael. 1958. The supply of storage. *American Economics Review*, 48, 50 – 72

Brunnermeier, Markus, and Lasse Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905–939.

Chang Eric C. 1985. Returns to speculators and the theory of normal backwardation. *Journal of Finance* 40, 193 – 208.

Cheng, Ing-Haw, Andrei Kirilenko, and Wei Xiong, 2012, Convective Risk Flows in Commodity Futures Markets, Working Paper.

Comerton-Forde, Carole, Terence Hendershott, Charles Jones, Pamela Moulton, and Mark Seasholes, 2010, Time variation in liquidity: The role of market maker inventories and revenues, *Journal of Finance* 65, 295~332.

Conrad, Jennifer, Allaudeen Hameed, and Cathy Niden, 1994, Volume and autocovariances in short-horizon individual security returns, *Journal of Finance* 49, 1305–1329.

De Roon Frans, Theo E. Nijman, and Chris Veld 2000, Hedging pressure effects in futures markets. *Journal of Finance* 55, 1437–56.

Dusak, Katherine 1973. Futures Trading and Investor Returns: An Investigation of Commodity Market Risk Premiums. *Journal of Political Economy,* 81: 1387-1406.

Ederington, Louis and Jae Ha Lee, 2002, Who trades futures and how: Evidence from the heating oil futures market, *Journal of Business* 75, 353-373.

Erb Claude, Harvey Campbell. 2006. The strategic and tactical value of commodity futures. *Financial Analyst Journal*, 62, 69 – 97.

Fama, Eugene, French Kenneth. 1987. Commodity futures prices: some evidence on forecast power, premiums, and the theory of storage. *Journal of Business*, 60, 55 – 73.

Fattouh, Bassam, Lutz Kilian and Lavan Mahadeva. 2012, The role of speculation in oil markets: what have we learned so far? Working paper, CEPR.

Friedman, Milton, 1960. "In Defense of Destabilizing Speculation". In Essays in Economics and Econometrics, edited by Ralph W. Pfouts, Chapel Hill: University of North Carolina Press, pp. 133-141.

Gorton Gary, Rouwenhorst K. Geert 2006. Facts and fantasies about commodity futures. *Financial Analyst Journal* 62, 47-68.

Gorton Gary, Hayashi Fumio, Rouwenhorst K. Geert 2012. The fundamentals of commodity futures returns. *Review of Finance* Forthcoming

Grossman, Sanford, and Merton Miller, 1988, Liquidity and market structure, *Journal of Finance* 43, 617–633.

Hameed, Allaudeen, Wenjin Kang, and S. Viswanathan, 2010, Stock market declines and liquidity, *Journal of Finance* 65, 257~293.

Hamilton, James, D. (2009), Causes and Consequences of the Oil Shock of 2007-2008.Working paper, UC San Diego.

Hartzmark, Michael 1987. Returns to Individual Traders of Futures: Aggregate Results. *Journal of Political Economy,* 95: 1292-1306.

Hicks, John Richard, 1939, Value and Capital: An Inquiry into Some Fundamental Principles of Economic Theory. Oxford, UK: Clarendon Press.

Hirshleifer David, 1988, Residual risk, trading costs and commodity futures risk premia, *Review of Financial Studies* 1,173 – 93.

Hong, Harrison, Motohiro Yogo (2012), What Does Futures Market Interest Tell Us about the Macroeconomy and Asset Prices? Journal of Financial Economics, 105, 473-490.

Houthakker H.S. 1957. Can speculators forecast prices? *Review of Economics Statistics* 39,143 – 51

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor trading and stock returns, *Journal of Finance* 63, 273–310.

Kaufmann, Robert K. 2011, The role of market fundamentals and speculation in recent price changes for crude oil. Energy Policy, 39,105-115.

Keynes John, 1923, Some aspects of commodity markets. *Manchester Guardian Commercial*, 13, 784 – 86.

Levin, Carl, 2011, Opening Statement at PSI Hearing on Excessive Speculation and Compliance with the Dodd-Frank Act, http://www.levin.senate.gov.

Marshall, Ben, Nhut H. Nguyen and Nuttawat Visaltanachoti 2012, Commodity Liquidity Measurement and Transaction Costs, *Review of Financial Studies*, 25, 599-638.

Miffre, Joelle and Rallis Georgios 2007. Momentum in commodity futures markets. *Journal of Banking and Finance* 31, 1863 – 86

Pirrong Craig. 2005. Momentum in futures markets. Working Paper, University of Houston.

Pirrong Craig. 2010. No Theory? No Evidence? No Problem! Cato Journal, summer, 38-44.

Rockwell, Charles S. 1967. Normal backwardation, forecasting and the returns to commodity futures traders. *Food Research Institute Studies* 7, 107 – 30.

Rouwenhorst, K. Geert, and Ke Tang, 2012, Commodity Investing, *Annual Review of Finance and Economics*, 447-467.

Singleton, Kenneth J. 2011, Investor Flows and the 2008 Boom/Bust in Oil Prices, Working paper, Stanford University.

Schwarz, Krista 2012, Are speculators informed? Journal of Futures Market, 32, 1-23.

Tang Ke, and Wei Xiong, 2012, Index investment and financialization of commodities. Financial Analyst Journal, 68, 54-74.

Telser, Lester 1958. Futures Trading and the Storage of Cotton and Wheat. *Journal of Political Economy*, 66: 233-255.

Xiong, Wei, 2001, Convergence trading with wealth effects: An amplification mechanism in financial markets, *Journal of Financial Economics* 62, 247–292.

Working Holbrook 1949. The theory of the price of storage. *American Economic Review*, 39, 1254 ‒ 62.

Table 1: Summary Statistics

In this table we report the summary statistics of our commodity futures sample obtained from CFTC COT dataset. We first report the summary statistics of excess returns and basis for our sample commodities in Panel A. The excess return 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 a certain futures contract. Note that when calculating excess returns, we use front-month contract. The front-month contract is rolled on the 7^{th} of a certain month (if 7^{th} is not a business day, the next business day is the rolling date). The log-basis is calculated as $B_{i,t} = (logF_i(t,T2) - logF_i(t,T1))/(T2 - T1)$, where T1 is the maturity of the front-month contract and T2 is that of the second-month contract. We report the time-series average and standard deviation of the annualized excess return and the basis for each type of commodity future.

