Who Provides Liquidity to Commodity Futures Markets?

Wenjin Kang (National University of Singapore)

K. Geert Rouwenhorst (Yale School of Management)

Ke Tang (Remin University of China)

First Draft: August 15, 2013

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.

* Contact method: Wenjin Kang: wenjinresearch@gmail.com; K. Geert Rouwenhorst: k.rouwenhorst@yale.edu; Ke Tang: ketang@ruc.edu.cn.

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 on the market. Milton Friedman (1960) argues that speculators in commodity futures markets ultimately perform the important function of providing liquidity for hedgers. This is consistent with the classical theory of normal backwardation, originated from Keynes (1923) and Hicks (1939), which argue that commercial producers take short position in the futures market to hedge their underlying long position in the physical commodity, while risk-averse speculators accommodate this hedging pressure by taking a long position in futures for which 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."

Because producers are unlikely to make major changes to their production plans on a day-to-day basis, it would seem that the same would apply to their hedging positions, and that the liquidity demands arising from producer hedging would likely be small over short horizons. However, Figure 1 shows substantial weekly variation in the

positions of commercial traders (normally considered as hedgers). For example, across all commodities, commercial traders hold on average 14% of open interest, with a weekly standard deviation of 17%. These position changes are large in magnitude. To the extent that commercial trading activity corresponds to hedging activity, it seems unlikely that these large position changes solely reflect adjustments to the hedging of underlying production plans. An alternative explanation is that short-horizon commercial trading activity is not driven by shocks to optimal hedging policies, but instead by the response to the shocks to non-commercial speculative traders.

In this paper we will examine whether observed short-term position changes are driven by 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 document how equity prices respond 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.

Our paper contributes to the debate about the role of speculators in commodity markets, which has received much attention with the rise in investors' interest in

commodities.[1] The G20 summit meeting in November 2011 at France prioritized the over-speculation problem in commodity futures market as one of the top subjects in the conference memorandum. UNCTAD (2012) documents that the volume of exchange-traded derivatives on commodity market is 20 to 30 times larger than the physical production of the underlying physical commodities, and speculation causes a large portion in the commodity price movements. Singleton (2011) finds that the trading behavior of speculators (e.g. money managers) can lead to substantial futures price fluctuation. Kaufmann (2011) argues that speculative trading tends to overreact the fundamental information in oil market. Cheng, Kirilenko, and Xiong (2012) shows that in crisis time, due to severe risk-aversion, speculators tend to leave futures markets and dry up liquidity accordingly. On the other hand, some other studies hold a more benevolent view of the role of speculators.[2] As we can see, up to now there is no clear stand from the commodity literature about whether speculation in the commodity futures market should be encouraged or regulated.

To fill the blank of the literature, our study examines the key question about who provides liquidity in commodity futures market from a comprehensive perspective, and also casts light to the debate regarding the role of speculation in this market. We show that *it is hedgers instead of speculators who provide liquidity to commodity futures market*. Analyzing the data from Commodity Futures Trading Commission (CFTC), we provide ample empirical evidence that supports our argument from the

[1] Please refer to Tang and Xiong (2012) for the background of financialization of commodities.

[2] For example, Hamilton (2009) and Fattouh, Kilian and Mahadeva (2012)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.

following perspectives.

First, we show that speculators are momentum followers and hedgers are contrarian traders, by observing that speculators would like to buy (sell) when commodity futures prices increase (decrease), while hedgers sell (buy) when commodity futures prices go up (down). The microstructure theory literature, represented by Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993), suggests that 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.[3] Furthermore, we show that speculators are more eager to trade; their trading propensity is on average as twice as that of hedgers. Therefore, we provide the first layer of empirical support to our argument that hedgers provide liquidity in the commodity futures market.

Next, we examine the commodity futures return predictability based on hedger's trading activity. The microstructure models mentioned above suggest that impatient investors who require immediacy need to offer price concessions to encourage risk-averse market makers taking the other side of their trades. Hence, market makers' contrarian trading strategy can bring them the compensation of providing liquidity by exploiting the subsequent price reversals. In practice, we regress weekly commodity futures returns on hedgers' net trading activity, and find that commodity futures price increases (decreases) significantly after hedgers' buying (selling) activity in the

[3] 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.

previous week. As a sharp contrast, after speculators' buying (selling) activity, commodity futures price goes down (climbs up). Combining these two results together, we provide another layer of empirical evidence that hedgers, as contrarian traders, are able to earn profit from their liquidity provision strategy, while speculators, as momentum chasers, consume liquidity from the market and pay a cost to hedgers so that their trading demands can be accommodated.

To illustrate the profitability of hedgers' liquidity provision strategy in a more vivid manner, we also construct portfolios based on hedgers' net buying and selling activity. We long the commodity futures that hedgers buy and short the commodity futures they sell in the previous week. Such trading strategy yields a significant profit with an annualized rate of return around 10% from 1994 to 2012. Our result here is related with the short-term reversal strategy literature, in which the portfolios are sorted by either stock return and volume (or order imbalance) information (e.g., Conrad, Hameed, and Niden (1994), Avramov, Chordia, and Goyal (2006)), or individual stock investors' trading activity (e.g., Kaniel, Saar, and Titman (2008)). All these strategies show a considerable amount of profitability, as a reward to the market making behavior on the stock market. We contribute to this line of literature by expanding the empirical test to another important capital market, that is, commodity futures market, and showing that market makers (i.e., hedgers) can make good profit by their liquidity-providing strategy on this market.

Our third layer of empirical evidence comes from the test on the microstructure theory predictions at a finer level. We find that when hedgers suffer a severe loss and

have a shrink capital base, they will be more reluctant to provide liquidity and demand a higher premium to do so, which is consistent with the collateral-constraint model (Brunnermeier and Pedersen (2009)) and wealth-effect model (Xiong (2001)). We also find that when hedgers have stronger inventory concern, which is estimated by whether they have traded in the same direction for the previous two weeks, they will be less willing to provide liquidity to the commodity future market. This observation is consistent with what Chordia, Roll, and Subrahmanyam (2002) find on the stock market.

One interesting feature of commodity future market is that on average hedgers are holding short positions. This suggests that they will respond to buy or sell orders asymmetrically. We find that for commodity futures with a high hedgers shorting degree, hedgers' selling activity leads to a stronger price decline than the price rebound after their buying activity. Our interpretation is that when it is very likely for hedgers to already hold short inventory positions, the buy order from speculators means they have to take additional short positions, which will make their inventory even more unbalanced. The increased inventory risk for hedgers when they short-sell should be compensated by higher premium extract from the expected price decline after they sell.

We also show that the cost of liquidity speculators pay increases when it is more difficult for them to find other speculators as the counterparty of their trades. Our interpretation is that when there is less number of speculators who are ready to trade with other speculators on the market, hedgers enjoy the role of a quasi-monopoly, and

therefore are able to extract higher economic profit from their liquidity-providing strategy.

Putting all these empirical evidence together, we clearly show that hedgers, as contrarian traders, provide liquidity to commodity futures market, while speculators consume liquidity when they commit to their momentum chasing strategy. Hedgers are able to earn a good amount of profit from their liquidity provision behavior, and this profitability increases when they have a smaller capital base or more unbalanced inventory position. To ensure the robustness of our results, we repeat our analysis based on different datasets and alternative return calculation method, and our main results hold true in all circumstances.

The rest of the paper is organized as follows. Section 2 describes the sample data and introduces the empirical measures used in this paper. Section 3 provides detailed analysis on the behavior of different types of investors in commodity futures market and the return predictability based on their trading behavior. Section 4 includes extended analysis on hedgers' liquidity provision and speculators' liquidity consumption. Section 5 conducts the robustness check by considering different datasets and futures return calculation methods. Section 6 concludes our paper.

2. Data and Summary Statistics

We use public available data provided by Commodity Futures Trading Commission (CFTC) to study the trading behavior of different types of investors in the commodity futures market. More specifically, we analyze the Commitment of

Trader (COT) dataset provided by CFTC, which contains weekly aggregate long and short positions of commodity traders labeled as commercials, non-commercials, and non-reportables. Starting from 1993, on each Tuesday CFTC collects information about positions of all exchange-traded futures on US-based exchanges, and announce the position breakdown on the following Friday. Our data sample covers from 1994/01/02 to 2012/06/29 on a weekly basis for 26 commodities that are traded on four North American exchanges (NYMEX, NYBOT, CBOT and CME).[4]

We follow the empirical literature, such as Houthakker (1957), Rockwell (1967), Chang (1985), Bessembinder (1992), De Roon, Nijman and Veld (2000), Hong and Yogo (2012), and Acharya, Lochstoerd and Ramadorai (2013), which has traditionally associated commercials with hedgers and non-commercials with speculators.[5] We are aware of the potential imperfection for the linkage between commercial and hedgers and between non-commercial and speculators. For example, Ederington and Lee (2002) suggest that it is possible for commercials to conduct speculative business under certain circumstances. Therefore, to ensure the robustness of our results, we also employ the Disaggregate Commitment of Trader (DCOT) and Commodity Index Trader (CIT) datasets in our empirical analysis.

These two additional datasets (DCOT and CIT) are provided by CFTC as a response to an increased interest of commodity futures study. CFTC has adopted a more detailed split method of the traditional trader categories in the DCOT reports,

[4] 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.

[5] 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)".

including producers / merchant / processor / user, swap dealers, money manager, and other reportable. The DCOT report is only available from January 2006, in a weekly frequency for 26 commodities. Starting from January 2006, the CFTC also publishes a weekly CIT supplement, which reports the allocations of index traders to 12 agricultural commodities[6] – index traders consist of the subset of swap dealer positions which offset index investments by their clients, as well as direct futures investments by index funds.

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 unsigned size of speculator's long, speculator's short, hedger's long, hedger's short positions and open interest, respectively, for commodity *i* in week *t*. In Table 1, we first provide the statistics of hedging pressure, $N_{i,t}$, for hedgers in the 26 commodities, which are defined as the net short (short minus long) position of hedgers in commodity futures contracts of all maturities for a given type of commodity divided by its total open interest as follows.

$$N_{i,t} = \frac{HS_{i,t} - HL_{i,t}}{OI_{i,t}} \quad (1)$$

Table 1 Panel A shows that across all commodities about 72% of the time hedgers are holding net short positions. Furthermore, we observe a high volatility of hedging pressure over time, which is on average 17% on weekly frequency. Combined with the number of average hedging pressure as 14%, it is suggests that a change from one standard deviation below the mean to one standard deviation above the mean for the hedging pressure would be a jump from -3% to 31% in terms of hedger's net short

[6] These include corn, soybeans, Chicago wheat, Kansas wheat, soybean oil, coffee, cotton, sugar, cocoa, feeder cattle, lean hogs, and live cattle.

position. This indicates that hedgers trade more actively than what is perceived by the classical theory of normal backwardation. According to this theory, hedgers enter into commodity futures market only to hedge their production, and given the persistency of their production, their holding positions should not change so much, especially over a weekly frequency. This suggests that hedgers must trade for other reasons as well. Figure 1 presents the time-series fluctuation of the hedging pressure for four commodities (oil, copper, coffee, and wheat) in a more vivid manner.

Next, we construct the trading measure for each type of commodity futures investors. As a first step, we calculate the net long position of a certain type of commodity futures investors by subtracting the aggregate short position held by these investors from their aggregate long positions in each week. Then for the given type of investors, we construct their weekly trading measure, $Q_{i,t}$, as the change of their net long position as introduced above from previous week *t*-1 to current week *t*, normalized by the commodity future's total open interest, as below.

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

Table 1 Panel B presents the summary statistics of the weekly trading measure for different types of investors. On average hedgers trade 3.6% of the total open interest for the commodity futures in terms of their net buying or selling activity per week, and speculators trade at a similar magnitude as of 3.1%. Somehow small traders trade less actively, which implies that they probably play a less important role on commodity futures market.

We then calculate returns of commodity futures. The main data used here are

obtained from the Pinnacle Corp., which include the price of 26 commodity futures in our sample for the same sample period from 1994/01/02 to 2012/06/29. For each commodity, we follow Gorton and Rouwenhorst (2006) and Erb and Harvey (2006) to construct a weekly return index (Tuesday to Tuesday) from rolling the front-month (nearest-to-maturity) contract. More specifically, we construct a hypothetical investment position in the front-month futures contract of the commodity on a fully collateralized basis. We hold the contract until the 7th calendar day of its maturity month before rolling into the second-month contract. If 7th is not a business day, the next business day is used as the rolling date. Therefore, the rolling strategy is always constructed based on the most liquid contract. 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. For simplicity, we uniformly specify one-day roll strategy on the seventh calendar day of each maturity month for all 26 commodities. In the later section of this paper, we also use returns with longer futures maturity to perform a robustness check. The excess return $R_{i,t}$ of this investment strategy represents the excess futures return to the initial capital:

$$R_{i,t} = \frac{F_i(t,T) - F_i(t-1,T)}{F_i(t-1,T)} \tag{3}$$

where $F_i(t,T)$ is price of the futures contract held on week *t* with a maturity date *T*. Besides the return variable, we also introduce the log basis $B_{i,t}$ as follows

$$B_{i,t} = \frac{logF_i(t,T2) - logF_i(t,T1)}{T2-T1} \tag{4}$$

where $T1$ is the maturity of the front-month contract and $T2$ is that of the second-month contract. The log basis variable constructed here will be used as one of controls in regressions of later section.

The summary statistics of weekly futures excess returns and basis for all the 26 commodity futures in our sample are provided in Table 1, Panel C. The average annualized return of all commodities is around 4.2% per year, with a large average time-series standard deviation of 28.8%. We find on average the energy and metal sectors produce higher returns than the agricultural sectors (grains, soft, and live cattle). In the meanwhile, in recent years commodity futures curves tend to be contango, which drives up the average basis of the sample. On average, the annualized basis for all commodities is 4.9%.