In Panel B, we report the attributes of hedging pressure. The hedging pressure, $N_{i,t}$, is defined as the net short (short minus long) position of hedgers in commodity futures contracts of all maturities divided by its total open interest, i.e., $N_{i,t} = (HedgerShort_{i,t} - HedgerLong_{i,t})/OpenInterest_{i,t}$, for a given type of commodity future *i* at week *t*. In our study, the hedging pressure is first computed at weekly frequency from 1994/01/02 to 2012/06/29 for 26 US traded commodities. Then we report the time-series average and standard deviation of the hedging pressure for each type of commodity future. We also provide the statistics of probability of short (long) hedging, which is defined as the percentage of time when hedgers hold net short (long) positions for a given type of commodity.

In Panel C, we report summary statistics of the trading measure, Q, which is defined as the change of net long position for various types of commodity market participants, normalized by open interest, over weekly frequency from 1994/01/02 to 2012/06/29.

$Q_{i,t} = (Investors'\ netlong\ position_{i,t} - Investors'\ netlong\ position_{i,t-1})/\ Open\ Interest_{i,t-1}$.

where *i* is the type of commodities and *t* denotes the number of weeks. We report the time-series average of the absolute value, as well as the standard deviation, of the trading measure for all three types of commodity market participants for each type of commodity future.

In Panel D, we examine the difference of the propensity of adjusting portfolio positions between speculators and hedgers. We first denote SL, SS, HL and HS as the size of speculator's long, speculator's short, hedger's long, hedger's short positions, respectively. At each week *t*, we construct a proxy of the propensity of adjusting portfolio positions for a given type of commodity futures investors (hedger or speculator) as follows.

$$PY_{i,t}^{Hedger} = \frac{abs(HL_{i,t}-HL_{i,t-1})+abs(HS_{i,t}-HS_{i,t-1})}{HL_{i,t-1}+HS_{i,t-1}};\ PY_{i,t}^{Spec} = \frac{abs(SL_{i,t}-SL_{i,t-1})+abs(SS_{i,t}-SS_{i,t-1})}{SL_{i,t-1}+SS_{i,t-1}};$$

Next, we take the difference between the *PY* measure of speculators and hedgers as follows.

$DiffPY_{i,t} = PY_{i,t}^{Spec} - PY_{i,t}^{Hedge}$.

We then test whether the time-series mean of *DiffPY* is significantly higher than zero by using the Newy-West method to calculate the *t*-statistics with 52 lags for both *DiffPY* time series. We also provide the cross-sectional average of *DiffPY* across all types of commodity futures with the associated *t*-statistics.

Panel A: Summary statistics of commodity future returns and basis

Sector	Commodity	Mean (Annualized Excess Return)	Standard Deviation (Annualized Excess Return)	Mean (Annualized Basis)	Standard Deviation (Annualized Basis)
Energy	Oil	11.1%	33.0%	0.2%	22.9%
	Heating Oil	11.1%	32.1%	2.4%	24.2%
	Natural Gas	-8.4%	48.8%	20.5%	61.7%
Metals	Platinum	10.7%	22.3%	-1.0%	3.9%
	Palladium	14.0%	35.6%	0.5%	6.7%
	Silver	10.8%	29.6%	3.1%	2.1%
	Copper	10.9%	25.9%	-0.8%	9.8%
	Gold	5.9%	16.6%	3.1%	1.8%
Grains	Wheat	-3.3%	29.4%	10.6%	17.0%
	Kansas Wheat	6.5%	27.8%	3.6%	16.6%
	Minn Wheat	12.5%	27.1%	-0.7%	19.2%
	Corn	-2.7%	27.4%	11.2%	16.9%
	Oat	6.4%	34.5%	6.3%	26.7%
	Soybean	7.6%	23.8%	-1.4%	23.3%
	Soybean Oil	2.7%	24.4%	5.2%	9.3%
	Soybean Meal	14.3%	26.8%	-7.5%	27.0%
	Rough Rice	-5.4%	27.9%	12.0%	22.5%
Softs	Cotton	-2.2%	29.7%	7.6%	20.1%
	Orange Juice	1.1%	32.3%	8.4%	15.5%
	Lumber	-13.2%	33.9%	14.5%	28.1%
	Cocoa	3.2%	31.5%	6.5%	8.8%
	Sugar	14.2%	33.5%	-3.1%	22.6%
	Coffee	4.7%	38.8%	7.6%	17.3%
Live stock	Lean Hogs	-7.5%	25.7%	16.0%	51.1%
	Live Cattle	-0.1%	15.6%	3.2%	20.5%
	Feed Cattle	3.9%	14.3%	0.5%	12.3%
	Average	4.2%	28.8%	4.9%	19.5%

Panel B: Summary statistics of hedging pressure

Sector	Commodity Type	Mean (hedging pressure)	Standard Deviation (hedging pressure)	Probability of long hedging	Probability of short hedging
Energy	Oil	3%	8%	32%	68%
	Heating Oil	10%	9%	13%	87%
	Natural Gas	2%	12%	41%	59%
Metals	Platinum	49%	24%	5%	95%
	Palladium	33%	34%	24%	76%
	Silver	43%	15%	0%	100%
	Copper	11%	21%	32%	68%
	Gold	23%	29%	26%	74%
Grains	Wheat	4%	15%	47%	53%
	Kansas Wheat	9%	15%	26%	74%
	Minn Wheat	8%	13%	27%	73%
	Corn	2%	14%	43%	57%
	Oat	34%	18%	5%	95%
	Soybean	11%	17%	27%	73%
	Soybean Oil	15%	18%	25%	75%
	Soybean Meal	19%	16%	16%	84%
	Rough Rice	14%	22%	28%	72%
Softs	Cotton	5%	22%	40%	60%
	Orange Juice	24%	23%	16%	84%
	Lumber	10%	19%	34%	66%
	Cocoa	11%	17%	27%	73%
	Sugar	17%	18%	21%	79%
	Coffee	15%	15%	21%	79%
Live stock	Lean Hogs	0%	13%	48%	52%
	Live Cattle	4%	10%	39%	61%
	Feed Cattle	-7%	11%	73%	27%
	Average	14%	17%	28%	72%