3. Liquidity Provision in the Commodity Futures Market

In this section we seek the answer for an important question, that is, who provides liquidity in the commodity futures market.

3.1 Trading Behavior of Hedgers and Speculators

As a first step, we examine that, for different types of investors in the commodity futures market, e.g., hedgers (commercials), speculators (non-commercials), and small traders (non-reportable), whether they are contrarian traders or momentum followers. The reason we conduct this analysis is that the microstructure literature suggests contrarian traders are usually liquidity providers and momentum followers tend to be liquidity consumers. For example, Campbell, Grossman, and Wang (1993) argue that

when some investors desire to sell the stock for exogenous reasons, other risk-averse utility maximizers (market makers) are willing to accommodate the selling pressure and the related price movement by buying the stock at a lower price so that they can receive higher expected returns. As an empirical support to this argument, Comerton-Forde et al. (2010) 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.

We first examine how the trading behavior of different types of commodity futures investors correlates with commodity price movements by running the following contemporaneous regression, in which the trading measure $Q_{i,t}$ (the weekly change of net long position) introduced in the previous section is regressed on commodity futures returns in the same week as below:

$$Q_{i,t} = a_0 + a_1 R_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $R_{i,t}$ is the excess return of the i^{th} type of commodity futures in week *t*; $Q_{i,t}$ is trading measure of the particular type of commodity futures investors (hedgers, speculators, or small traders) in week *t*. Here we take the Fama-Macbeth regression approach – we first run the cross-sectional regression as described above for each week, and then report the time-series average of the cross-sectional regression coefficient estimates. The regression coefficient estimates in Table 2 Panel A show that, in our sample period from 1994 to 2012, hedgers' trading activity is strongly negatively correlated with contemporaneous commodity futures price changes, and as a strong contrast, the trading activity of speculators and small traders strongly

positively co-vary with commodity future returns. This empirical result is consistent with the earlier findings of Houthakker (1957).

We then test how various types of commodity futures investors change their positions according to past returns by the following Fama-Macbeth regression

$$Q_{i,t} = a_0 + a_1 R_{i,t-1} + a_2 Q_{i,t-1} + \varepsilon_{i,t} \quad (6)$$

where $Q_{i,t}$ and $R_{i,t}$ are defined in the same way as above. We employ a Fama-Macbeth approach for this regression. In Table 3 Panel B, during the whole sample period, the coefficient of lag returns is strongly positive for speculators and strongly negative for hedgers, with a *t*-statistics above 10. There seems to be some positive relationship between small traders' trading in week *t* and commodity future return in week *t*-1, but its statistical significance is much lower than what we observe for hedgers and speculators. The result we obtain here echoes well with what Rouwenhorst and Tang (2012) find using a time-series regression approach. In the meanwhile, the coefficient estimate on the previous-week trading measure is significantly positive for both hedgers and speculators, which indicates positive autocorrelation structure of their trading behaviour.

Combine the results we obtain from the two regressions described above together, we find that speculators and small traders tend to buy (sell) when commodity futures prices go up (down), and as a sharp contrast, hedgers sell (buy) when commodity futures prices increase (decrease). In other words, speculators and small traders are *momentum* traders and hedgers are *contrarian* traders. We also want to mention that for the above two regressions, besides the test conducted in the overall sample period,

we also repeat the analysis in the following two sub-sample periods: one from 1994/1/2 to 2003/12/31, and the other from 2004/1/2 to 2012/6/29. All the empirical results are robust for these two sub-sample periods as shown in Table 2.

Next, we examine the difference of the propensity to adjust their positions between speculators and hedgers. 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.

$$PY_{i,t}^{Hedger} = \frac{abs(HL_{i,t}-HL_{i,t-1})+abs(HS_{i,t}-HS_{i,t-1})}{HL_{i,t-1}+HS_{i,t-1}} \quad (7)$$

$$PY_{i,t}^{Spec} = \frac{abs(SL_{i,t}-SL_{i,t-1})+abs(SS_{i,t}-SS_{i,t-1})}{SL_{i,t-1}+SS_{i,t-1}} \quad (8)$$

We then take the difference between the *PY* measure of speculators and hedgers as $DiffPY_{i,t} = PY_{i,t}^{Spec} - PY_{i,t}^{Hedge}$. We examine whether the time-series average of $DiffPY_{i,t}$ is significantly higher than zero by using the Newy-West method to calculate the *t*-statistics with 52 lags for the $DiffPY_{i,t}$ time series. Among the 26 sample commodities, speculators exhibit a significantly higher propensity to adjust their holding positions than hedgers in 25 of them. As shown by the overall cross-sectional average, the speculators' propensity is almost as high as twice of the hedgers'. This comparison indicates that speculators are less patient than hedgers, and are more eager to adjust their position. The microstructure literature (e.g., Amihud and Mendelson (1986)) suggest that investors with more patience are more likely to be liquidity providers.

3.2 Return Predictability and Liquidity Provision

The fact that hedgers in commodity futures market are contrarian traders and are more patient than speculators suggests that they are more likely to be the liquidity providers in commodity market. Next, we are going to explore the nature of the trading behavior of hedgers and speculators in more depth by examining the relationship between their trading activity and the following-week commodity futures return to further ascertain who is the liquidity provider in the commodity market. This approach is inspired by the microstructure theory (e.g. Grossman and Miller (1988), and Campbell, Grossman, and Wang (1993)) that suggests impatient investors who require immediacy need to offer price concessions to encourage risk-averse market makers taking the other side of their trades. One implication from this line of theoretical models is that market makers typically trade against the market trend, and their contrarian trading strategy can bring them compensation of providing liquidity by exploiting the subsequent price reversals. In fact, there is a rich empirical literature that examines the short-term (weekly) reversals in the stock market, represented by Conrad, Hameed, and Niden (1994), Avramov, Chordia, and Goyal (2006), and Kaniel, Saar, and Titman (2008). All these studies show that stock market liquidity providers are able to earn a profit from the short-term reversals as the compensation of their liquidity provision.

Although there are a number of studies about the profitability of market maker's liquidity provision behavior and the related short-term reversals in the stock market, we still know little about it in commodity futures market. To fill this blank in the literature, we conduct the following return-predicting regression: commodity futures

return in week *t*+1 is regressed on a certain type of investors' net buying or selling activity (the trading measure *Q*) in week *t*, together with other control variables in a Fama-Macbeth framework as follows.

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

where $\hat{v}_{i,t}$ is the annualized standard deviation of the residuals from the regression of futures returns on S&P500 returns (calculated by 52 weeks 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. To make our empirical test complete; we conduct this regression analysis on all three types of commodity future investors, that is, hedgers, speculators, and small traders.

We have the (log) basis variable in our regression because many papers associated with the theory of storage, proposed as early as by Working (1949) and Brennan (1958) find empirical evidences linking basis to the commodity futures risk premiums. 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), Erb and Harvey (2006), and Gorton, Hayashi and Rouwenhorst (2012) form portfolios by sorting different commodities on the basis and find significant differences between high and low basis portfolios.