Panel C: Summary statistics of trading measure Q for different investors

Sector	Commodity Type	Hedger		Speculator		Small Trader	
		Mean Absolute Value	Standard Deviation	Mean Absolute Value	Standard Deviation	Mean Absolute Value	Standard Deviation
Energy	Oil	1.99%	2.87%	1.57%	2.18%	0.82%	1.16%
	Heating Oil	2.69%	3.70%	1.97%	2.72%	1.23%	1.67%
	Natural Gas	1.82%	2.80%	1.54%	2.33%	0.66%	0.93%
Metals	Platinum	6.65%	9.80%	5.71%	8.63%	1.93%	2.56%
	Palladium	4.56%	7.08%	3.59%	5.54%	1.89%	3.25%
	Silver	3.94%	5.91%	3.59%	5.39%	1.20%	1.88%
	Copper	4.33%	6.29%	3.33%	4.81%	1.61%	2.27%
	Gold	5.38%	7.90%	4.33%	6.27%	1.46%	2.23%
Grains	Wheat	3.29%	4.68%	2.82%	4.09%	1.24%	1.81%
	Kansas Wheat	3.06%	4.24%	2.41%	3.50%	1.39%	2.05%
	Minn Wheat	3.09%	4.22%	2.23%	3.17%	2.09%	2.93%
	Corn	2.53%	3.55%	2.29%	3.28%	0.78%	1.10%
	Oat	4.17%	6.08%	2.88%	4.17%	2.87%	4.18%
	Soybean	2.95%	3.92%	2.74%	3.64%	1.04%	1.42%
	Soybean Oil	4.29%	6.06%	3.21%	4.44%	1.54%	2.24%
	Soybean Meal	3.81%	5.36%	2.91%	4.08%	1.42%	1.98%
	Rough Rice	3.90%	5.49%	2.76%	3.85%	2.74%	4.00%
Softs	Cotton	4.74%	6.97%	4.07%	6.07%	1.13%	1.60%
	Orange Juice	4.78%	6.86%	4.00%	5.76%	1.63%	2.27%
	Lumber	4.45%	6.83%	4.40%	6.37%	3.40%	5.14%
	Cocoa	3.03%	4.17%	2.62%	3.66%	0.92%	1.25%
	Sugar	4.15%	6.39%	2.86%	4.48%	1.74%	2.50%
	Coffee	4.15%	6.15%	3.66%	5.61%	1.16%	1.66%
Live stock	Lean Hogs	2.74%	3.85%	2.99%	4.16%	1.61%	2.35%
	Live Cattle	1.88%	2.56%	2.31%	3.15%	1.32%	1.90%
	Feed Cattle	2.34%	3.14%	3.38%	4.56%	2.51%	3.37%
	Average	3.64%	5.26%	3.08%	4.46%	1.59%	2.30%

Panel D: Propensity of adjusting positions for speculators and hedgers

		PY^{Spec}	PY^{Hedger}	*DiffPY*	*t*-statistics of *DiffPY*
Energy	Oil	7.5%	3.5%	4.1%	5.7
	Heating Oil	11.1%	4.3%	6.8%	7.5
	Natural Gas	8.5%	3.8%	4.8%	4.9
Metals	Platinum	12.5%	7.9%	4.6%	6.4
	Palladium	10.8%	6.1%	4.7%	3.9
	Silver	7.7%	6.1%	1.7%	4.5
	Copper	11.6%	5.6%	6.0%	7.3
	Gold	9.0%	6.5%	2.5%	4.5
Grains	Wheat	7.6%	5.2%	2.4%	8.4
	Kansas Wheat	11.2%	5.0%	6.2%	6.0
	Minn Wheat	20.1%	6.2%	13.9%	5.5
	Corn	7.0%	3.6%	3.4%	9.5
	Oat	13.4%	6.3%	7.1%	9.5
	Soybean	7.5%	4.7%	2.8%	12.6
	Soybean Oil	8.9%	5.5%	3.4%	7.5
	Soybean Meal	9.6%	5.1%	4.6%	7.6
	Rough Rice	12.5%	6.4%	6.0%	4.5
Softs	Cotton	10.6%	5.2%	5.3%	7.4
	Orange Juice	10.4%	6.1%	4.2%	8.5
	Lumber	13.8%	14.3%	-0.5%	-0.8
	Cocoa	9.4%	3.5%	5.9%	8.3
	Sugar	11.2%	4.9%	6.3%	6.2
	Coffee	10.3%	5.4%	5.0%	7.9
Live stock	Lean Hogs	8.7%	5.5%	3.2%	6.6
	Live Cattle	6.7%	3.4%	3.3%	8.4
	Feed Cattle	9.6%	7.8%	1.9%	4.5
	Average	10.3%	5.7%	4.6%	6.6

Table 2: Trading Behaviour of Hedgers and Speculators

This table reports the trading behaviour of hedgers and speculators in commodity futures market.

In Panel A, we run the following Fama-Macbeth regression:

$$Q_{i,t} = a_{0,t} + a_{1,t}R_{i,t} + \varepsilon_{i,t}$$

In Panel B, we run the following Fama-Macbeth regression:

$$Q_{i,t} = a_{0,t} + a_{1,t}R_{i,t-1} + a_{2,t}Q_{i,t-1} + \varepsilon_{i,t}.$$

where $R_{i,t}$ is the excess return of the i^{th} type of commodity in week *t*; $Q_{i,t}$ is change of net long position of a given type of commodity futures investors (hedgers, speculators, or others) in week *t*.

We first run Fama-Macbeth cross-sectional regression each week, and then report the time-series average of the weekly cross-sectional regression coefficient estimates. The R^2 is the time-series average of the adjusted R^2 estimates from the cross-sectional regression in each week. The sample period is from 1994/1/2 to 2012/6/29. We also divide the sample period into two sub-sample periods: from 1994/1/2 to 2003/12/31, and from 2004/1/2 to 2012/6/29. Futures returns are in the unit of percentage points. The *t*-statistics are reported in brackets below the associated coefficients.