Bessembinder (1992) tests the hypothesis proposed 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). Thus, $S_{i,t}\hat{v}_{i,t}$ is included in his empirical model as the proxy of idiosyncratic risk in commodity futures, which is also in our regression.

Pirrong (2005), Erb and Harvey (2006), and Miffre and Rallis (2007) document momentum in commodity futures returns. We hence include the lag of futures returns in our regression. Overall, we use all these control variables in a consistent manner with the commodity literature. The regression results are shown in Table 3.

We find that commodity futures price in week *t*+1 increases (decreases) significantly after hedgers' buying (selling) activity in week *t*. The regression coefficient suggests that if hedgers in net buy 3.6% of the total open interest of a given type of commodity futures in the market, the price of commodity futures is expected to increase by 0.16% in the following week, or at an annualized return rate of 9.0% per year.[7] This suggests that hedgers' contrarian strategy can earn a good amount of profit from the short-term return pattern, and this profit should be interpreted as their liquidity provision compensation.

As a sharp contrast, commodity future price in week *t*+1 decreases (increases) significantly after speculators' buying (selling) activity in week *t*. Our regression estimate imply that when speculators net buy 3.1% of the total open interest of a given type of commodity futures, its price is going to decrease by 0.16% in the next week, or at an annualized return rate of -8.2% per year. This suggests that speculators in the commodity market consume liquidity and their short-term loss can be understood as a cost for them to meet their trading immediacy demands from their momentum-

[7] Here we choose the number of 3.6% because it is the average amount of net trading by hedgers according to Table 2. Later we also use the number of 3.1%, which is the average amount of net trading by speculators, to calibrate the price of liquidity consumption speculators pay for their momentum-chasing strategy.

chasing strategy. We somehow do not find too much significant result for small traders, which implies that they probably play a less important role in the commodity market. We want to emphasize that our empirical findings hold true for both sub-sample periods before and after 2004.

Combining all the empirical results we obtain so far leads to a clear picture about who provides liquidity in the commodity market. Hedgers are more patient and trade as contrarians – they provide liquidity by buying after market drops and selling after price rises, and they can extract considerable amount of profit from their liquidity provision strategy. Speculators are momentum-chasers – they buy in a market uptrend and sell in a downtrend. Obviously, such trading behavior consumes liquidity, and speculators have to pay a cost to the hedgers so that they can accommodate the trading demands from speculators.

Kaniel, Saar, and Titman (2008) show that in stock market, individual investors tend to be contrarian and provide liquidity to institutional investors who are momentum chasers. Our study shares a common view with them by finding that speculators, who are mainly money managers or institutional investors, consume liquidity in commodity future market. But as for the question about who provides liquidity, we find a very different result, that is, it is hedger that provides liquidity, while small traders contribute little to the liquidity provision in commodity futures market.

3.3 Portfolio Sorting

To further illustrate the economic importance of understanding the liquidity provision mechanism in commodity futures market, we take a portfolio sorting approach and form the portfolio based on the previous week's hedgers or speculators' trading measure *Q*. More particularly, in each week we sort commodity futures based on their previous week *Q* number for hedgers or speculators, and then place them into either two equal portfolios, each of which consists of 13 commodity futures, or five quintile portfolios, which are composed of 5, 5, 6, 5, and 5 commodity futures accordingly. Our trading strategy is to long the portfolio that hedgers buy most in the previous week and short the portfolio that hedgers sell most. Alternatively, we can also take long position in the portfolio that speculators sell most and short position in the portfolio that speculators buy most. Each portfolio is constructed on an equally-weighted method. The commodity futures portfolios are rebalanced every week – we close the position in the old portfolio in Tuesday of each week and form a new portfolio.

We observe the portfolio returns throughout our sample period from 1994/01/02 to 2012/06/29, and then present average returns of each commodity future portfolio and of the long-short strategy described above also. The returns of portfolios constructed based on hedgers' trading activity are presented in Table 4, Panel A. When we divide our sample commodities into two equal portfolios, we find that, before the portfolio formation (from day -10 to day -1), the portfolio hedgers buy (sell) experiences a return of -0.58% (0.93%). This result echoes well with what we find in previous sections, that is, hedgers act as contrarians and they buy (sell) past losers (winners).

After the portfolio formation, we show that, in an investment horizon up to post 20 days, the portfolio hedgers buy substantially outperform the portfolio hedgers sell by a statistically significant return difference of 0.43%, which is consistent with what we find in the section above.[8]

Furthermore, we divide the post-formation period into two periods, day 1 to day 4 and day 5 to day 20. We form our portfolio on each Tuesday, the day when CFTC collect information about positions of all exchange-traded commodity futures. At the same time, we also realize that CFTC actually announce the hedgers' or speculators' position information on the following Friday. Therefore, from a practical point of view, a fund manager who wants to exploit this commodity return predictability can only take the corresponding positions from day 5 onwards. The empirical results show that the relative strategy that takes long (short) positions in the commodity futures that hedgers buy (sell) most earns 0.20% from day 1 to 4, and 0.23% from day 5 to 20. The economic profits are statistically significant in both periods.

We can strengthen our results by increase the number of commodity future portfolios. When we sort the commodity futures into five quintile portfolios, we find even larger return difference between the commodities that are bought or sold most by hedgers. The strategy that takes long position in the commodity quintile portfolio that hedgers buy most and short position in the quintile portfolio that hedgers sell most produces an overall return of 0.67% from day 1 to 20 since the portfolio formation. From day 1 to 4, the relative strategy earns a return of 0.23%, and from day 5 to 20, it

[8] What we report in this section is the unleveraged profits. This strategy can be levered since the collateral required in futures market is usually no more than 10% of futures market prices.

produces a return of 0.43%, with both being statistically significant.

As a mirror image, we find that when the portfolios are sorted by speculators' trading measure, the commodity portfolio speculators buy significantly underperform the commodity portfolio speculators sell. The relative strategy that takes long position in the speculator-buy portfolio and short position in the speculator-sell portfolio produces a significant negative return, being -0.29% based on two-equal-portfolio approach and -0.65% based on five-quintile-portfolio approach during the period from day 1 to day 20. We also find such strategy yields negative returns from day 1 to 4 and from day 5 to 20.

Our portfolio sorting results commensurate well with what we obtain from the Fama-Macbeth regressions in previous sections, in the sense that both methods find that first, hedgers are contrarians while speculators are momentum chasers, and more importantly, the commodity futures that are bought (sold) by hedgers as the liquidity provider will produce higher (lower) returns in the following week, while the commodity futures speculators buy (sell) will observe lower (higher) returns in the following week. This intuition is consistent with what previous research has found in stock markets. Avramov, Chordia, and Goyal (2006) find that stocks with large price decline and higher selling pressure (more negative order imbalance) can observe a stronger return rebound in the following week. Kaniel, Saar, and Titman (2008) show that stocks that are most bought by individual investors, who tend to be liquidity providers in stock market, will outperform stocks that are most sold by them by around 0.38% during the following week.