Panel A: Trading Behaviour with Contemporaneous Commodity Future Returns

	All Sample Period			Sub Sample Period: 1994~2003			Sub Sample Period: 2004~2012		
Trader's Type	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others
$R_{i,t}$	-0.0066	0.0052	0.0014	-0.0083	0.0064	0.0019	-0.0047	0.0039	0.0007
	(-46.95)	*(43.77)*	*(22.99)*	*(-40.23)*	*(35.14)*	*(19.98)*	*(-33.62)*	*(31.75)*	*(14.89)*
R^2	20.9%	17.4%	6.1%	22.0%	17.7%	7.3%	19.5%	17.0%	4.7%

Panel B: Trading Behaviour with Lag Commodity Future Returns

	All Sample Period			Sub Sample Period: 1994~2003			Sub Sample Period: 2004~2012		
Trader's Type	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others
$R_{i,t-1}$	-0.0019	0.0021	0.0002	-0.0024	0.0027	0.0002	-0.0014	0.0014	0.0002
	(-15.26)	*(19.89)*	*(3.22)*	*(-11.83)*	*(16.41)*	*(1.62)*	*(-10.38)*	*(12.02)*	*(4.80)*
$Q_{i,t-1}$	0.161	0.139	-0.021	0.143	0.130	-0.032	0.182	0.151	-0.009
	(15.06)	*(13.67)*	*(-1.87)*	*(9.56)*	*(9.24)*	*(-2.07)*	*(11.95)*	*(10.19)*	*(-0.57)*
R^2	8.8%	8.7%	5.0%	7.3%	8.0%	4.9%	10.5%	9.6%	5.2%

Table 3: Liquidity Provision and Return Predictability in Commodity Futures Markets

This table examines the commodity futures return predictability based on different types of investors' trading behaviour in commodity futures market.

We run the following Fama-Macbeth regression

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

where $R_{i,t}$ is the return of the i^{th} type of front-month commodity futures in week t; $Q_{i,t}$ is the change of net long position of the particular type of commodity futures investors normalized by the total open interest; B is the log-basis; v is the annualized standard deviation of the residuals from the regression of futures returns on SP500 returns (calculated by 52 weeks rolling window); S is a dummy on speculation, i.e. it is 1 when speculators are net long and -1 when speculators are net short.

We first run Fama-Macbeth cross-sectional regression each week, and then report the time-series average of the weekly cross-sectional regression coefficient estimates. The R^2 is the time-series average of the adjusted R^2 estimates from the cross-sectional regression in each week. The sample period is from 1994/1/2 to 2012/6/29. We also divide the sample period into two sub-sample periods: from 1994/1/2 to 2003/12/31, and from 2004/1/2 to 2012/6/29. Futures returns are in the unit of percentage points. The *t*-statistics are reported in brackets below the associated coefficients.

	All Sample Period			Sub Sample Period: 1994~2003			Sub Sample Period: 2004~2012		
Trader's Type	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others
$Q_{i,t}$	**4.58**	**-5.36**	**-2.09**	**3.81**	**-4.11**	**-2.08**	**5.57**	**-7.01**	**-1.92**
	(5.93)	***(-6.68)***	***(-1.28)***	***(5.32)***	***(-5.05)***	***(-1.46)***	***(3.86)***	***(-4.80)***	***(-0.62)***
$B_{i,t}$	-0.72	-0.71	-0.75	-0.67	-0.69	-0.73	-0.80	-0.75	-0.78
	(-3.83)	*(-3.68)*	*(-3.86)*	*(-2.90)*	*(-2.88)*	*(-3.07)*	*(-2.59)*	*(-2.42)*	*(-2.49)*
$S_{i,t}\hat{v}_{i,t}$	-0.01	0.02	-0.05	-0.14	-0.10	-0.16	0.11	0.14	0.07
	(-0.10)	*(0.16)*	*(0.35)*	*(-0.81)*	*(-0.60)*	*(-0.92)*	*(0.52)*	*(0.66)*	*(0.30)*
$R_{i,t}$	0.04	0.04	0.02	0.06	0.06	0.03	0.03	0.03	0.03
	(3.57)	*(3.58)*	*(1.68)*	*(3.46)*	*(3.33)*	*(2.03)*	*(1.53)*	*(1.68)*	*(0.24)*
R^2	11.7%	11.6%	11.4%	12.7%	12.6%	12.7%	10.6%	10.6%	10.0%

Table 4: Return Predictability: Portfolio Sorting Approach

This table studies commodity futures portfolio return predictability based on the previous week's trading measure Q, which is defined as the change of net long position of a given type of commodity futures investors normalized by the total open interest for a given type of commodity investors.

In each week, we group our sample commodities into 2 equal portfolios with 13 commodities in each or 5 quintile portfolios with 5, 5, 6, 5, 5 commodities in each. The portfolios are ranked from small to large according to the trading measure (Q) for either speculators or hedgers.

The CFTC collects the trading positions of different players on each Tuesday. Note that CFTC announce the COT data after the close of market on the following Friday. On each Tuesday, we use Q of hedgers and speculators to construct equal weighted and five quintile portfolios (from smallest to largest) and hold until 20 business days. We first calculate 1 to 10 days cumulative returns *previous* to the portfolio construction date. We then calculate the cumulative returns from the 1^{st} day to the 4^{th} day and from 5^{th} to 20^{th} day after the portfolio construction date. We present the returns difference between the highest-Q portfolio and lowest-Q portfolio. We present the returns of the portfolios sorted by hedgers' trading activity in Panel A and the returns of the portfolios sorted by speculators' trading activity in Panel B.