Furthermore, by considering the post-portfolio-construction return from day 5 onwards, we show that what we find in this paper not only has academic importance of shedding light on the question who provides liquidity in the commodity futures market, but also carries practical implication that can provide useful guide to the investment practice in this market.

Before ending this section, we would like to discuss the possibility of an alternative explanation for our finding, that is, the reason for the short-term excess returns following hedger's trading activity is that hedgers have private information about the fundamental information of commodities. While theoretically possible, we find this explanation less appealing since it is unclear how hedgers could gain better information in discovering private information and trading on it profitably. In contrast, using the CFTC data on equity futures, Schwarz (2012) shows that speculators are more informative than hedgers. Since speculators are mainly financial institutions, it is natural that they get themselves better informed.

Moreover, from Table 2 we show that price movements during the hedger's trading week go in the opposite direction to what this private information hypothesis would imply: negative returns when hedgers buy and positive returns when they sell. In other words, it would be hard to believe that when informed investors buy, the price drops simultaneously. Furthermore, the private information hypothesis also cannot explain the empirical evidence supported by the microstructure theory models as mentioned in Section 4 below.

Kaniel, Saar and Titman (2008) examine whether individual traders have private

information by looking at the trend of the cumulative excess returns after intense buying or selling activity of individual traders. We follow their strategy by plotting the cumulative excess returns up to two months (45 business days) following a week with hedgers trading activity measure $Q_{i,t}^{hedger}$ in Figure 2. It seems that the magnitude of the excess returns stabilizes starting 20 business days (4 weeks) after hedgers' trades. Therefore, hedger's trading activity does not predict commodity returns more than a month, which is difficult to reconcile with the private information story. Also, as shown in Table 1 Panel B, hedgers only trade 3.6% of the total open interest, which correspond to an average 27 weeks holding period. Hence, it seems that hedgers do not trade frequently enough to take advantage of whatever short-lived private information they might have.

In next section, we are going to conduct more in-depth analysis and provide additional empirical evidence to strengthen our arguments.

4. Extended Analysis

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 hedgers' liquidity provision

Based on the microstructure literature, we introduce conditional variables that are proxy of market makers' capital constraint, order imbalance pressure, and inventory concern, and use panel regressions including these conditional variables to further

study the mechanism about how hedgers provide liquidity to commodity futures market.

Recent microstructure models suggest that a deterioration of the wealth or the collateral base for market makers can hinder their liquidity provision, as illustrated by Xiong (2001), Brunnermeier and Pedersen (2009). We first calculate capital loss for hedgers at week *t* by multiplying $N_{i,t-1}$ with $R_{i,t}$, 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 capital loss dummy variable, $Dm(CapitalLoss)$, which is set equal to one if hedgers receive large loss in previous week. More specifically, it is set to be one if hedgers hit a loss in the most severe 10% percentile, and zero otherwise. Then we conduct the following panel regression.

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

where the control variables are defined in the same way as in the section above. In this section we use panel regression method 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 variation in the dummy variable, which would make the Fama-Macbeth approach less appropriate here. In the panel regression, we put a fixed effect (u_i) on returns for each commodity. We use the Newey-West method with four lags to adjust for the heteroskedasticity and serial correlation of error terms.

From the regression coefficient estimates shown in Table 5, we find that when

hedgers receive large loss and face more binding capital constraints in the previous week, they are less willing to provide liquidity to commodity market, demand (and also receive) a higher compensation of their liquidity provision as shown by the coefficient of the interactive variable based on this capital loss dummy. During the normal time, if hedgers buy 1% of the commodity futures contract open interest, they would expect the price to increase by 2.7 basis points in the next week. But if hedgers suffer a severe capital loss, they would be less willing to provide liquidity, and therefore will ask for a higher premium (6.2 basis points) to do that. 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) find in the stock market.

Chordia, Roll, and Subrahmanyam (2002) show that excess order imbalance reduce liquidity in stock market since market maker's inventory concern can be exacerbated when facing large order imbalance. In our study, we introduce the dummy variable, $Dm(OrderImbalance)$, that is set to be one when hedgers (as liquidity providers) trade in the same direction continuously in previous two weeks. Our rationale here is that when hedgers have bought or sold in a straight row of two weeks, it is likely to they have accumulated a large amount of inventory that deviates away from their optimal position. With a stronger 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. More specifically, to test our

hypothesis, we run the following regressions.

$$R_{i,t+1} = b_1 Q_{i,t}^{hedger} + b_2 Dm(OrderImbalance) Q_{i,t}^{hedger} + controls + u_i + \varepsilon_{i,t+1} \quad (11)$$

where all variables are defined in a similar way as above. We find that the coefficient of the order imbalance dummy interactive variable (b_2) is significantly higher than zero, which suggests that the commodity futures price return predictability based on hedgers' trading behavior is stronger when hedgers have trade in the same direction during the previous two weeks. This is consistent with our order imbalance hypothesis described above.

The summary statistics in Table 1 suggests that hedgers in commodity futures market are mainly short-sellers – they hold aggregate short positions at 72% of the time in our sample period. This implies that they will respond to buy or sell activities in an asymmetric manner. More particularly, at the beginning of week *t*, since it is likely for hedgers to already hold short position in the commodity futures as their inventory carried from previous weeks, a net selling activity for hedgers in week *t* will move their inventory holding further way from their desired position. As a result, risk-averse hedgers will be more reluctant to provide liquidity to commodity market. To test this particular hypothesis, we define the dummy variable, $Dm(shortsell)$, to be one when hedgers' trading measure $Q_{i,t}^{hedger}$ is negative and otherwise zero, and then multiplied it with the short hedging degree of the i^{th} type of commodity (SH_i) to form the interactive variable. The short hedging degree measures the extent that hedgers of a certain commodity are like to take short positions. It is calculated as the frequency that hedgers is net short, then deducted by 0.5.

Then the interactive variable is multiplied with $Q_{i,t}^{hedger}$ to test our hypothesis, as shown in the regression below.

$$R_{i,t+1} = b_1 Q_{i,t}^{hedger} + b_2 Dm(shortsell) \cdot SH_i \cdot Q_{i,t}^{hedger} + controls + u_i + \varepsilon_{i,t+1} \quad (12)$$

where all variables are defined in a similar way as above.

The empirical result presented in Table 5 suggests that for commodity futures with high shorting degree, the price declines after hedgers' selling activity is stronger than the price climes after hedgers' buying activity. Our interpretation for this empirical observation is that for hedgers who are making the market for high-shorting-degree commodity futures, they hold short positions at most of the time. When other investors, especially speculators, want to buy from them, hedgers need to open additional short positions, and this will make their inventory even more unbalanced. Therefore, hedgers are willing to accommodate the outside buying pressure and conduct the shortselling activity only at sufficient high price levels to ensure their increased inventory risk can be justified by enough risk premium extracted from the expected subsequent price decline.

Overall, the empirical results presented in Table 5 are consistent with what we expect in the corresponding hypothesis. In other words, the way hedgers provide liquidity to commodity futures market matches well with the prediction from microstructure theories.