Panel A: Portfolios sorted by hedger's trading activity

Two Equal-Portfolio Approach	-10 to -1 days	1-20 days	1-4 days	5-20 days
Portfolio 1 (smallest Q)	0.929%	0.182%	0.010%	0.171%
Portfolio 2 (largest Q)	-0.575%	0.612%	0.212%	0.400%
Portfolio 2- Portfolio 1	-1.503%	0.431%	0.202%	0.229%
(*t*-statistics)	*(-20.08)*	*(4.16)*	*(4.20)*	*(2.42)*

Five Quintile-Portfolio Approach	-10 to -1 days	1-20 days	1-4 days	5-20 days
Portfolio 1 (smallest Q)	1.554%	0.092%	-0.019%	0.111%
Portfolio 2	0.759%	0.220%	0.023%	0.198%
Portfolio 3	0.084%	0.430%	0.112%	0.318%
Portfolio 4	-0.461%	0.477%	0.225%	0.252%
Portfolio 5 (largest Q)	-1.032%	0.759%	0.215%	0.544%
Portfolio 5 - Portfolio 1	-2.587%	0.667%	0.234%	0.433%
(*t*-statistics)	*(-22.89)*	*(4.02)*	*(3.12)*	*(2.92)*

Panel B: Portfolios sorted by speculator's trading activity

Two Equal-Portfolio Approach	-10 to -1 days	1-20 days	1-4 days	5-20 days
Portfolio 1 (smallest Q)	-0.643%	0.542%	0.207%	0.336%
Portfolio 2 (largest Q)	0.997%	0.252%	0.016%	0.236%
Portfolio 2- Portfolio 1	1.640%	-0.290%	-0.191%	-0.099%
(*t*-statistics)	*(23.45)*	*(-2.72)*	*(-4.05)*	*(-1.05)*

Five Quintile-Portfolio Approach	-10 to -1 days	1-20 days	1-4 days	5-20 days
Portfolio 1 (smallest Q)	-1.133%	0.752%	0.273%	0.479%
Portfolio 2	-0.385%	0.362%	0.130%	0.232%
Portfolio 3	0.002%	0.382%	0.134%	0.248%
Portfolio 4	0.837%	0.393%	0.049%	0.343%
Portfolio 5 (largest Q)	1.599%	0.098%	-0.036%	0.134%
Portfolio 5 - Portfolio 1	2.732%	-0.654%	-0.309%	-0.345%
(*t*-statistics)	*(25.00)*	*(-4.15)*	*(-4.25)*	*(-2.40)*

Table 5: Hedger's Liquidity Provision Mechanism in Commodity Market

In this table, we examine the liquidity provision mechanism for hedgers. We run the following three regressions respectively using the panel data for all 26 commodities with each commodity having a fixed effect (u_i) on its returns. We employ a panel-regression methodology, using Newey-West method with 4 lags to adjust heteroskedasticity and serial correlation of error terms. More sspecifically, we have

1) Capital Constraint Proxy Model:

$$R_{i,t+1} = b_1 Q_{i,t}^{hedger} + b_2 Dm(CapitalLoss) Q_{i,t}^{hedger} + b_3 B_{i,t} + b_4 S_{i,t} \hat{v}_{i,t} + b_5 R_{i,t} + u_i + \varepsilon_{i,t+1}$$

2) Order Imbalance Proxy Model:

$$R_{i,t+1} = b_1 Q_{i,t}^{hedger} + b_2 Dm(OrderImbalance) Q_{i,t}^{hedger} + b_3 B_{i,t} + b_4 S_{i,t} \hat{v}_{i,t} + b_5 R_{i,t} + u_i + \varepsilon_{i,t+1}$$

In the capital constraint proxy model, we first calculate capital loss for hedgers at week *t* by $N_{i,t-1} \cdot R_{i,t}$, where $N_{i,t-1}$ is the hedging pressure for i^{th} commodity at week *t*-1. We then create the dummy variable $Dm(CapitalLoss)$, which is set to be 1 if $N_{i,t-1} \cdot R_{i,t}$ is below the most negative 10% cutoff value for a given type of commodity, and otherwise zero. In the order imbalance proxy model, we approximate the order imbalance by continuous buying or selling, i.e. $Q_{i,t-1}^{hedger} \cdot Q_{i,t}^{hedger}$. We then create the dummy variable $Dm(OrderImbalance)$ by setting positive $Q_{i,t-1}^{hedger} \cdot Q_{i,t}^{hedger}$ as 1 and otherwise 0.

	Capital Constraint	Order Imbalance
$Q_{i,t}^{hedger}$	2.68	1.40
	(5.18)	*(1.76)*
$Q_{i,t}^{hedger} \times$	3.47	2.40
Dummy	*(2.01)*	*(2.66)*
$B_{i,t}$	-0.25	-0.25
	(-1.33)	*(-1.36)*
$S_{i,t} \hat{v}_{i,t}$	-0.03	-0.03
	(-0.21)	*(-0.25)*
$R_{i,t}$	0.02	0.01
	(1.57)	*(1.23)*
R^2	0.33%	0.33%

Table 6: How Do Speculators Consume Liquidity in Commodity Market?

This table examines how speculators consume liquidity in commodity futures market.

First, we study the structure of speculators and its impacts on the market liquidity. We first denote *SL*, *SS*, *HL* and *HS* as speculator's long, speculator's short, hedger's long, hedger's short positions, respectively. We introduce the first ratio measure as $F^1_{i,t-1} = (SL_{i,t-1} + SS_{i,t-1})/(HL_{i,t-1} + HS_{i,t-1})$. We then introduce the dummy variable $Dm(FRatio1)_{i,t}$, which is equal to one when $F^1_{i,t-1}$are above its median, and zero otherwise.

We also introduce the second ratio measure as $F^2_{i,t-1} = min\left(SL_{i,t-1}, SS_{i,t-1}\right)/min(HL_{i,t-1}, HS_{i,t-1})$, where we label $min(SL_{i,t-1}, SS_{i,t-1})$ and $min(HL_{i,t-1}, HS_{i,t-1})$ as the balanced positions for hedgers and speculators, respectively. These balanced positions have the potential to provide liquidity to commodity futures market. We then introduce the dummy variable $Dm(FRatio2)_{i,t}$, which is equal to one when $F^2_{i,t-1}$are above its median, and zero otherwise.