4.2 How speculators consume liquidity?

In previous sections we have shown that hedgers provide liquidity in commodity futures market, and they will ask for higher compensation for their liquidity provision when they have a more binding capital constraint or larger inventory concern. In a rational setting, speculators should also realize that when they seek the liquidity provision from hedgers, they need to pay a price for this service as described above. Therefore, a cost-minimizing strategy for liquidity-demanding speculators is to look for other speculators with opposite trading intentions so that their trading orders can matched with each other, just like a large fund house would like to match the trading demands from its fund managers internally before submitting the order to outside open markets. As we can see, larger amount of speculators in the commodity futures market would make this strategy work better and reduce the price of liquidity in the commodity futures market.

Furthermore, although speculators in aggregate are liquidity consumers, it is still possible that there is some portion of speculators who have the money and patience and want to compete with hedgers for the business of providing liquidity to other liquidity-demanding speculators. If there is a higher portion of such speculators who can act as liquidity providers, hedgers face strong competition and hence the price of liquidity will be driven down by the competition. On the other hand, if there is only a small number of speculators who are able to provide liquidity, hedgers can enjoy the role of a quasi-monopoly and extract higher amount of profit from their liquidity provision service. Therefore, besides the number of speculators, we should also consider the positions speculators hold in the commodity futures market.

Motivated by the discussion above, in this section we construct the following conditional variables as the proxy of how easily speculators who demand liquidity can find other speculators as the counterparty of their trades.

First, we introduce the conditional variable that is based on speculators' holding position. At the beginning of week *t*, we calculate the net long position of speculators (*SpecPosition*) for 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 $SpecPosition_{i,t-1} = (SL_{i,t-1} - SS_{i,t-1})/OI_{i,t-1}$. We then introduce a dummy variable $Dm(SpecPosition)_{i,t}$, which is 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. Here the dummy variable $Dm(SpecPosition)_{i,t}$ actually capture the situation where it is difficult for liquidity-demanding speculators to find other speculators as the counterparty of their trades, since it is set to be one when speculators already hold a large amount of long (short) positions and some of them want to buy (sell) even more in week *t*.

Based on the dummy variable $Dm(SpecPosition)_{i,t}$ introduced above, we run the following panel regression.

$$R_{i,t+1} = b_1 Q_{i,t}^{spec} + b_2 Dm(SpecPosition)_{i,t} Q_{i,t}^{spec} + b_3 B_{i,t} + b_4 S_{i,t} \hat{v}_{i,t} + b_5 R_{i,t} + u_i + \varepsilon_{i,t+1} \quad (13)$$

where $Q_{i,t}^{Spec}$ is trading measure defined in equation (2), and all the control variables are defined in the same way as previous tables.

The regression coefficient estimates presented in the first column of Table 6 suggests that liquidity-demanding speculators pay a particularly high price of liquidity when they want to buy (sell) on the top of large amount of long (short) positions that are already accumulated by other speculators. For example, if speculators want to buy 3.1% of the total open interest, and other speculators have not accumulated particularly large long position, the price of liquidity speculators need to pay is 9.2 base points per week, or at annualized return rate of 4.9%. But if speculators want to buy 3.1% of the total open interest, and other speculators have accumulated lots of long position already, liquidity-demanding speculators need to pay an extra cost of liquidity as 14.2 base points per week, or at annualized return rate of 7.7%.

We then modify our panel regression specification as follows.

$$R_{i,t+1} = a_1 Q_{i,t}^{spec} + a_2 Dm(PosSpecPosition)_{i,t} Q_{i,t}^{spec} + a_2 Dm(NegSpecPosition)_{i,t} Q_{i,t}^{spec}$$
$$+ a_3 B_{i,t} + a_4 S_{i,t} \hat{v}_{i,t} + a_5 R_{i,t} + u_i + \varepsilon_{i,t+1} \quad (14)$$

where $Dm(PosSpecPosition)_{i,t}$ is equal to one when $Q_{i,t}^{spec} > 0$, and the value of $SpecPosition_{i,t-1}$ is positive and in the highest 20% quintile for commodity i, and zero otherwise; $Dm(NegSpecPosition)_{i,t}$ is set to be one when $Q_{i,t}^{spec} < 0$, and the value of $SpecPosition_{i,t-1}$ is negative and in the lowest 20% quintile for commodity i, and zero otherwise. As we can see, if we add these two dummy variables up, it is equal to the dummy variable $Dm(SpecPosition)_{i,t}$ introduced above. In the second column of Table 6, the coefficient estimates on both dummy

variables are significantly negative, carrying similar values as of the dummy variable coefficient of previous regression. Hence, here we show what we have found in previous regression holds true for both the speculators' buy and sell side alone.

Next, we construct two conditioning variables which are based on the ratio of the number of speculators to hedgers. We first calculate a ratio measure as $F^1_{i,t-1} = (SL_{i,t-1} + SS_{i,t-1})/(HL_{i,t-1} + HS_{i,t-1})$, and then introduce a dummy variable $Dm(FRatio1)_{i,t}$, which is equal to one when $F^1_{i,t-1}$ are below or equal its median value for commodity *i*, and zero otherwise. Here $F^1_{i,t-1}$ is the ratio of the total number of positions hold by speculators to those hold by hedgers. A lower $F^1_{i,t-1}$ ratio value suggests that there are less number of speculators on the market, and therefore it is less likely for a liquidity-demanding speculator to find other speculators as the counterparty of his trades. So our empirical hypothesis is that the cost of liquidity for speculators should be higher when $F^1_{i,t-1}$ is low, or in other words, when the dummy variable $Dm(FRatio1)_{i,t}$ is equal to one. To test this hypothesis, we run the following panel regression.

$$R_{i,t+1} = b_0 + b_1 Q^{Spec}_{i,t} + b_2 Dm(FRatio1)_{i,t} \cdot Q^{Spec}_{i,t} + b_3 B_{i,t} + b_4 S_{i,t}\hat{v}_{i,t} + b_5 R_{i,t} + u_i + \varepsilon_{i,t+1} \quad (15)$$

where all the variables are defined in the same way as previous tables. The coefficient estimates reported in the third column of Table 6 for b_2 are significantly negative. It suggests that when there are less number of speculators on the commodity futures market, it is more difficult for liquidity-demanding speculators to match his trades with other speculators, and therefore have to rely more on hedgers. As a result, the

cost of liquidity that speculators need to pay increases in this scenario.

We calculate another ratio measure as $F_{i,t-1}^{2} = min(SL_{i,t-1}, SS_{i,t-1})/min(HL_{i,t-1}, HS_{i,t-1})$, where $min\,(SL_{i,t-1}, SS_{i,t-1})$ and $min\,(HL_{i,t-1}, HS_{i,t-1})$ are labeled as the balanced positions for speculators and hedgers respectively. We focus on the balanced positions here because the balanced positions represent the amount of speculators or hedgers that are ready to trade with both buy or sell orders. We then introduce the dummy variable $Dm(FRatio2)_{i,t}$, which is equal to one when $F_{i,t-1}^{2}$ are below its median, and zero otherwise. We run the panel regression based on the dummy variable $Dm(FRatio2)_{i,t}$ as follows.

$$R_{i,t+1} = b_0 + b_1 Q_{i,t}^{Spec} + b_2 Dm(FRatio2)_{i,t} \cdot Q_{i,t}^{Spec} + b_3 B_{i,t} + b_4 S_{i,t}\hat{v}_{i,t} + b_5 R_{i,t} + u_i + \varepsilon_{i,t+1} \quad (16)$$

where all the variables are defined in the same way as previous tables. Similar with above, in the fourth column of Table 6, we also find a significant negative coefficient estimate for b_2. In other words, the cost of liquidity for liquidity-demanding speculators increases significantly when there is less number of balanced positions held by speculators relative to hedgers.

5. Robustness Test

In this section, we perform two robustness checks. In the first one, we use different trader classification to calculate the trader's measure *Q*. The second robustness check is based on using different-maturity futures contract to calculate excess returns.

5.1 DCOT and CIT datasets

Starting from January 2006, the CFTC announces the disaggregate CFTC reports (DCOT) in a weekly frequency for all 26 commodities, which classifies commodity traders into five groups, i.e. producers/merchant/processor/user, money managers, swap dealers, other reportable, and non-reportable (or small investors). Among these five groups, the group of producers/merchant/processor/users, which is abbreviated as the producer group in later parts, is usually considered as hedgers, and money managers are mainly interpreted as major speculators. We calculate the trading measure *Q* for all the five groups of commodity traders, and run the Fama-Macbeth regression as described by equation (6) in Section 3.2. The regression estimates are exhibited in Table 7, Panel A.

Similar with previous sections, we find that the producer group's trading activity can forecast subsequent commodity future returns. The regression coefficient suggests 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% in the following week, or at an annualized return rate of 11.1% per year.[9] In contrast, commodity price decreases (increases) significantly after money managers' buying (selling) activity.

Therefore, all these findings show clearly that the producer group, which includes producers / merchant / processor / users who are major types of hedgers on the commodity market, provide liquidity to the futures market, while money managers,

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

who are the main speculators, consume liquidity instead. Somehow we do not find too much significant result for swap dealers, other reportable, and small traders.

CFTC also publishes a weekly Commodity Index Trader (CIT) from January 2006 for 12 agricultural commodities, which classifies traders into commercial (hedgers), non-commercial (speculators), index traders, and non-reportable (small investors). We calculate the trading measure *Q* for these four types of commodity traders and run the Fama-Macbeth regression in a similar manner as above. The empirical results are presented in Table 7, Panel B.

Similar with what we find in Section 3.2 and also the results for DCOT dataset (in Table 7 Panel A), hedgers can make a significant profit by exploiting the price increase (decrease) after their buying (selling) activity. This again suggests that hedgers provide liquidity to commodity futures market. We also find a negative regression coefficient for speculators' trading measure, although its *t*-statistics is insignificant. The small t-statistic is probably caused by a much smaller sample size (only 12 types of commodity futures for each regression). In general, the results based on DCOT data are consistent with what we have observed from COT and CIT datasets.

From preliminary analysis, we find that index investors do not trade quite often as hedgers and speculators do. The results for index traders in Table 7 do not provide significant evidence about whether index traders are liquidity providers or consumers.

5.2 Longer-Maturity futures returns

In all previous sections, we use the front-month commodity futures returns when running our return predictability test. In this section, we check the robustness of our return predictability regression, particularly; the one described in Section 3.2, by considering longer-maturity commodity futures returns. Specifically, we construct *second*-month future excess returns, and roll to third-month contracts on the 7th calendar day two months before the second-month contract matures. The trading measure *Q* is still constructed from the COT dataset. We run the Fama-Macbeth regression as described by equation (8), with all other control variables are constructed in a same manner. The regression coefficient estimates are presented in Table 8.

Consistent with the sections above, we find that hedgers provide liquidity and speculators consume liquidity in the commodity futures market, as suggested by the coefficient estimates of their corresponding trading measure *Q*. The empirical results based on second-month futures excess returns are also significant for both hedgers and speculators. We repeat our analysis in two subsample period of before and after 2003, and find similar results.

In brief, our conclusion that in commodity market, hedgers are liquidity providers and speculators consume liquidity is robust to all kinds of dataset based on various trader-type identifications, also robust to alternative return calculation method.

6. Conclusion

In this paper, we study an important but understudied research question, that is,

who provides liquidity to commodity futures markets. We find that hedgers provide liquidity to the commodity futures market, while speculators consume liquidity. More specifically, we show that hedgers, as contrarian traders, buy (sell) when commodity futures price decreases (increases), and after their buying (selling) activity, commodity futures price rebounds (retreats). As a sharp contrast, speculators adopt momentum-chasing strategy, buying (selling) when commodity future prices goes up (down), and after speculators' buying (selling), commodity futures price decreases (increases).

These empirical results can be interpreted as clear evidence suggesting that hedgers provide liquidity by buying after market drops and selling after price rises, and their liquidity provision strategy earns a good amount of profit, while speculators consume liquidity and need to pay a cost so that their trading immediacy demands can be accommodated by hedgers.

We further show that the economic profit from hedgers' liquidity provision behavior increases when they have less amount of capital available for market making or face higher inventory pressure. The increased profitability reflects hedgers' reluctance in providing liquidity under such circumstances, which is consistent with microstructure models. We also show that the cost of liquidity speculators pay increases when there is less number of speculators relative to hedgers or speculators hold 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.

Our paper casts policy implications for the role of speculators on commodity futures market. As we show in the paper, equal amount of long and short positions for speculators can be good for the market, i.e., speculators can trade with themselves and are unlikely to post a high demand of liquidity from hedgers. However, large unbalanced speculative positions can dry up the market liquidity and make commodity prices deviate far away from its fundamental value, at least temporarily. One suggestion from our paper is that policy makers should treat unbalanced and balanced speculative positions differently, and the focus of their regulation should be about how to curb the excessive unbalanced speculative trading in commodity futures market.

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.

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.

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

Gorton Gart, Hayashi Fumio, Rouwenhorst Geert K. 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.

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.

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

UNCTAD (2012) Correlations between financial speculation and commodity prices,

policy brief, No. 25.

Working Holbrook 1949. The theory of the price of storage. *American Economics 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 attributes of hedging pressure in Panel A. 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 B, 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 C, we report the summary statistics of excess returns and basis for our sample commodities. 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 7th of a certain month (if 7th 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.

Panel A: 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 Cattle	Lean Hogs	0%	13%	48%	52%
	Live Cattle	4%	10%	39%	61%
	Feed Cattle	-7%	11%	73%	27%
	Average	14%	17%	28%	72%

Panel B: 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 Cattle	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 C: 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 Cattle	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%

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.

In Panel C, 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.