We run the following two panel regressions.
Model 1:

$$R_{i,t+1} = b_0 + b_1 Q^{Spec}_{i,t} + b_2 Dm(FRatio1)_{i,t} \cdot Q^{Spec}_{i,t} + b_3 B_{i,t} + b_4 S_{i,t}\hat{v}_{i,t} + b_5 R_{i,t} + \varepsilon_{i,t+1}$$

Model 2:

$$R_{i,t+1} = b_0 + b_1 Q^{Spec}_{i,t} + b_2 Dm(FRatio2)_{i,t} \cdot Q^{Spec}_{i,t} + b_3 B_{i,t} + b_4 S_{i,t}\hat{v}_{i,t} + b_5 R_{i,t} + \varepsilon_{i,t+1}$$

where $R_{i,t}$ is the return of the i^{th} type of front-month commodity futures in week t,$Q^{Spec}_{i,t}$ is the change of net long position of speculators normalized by the total open interest, and all the control variables are defined in the same way as previous tables.

Next, we study whether the price of liquidity consumption speculators pay is related to their holding position. At the beginning of week *t*, we calculate the net long position of speculators for a certain type of commodity *i* at the end of week *t*-1, normalizing it by the total open interest at the end of week *t*-1. More specifically, we have $SpecPosition_{i,t-1} = (SpecLong_{i,t-1} - SpecShort_{i,t-1})/OI_{i,t-1}$.

We construct a dummy variable $Dm(SpecPosition)_{i,t}$ based on the value of $SpecPosition_{i,t-1}$. When speculators are buying in week *t* ($Q^{spec}_{i,t} > 0$), the dummy variable is equal to 1 if the value of $SpecPosition_{i,t-1}$ is positive and in the highest 20% (top quintile) for commodity *i*, and zero otherwise; when speculators are selling in week *t* ($Q^{spec}_{i,t} < 0$), the dummy variable is equal to 1 if the value of $SpecPosition_{i,t-1}$ is negative and in the lowest 20% (bottom quintile) for commodity *i*, and zero otherwise.

Then we run a panel regression as follows.
Model 3:

$$R_{i,t+1} = b_1 Q^{spec}_{i,t} + b_2 Dm(SpecPosition)_{i,t} Q^{spec}_{i,t} + b_3 B_{i,t} + b_4 S_{i,t}\hat{v}_{i,t} + b_5 R_{i,t} + u_i + \varepsilon_{i,t+1}$$

where $R_{i,t}$ is the return of the i^{th} type of front-month commodity futures in week t,$Q^{Spec}_{i,t}$ is the change of net long position of speculators normalized by the total open interest, and all the control variables are defined in the same way as previous tables.

We also run another panel regression with slightly different specifications as follows.

Model 4:

$$R_{i,t+1} = a_1 Q_{i,t}^{spec} + a_2 Dm(PosSpecPosition)_{i,t} Q_{i,t}^{spec} + a_2 Dm(NegSpecPosition)_{i,t} Q_{i,t}^{spec} + a_3 B_{i,t} + a_4 S_{i,t} \hat{v}_{i,t} + a_5 R_{i,t} + u_i + \varepsilon_{i,t+1}$$

where $Dm(PosSpecPosition)_{i,t}$ is set to be 1 when $Q_{i,t}^{spec} > 0$, and the value of $SpecPosition_{i,t-1}$ is positive and in the highest 20% (top quintile) for commodity *i*, and zero otherwise; $Dm(NegSpecPosition)_{i,t}$ is set to be 1 when $Q_{i,t}^{spec} < 0$, and the value of $SpecPosition_{i,t-1}$ is negative and in the lowest 20% (bottom quintile) for commodity *i*, and zero otherwise.

For all regression models in this table, we run the regressions respectively using the panel data for all 26 commodities with each commodity having a fixed effect (u_i) on returns. We employ a panel-regression methodology using Newey-West technique with 4 lags to adjust heteroskedasticity and serial correlation of error terms.

	Model 1	Model 2	Model 3	Model 4
$Q_{i,t}^{spec}$	-2.846	-2.747	-2.998	-2.998
	(-4.74)	*(-4.59)*	*(-5.13)*	*(-5.13)*
$Q_{i,t}^{spec} \times Dm(FRatio1)_{i,t}$	-2.981			
	(-2.44)			
$Q_{i,t}^{Spec} \times Dm(FRatio2)_{i,t}$		-3.743		
		(-3.03)		
$Q_{i,t}^{spec} \times Dm(SpecPosition)_{i,t}$			-4.636	
			(-2.67)	
$Q_{i,t}^{spec} \times Dm(PosSpecPosition)_{i,t}$				-4.55
				(-2.00)
$Q_{i,t}^{spec} \times Dm(NegSpecPosition)_{i,t}$				-4.76
				(-1.88)
$B_{i,t}$	-0.046	-0.046	-0.046	-0.046
	(-0.25)	*(-0.25)*	*(-0.25)*	*(-0.25)*
$S_{i,t}\hat{v}_{i,t}$	-0.000	-0.001	0.000	0.000
	(-0.37)	*(-0.46)*	*(0.13)*	*(0.13)*
$R_{i,t}$	0.014	0.014	0.014	0.014
	(1.45)	*(1.45)*	*(1.44)*	*(1.44)*
R^2	0.3%	0.3%	0.3%	0.3%

Table 7: CIT and DCOT data

In this table, we test the robustness of our previous regression results based on two alternative datasets different from the COT dataset, i.e. the disaggregate commitment of traders (DCOT) and the Commodity Index Traders (CIT) dataset. Both CIT and DCOT samples are from 2006/01/03 to 2012/06/29 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 CIT data classify traders into commercials, non-commercials, index traders, and non-reportables for 12 agricultural commodities: wheat, Kansas wheat, corn, soybeans, soybean oil, cotton, cocoa, sugar, coffee, lean hogs, live cattle and feeder cattle.

We run the following Fama-Macbeth regression for different type of commodity investors using CIT and DCOT datasets and report the corresponding results in Panel A and B, respectively:

$$R_{i,t+1} = a_0 + a_1 Q_{i,t} + a_2 R_{i,t} + a_3 B_{i,t} + a_4 S_{i,t} \hat{v}_{i,t} + \varepsilon_{i,t+1}$$

where $R_{i,t}$ is the return of the i^{th} type of commodity futures in week t, $Q_{i,t}$ is the change of net long position of the particular type of commodity future investors normalized by the total open interest, and all the control variables are defined in the same way as previous tables.

We first run Fama-Macbeth cross-sectional regression each week, and then report the time-series average of the weekly cross-sectional regression coefficient estimates. The R^2 is the time-series average of the adjusted R^2 estimates from the cross-sectional regression in each week. The sample period is from 1994/1/2 to 2012/6/29. We also divide the sample period into two sub-sample periods: from 1994/1/2 to 2003/12/31, and from 2004/1/2 to 2012/6/29. Futures returns are in the unit of percentage points. The *t*-statistics are reported in brackets below the associated coefficients.

Panel A: Regression results using the DCOT dataset

	Producer	Money Manager	Swap Dealer	Other Reportable	Small Investor
$Q_{i,t}$	8.71	-6.86	-4.21	-3.12	-2.09
	(4.76)	*(-3.24)*	*(-1.09)*	*(-0.86)*	*(-0.51)*
$R_{i,t}$	0.0370	0.0359	0.0060	0.0047	0.0043
	(1.91)	*(1.79)*	*(0.34)*	*(0.26)*	*(0.25)*
$B_{i,t}$	-0.80	-0.80	-0.85	-0.74	-0.82
	(-2.19)	*(-2.13)*	*(-2.27)*	*(-1.96)*	*(-2.20)*
$S_{i,t}\hat{v}_{i,t}$	0.11	0.07	0.06	0.05	0.04
	(0.39)	*(0.26)*	*(0.23)*	*(0.20)*	*(0.14)*
R^2	11.3%	11.5%	10.5%	11.0%	10.2%

Panel B: Regression results using the CIT dataset

	Hedger	Speculator	Index Trader	Small Investors
$Q_{i,t}$	9.46	-5.87	-13.24	14.16
	(2.31)	*(-1.29)*	*(-0.92)*	*(1.42)*
$R_{i,t}$	0.0375	0.0305	0.0133	0.0025
	(1.09)	*(0.91)*	*(0.46)*	*(0.09)*
$B_{i,t}$	-1.18	-1.33	-1.00	-1.00
	(-1.64)	*(-1.78)*	*(-1.31)*	*(1.31)*
$S_{i,t}\hat{v}_{i,t}$	0.01	0.16	0.30	0.08
	(0.03)	*(0.48)*	*(0.92)*	*(0.25)*
R^2	9.1%	9.6%	8.2%	7.1%

Table 8: Longer-Maturity Commodity Futures Returns

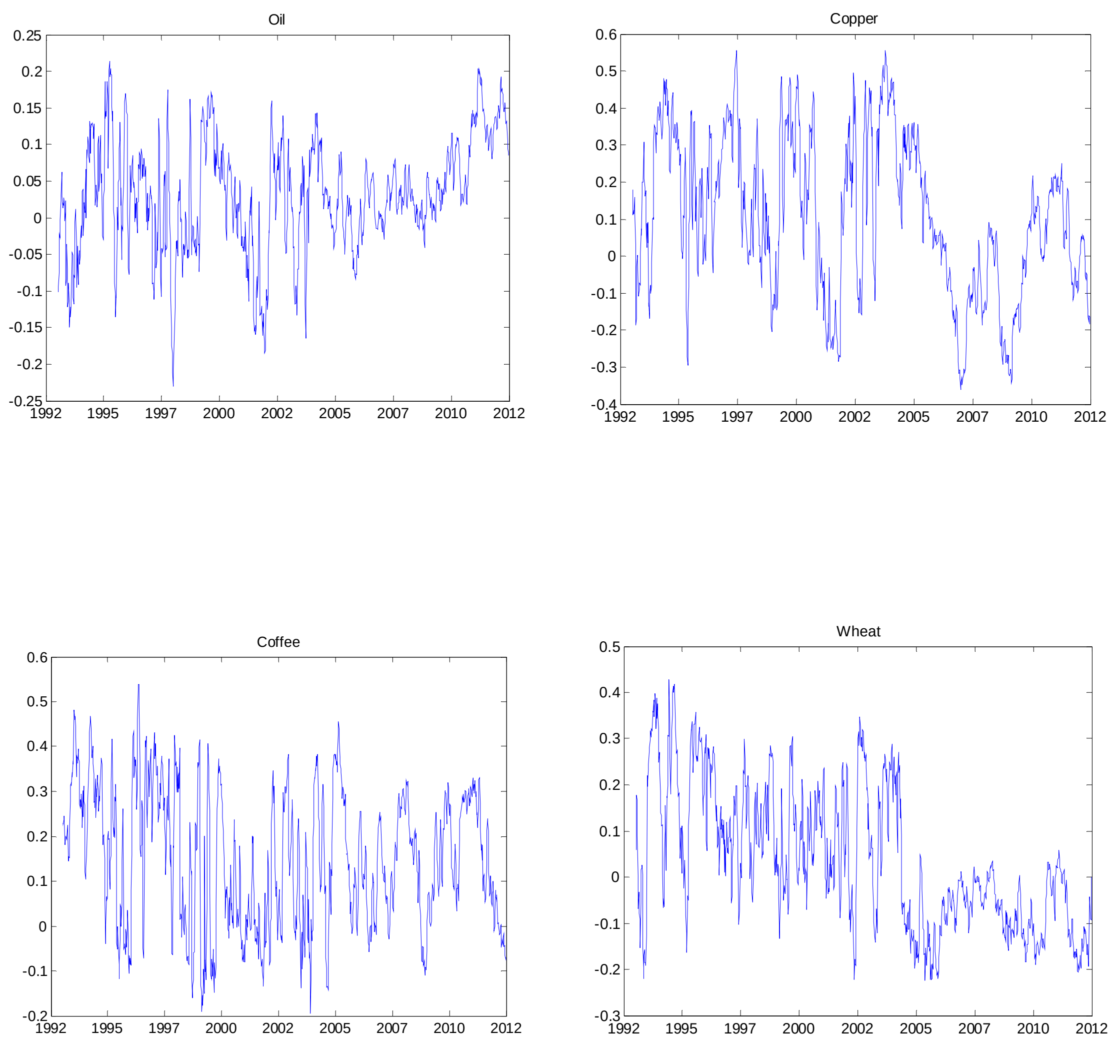
In this table, we conduct robustness test based on longer maturity futures returns. More specifically, we construct second-month futures excess returns, and roll to third-month contracts on the 7th calendar day two months before the second-month contract matures.

We run the following Fama-Macbeth regression for different players and report results respectively:
$R_{i,t+1} = a_0 + a_1 Q_{i,t} + a_2 R_{i,t} + a_3 B_{i,t} + a_4 S_{i,t} \hat{v}_{i,t} + \varepsilon_{i,t+1}$
where $R_{i,t}$ is the return of the i^{th} type of commodity futures in week *t*; $Q_{i,t}$ is the change of net long position of the particular type of commodity future investors normalized by the total open interest. B is the log-basis. v is the annualized standard deviation of the residuals from the regression of futures returns on SP500 returns (calculated by 52 weeks rolling window). S is a dummy on speculation, i.e. it is 1 when speculators are netlong and -1 when speculators are net short.

We first run Fama-Macbeth cross-sectional regression each week, and then report the time-series average of the weekly cross-sectional regression coefficient estimates. The R^2 is the time-series average of the adjusted R^2 estimates from the cross-sectional regression in each week. The sample period is from 1994/1/2 to 2012/6/29. We also divide the sample period into two sub-sample periods: from 1994/1/2 to 2003/12/31, and from 2004/1/2 to 2012/6/29. Futures returns are in the unit of percentage points. The *t*-statistics are reported in brackets below the associated coefficients.

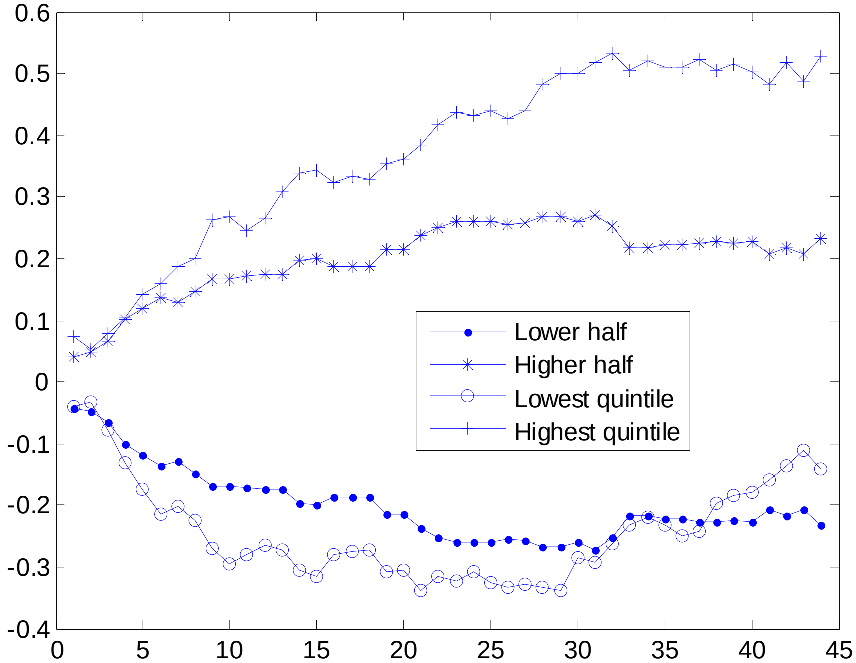
	All Sample Period			Sub Sample Period: 1994~2003			Sub Sample Period: 2004~2012		
Trader's Type	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others
$\boldsymbol{Q_{i,t}}$	3.459	-4.221	-0.887	3.043	-3.453	-0.710	4.028	-5.296	-0.921
	(4.87)	*(-5.52)*	*(-0.60)*	*(4.52)*	*(-4.55)*	*(-0.57)*	*(3.05)*	*(-3.77)*	*(-0.33)*
$B_{i,t}$	-0.541	-0.518	-0.541	-0.428	-0.419	-0.439	-0.687	-0.651	-0.675
	(-3.57)	*(-3.38)*	*(-3.46)*	*(-2.42)*	*(-2.32)*	*(-2.39)*	*(-2.69)*	*(-2.54)*	*(-2.58)*
$S_{i,t}\hat{v}_{i,t}$	0.051	0.071	0.021	0.008	0.035	0.014	0.082	0.092	0.016
	(0.37)	*(0.52)*	*(0.15)*	*(0.05)*	*(0.20)*	*(0.08)*	*(0.38)*	*(0.42)*	*(0.08)*
$R_{i,t}$	0.034	0.034	0.013	0.047	0.046	0.022	0.018	0.020	0.002
	(2.78)	*(2.84)*	*(1.18)*	*(2.82)*	*(2.76)*	*(1.49)*	*(1.05)*	*(1.19)*	*(0.11)*
R^2	9.94%	9.82%	9.43%	10.67%	10.45%	10.23%	9.08%	9.12%	8.49%

Figure 1: Hedging Pressure for Four Commodities



This figure shows the time series of hedging pressure for oil, copper, coffee, and wheat. The hedging pressure is defined as by the short position minus long position and then divided by the total open interest for each commodity. The weekly commodity futures long and short positions are obtained from the COT dataset provided by CFTC from January 1994/01/02 to July 2012/06/29.

Figure 2: Cumulative Returns following Hedger's Trading Activity



This figure presents cumulative market-adjusted returns following weeks with buying and selling activity of hedgers as given by the hedger's trading measure ($Q_{i,t}^{hedger}$). For each week in the sample period, we use the previous week's $Q_{i,t}^{hedger}$ to form equal weighted and five quintile portfolios in the current week. We present the results for four portfolios: (i) lower-half portfolio, (ii) higher-half portfolio, (iii) lowest-quintile portfolio and (iv) highest-quintile portfolio. We calculate cumulative returns for each portfolio: $CR(t + 1, t + k)$, where t is the last day of the portfolio formation week and k is the number of days in the cumulative return calculation. The return on each portfolio is then adjusted by subtracting the return on a market proxy (the equal-weighted portfolio of all 26 commodities in the sample).