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

We also construct a proxy of the trading turnover rate for a given type of commodity futures investors (hedger or speculator) as follows.

$$PT_{i,t}^{Hedger} = \frac{abs(HL_{i,t}-HL_{i,t-1})+abs(HS_{i,t}-HS_{i,t-1})}{2\times OI_{i,t-1}};\ PT_{i,t}^{Spec} = \frac{abs(SL_{i,t}-SL_{i,t-1})+abs(SS_{i,t}-SS_{i,t-1})}{2\times OI_{i,t-1}}.$$

where $OI_{i,t}$ is the total open interest aggregated from all types of commodity future investors for commodity *i* in week *t*.

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

$$DiffPY_{i,t} = PY_{i,t}^{Spec} - PY_{i,t}^{Hedge};\ DiffPT_{i,t} = PT_{i,t}^{Spec} - PT_{i,t}^{Hedge}.$$

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

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%

Panel C: Propensity of adjusting positions for speculators and hedgers

	PY^{Spec}	PY^{Hedger}	*DiffPY*	t-stat of *DiffPY*	PT^{Spec}	PT^{Hedger}	*DiffPT*	t-stat of *DiffPT*
Wheat	0.076	0.052	0.024	8.407	0.022	0.023	-0.001	-1.012
Kansas Wheat	0.112	0.050	0.062	5.970	0.017	0.027	-0.010	-5.402
Minn Wheat	0.201	0.062	0.139	5.455	0.018	0.034	-0.016	-7.659
Corn	0.070	0.036	0.034	9.522	0.016	0.018	-0.002	-3.129
Oat	0.134	0.063	0.071	9.504	0.022	0.033	-0.011	-10.925
Soybean	0.075	0.047	0.028	12.556	0.021	0.022	-0.001	-1.726
SoybeanOil	0.089	0.055	0.034	7.463	0.024	0.028	-0.005	-7.636
SoybeanMeal	0.096	0.051	0.046	7.602	0.021	0.027	-0.005	-11.746
RoughRice	0.125	0.064	0.060	4.469	0.025	0.031	-0.006	-4.825
Oil	0.075	0.035	0.041	5.745	0.014	0.022	-0.009	-5.369
HeatingOil	0.111	0.043	0.068	7.533	0.015	0.027	-0.011	-10.286
NaturalGas	0.085	0.038	0.048	4.908	0.015	0.023	-0.009	-2.780
Cotton	0.106	0.052	0.053	7.363	0.025	0.031	-0.005	-7.814
OrangeJuice	0.104	0.061	0.042	8.477	0.029	0.034	-0.005	-4.362
Lumber	0.138	0.143	-0.005	-0.787	0.039	0.031	0.008	3.480
Cocoa	0.094	0.035	0.059	8.277	0.019	0.023	-0.004	-5.077
Sugar	0.112	0.049	0.063	6.159	0.018	0.030	-0.011	-10.080
Coffee	0.103	0.054	0.050	7.926	0.026	0.029	-0.003	-3.390
Platinum	0.125	0.079	0.046	6.409	0.036	0.041	-0.004	-4.851
Palladium	0.108	0.061	0.047	3.927	0.024	0.033	-0.009	-6.536
Silver	0.077	0.061	0.017	4.486	0.026	0.027	-0.001	-1.493
Copper	0.116	0.056	0.060	7.313	0.027	0.030	-0.003	-1.712
Gold	0.090	0.065	0.025	4.462	0.028	0.033	-0.005	-3.577
LeanHogs	0.087	0.055	0.032	6.596	0.029	0.019	0.010	8.124
LiveCattle	0.067	0.034	0.033	8.351	0.019	0.015	0.004	5.438
FeedCattle	0.096	0.078	0.019	4.536	0.029	0.020	0.009	8.112
Average	0.103	0.057	0.046	6.640	0.023	0.027	-0.004	-3.701

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

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 1st day to the 4th day and from 5th to 20th 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 specifically, 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:

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

3) Inventory Imbalance Proxy Model:

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

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. For the inventory imbalance proxy model, for a commodity with mainly short-selling hedgers (i.e. $SH_i > 0$), its hedgers is less willing to to provide liquidity by making inventory more imbalanced when he/she has to do additional amount of short-sell (i.e. increase his/her selling inventory). We thus set $Dm(InventImbalance)$ as 1 when $Q_{i,t}^{hedger}$ is negative and otherwise 0.

	Capital Constraint	Order Imbalance	Inventory Imbalance
$Q_{i,t}^{hedger}$	2.68	1.40	2.01
	(5.18)	*(1.76)*	*(3.21)*
$Q_{i,t}^{hedger} \times$ *Dummy*	3.47	2.40	6.92
	(2.01)	*(2.66)*	*(2.07)*
$B_{i,t}$	-0.25	-0.25	-0.25
	(-1.33)	*(-1.36)*	*(-1.61)*
$S_{i,t}\hat{v}_{i,t}$	-0.03	-0.03	-0.05
	(-0.21)	*(-0.25)*	*(-0.41)*
$R_{i,t}$	0.02	0.01	0.01
	(1.57)	*(1.23)*	*(1.50)*
R^2	0.33%	0.33%	0.32%

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

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

First, 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* ($Q_{i,t}^{spec} > 0$), 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* ($Q_{i,t}^{spec} < 0$), 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.

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

where $R_{i,t}$ is the return of the i^{th} type of front-month commodity futures in week *t*, $Q_{i,t}^{Spec}$ 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.

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

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.

Next, 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 $F_{i,t-1}^{1} = (SL_{i,t-1} + SS_{i,t-1})/(HL_{i,t-1} + HS_{i,t-1})$. We then introduce the dummy variable $Dm(FRatio1)_{i,t}$, which is equal to one when $F_{i,t-1}^{1}$ are above its median, and zero otherwise.

We also introduce the second ratio measure as $F_{i,t-1}^{2} = min(SL_{i,t-1}, SS_{i,t-1}) / min\,(HL_{i,t-1}, HS_{i,t-1})$, 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 $F_{i,t-1}^{2}$ are above its median, and zero otherwise.

We run the following two panel regressions.

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

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

where $R_{i,t}$ is the return of the i^{th} type of front-month commodity futures in week *t*, $Q_{i,t}^{Spec}$ 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.

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
$Q_{i,t}^{spec}$	-2.998	-2.998	-2.846	-2.747
	(-5.13)	*(-5.13)*	*(4.74)*	*(-4.59)*
$Q_{i,t}^{spec} \times Dm(SpecPosition)_{i,t}$	-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)		
$Q_{i,t}^{spec} \times Dm(FRatio1)_{i,t}$			-2.981	
			(-2.44)	
$Q_{i,t}^{Spec} \times Dm(FRatio2)_{i,t}$				-3.743
				(-3.03)
$B_{i,t}$	-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	0.000	-0.000	-0.001
	(0.13)	*(0.13)*	*(-0.37)*	*(-0.46)*
$R_{i,t}$	0.014	0.014	0.014	0.014
	(1.44)	*(1.44)*	*(1.45)*	*(1.45)*
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 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:

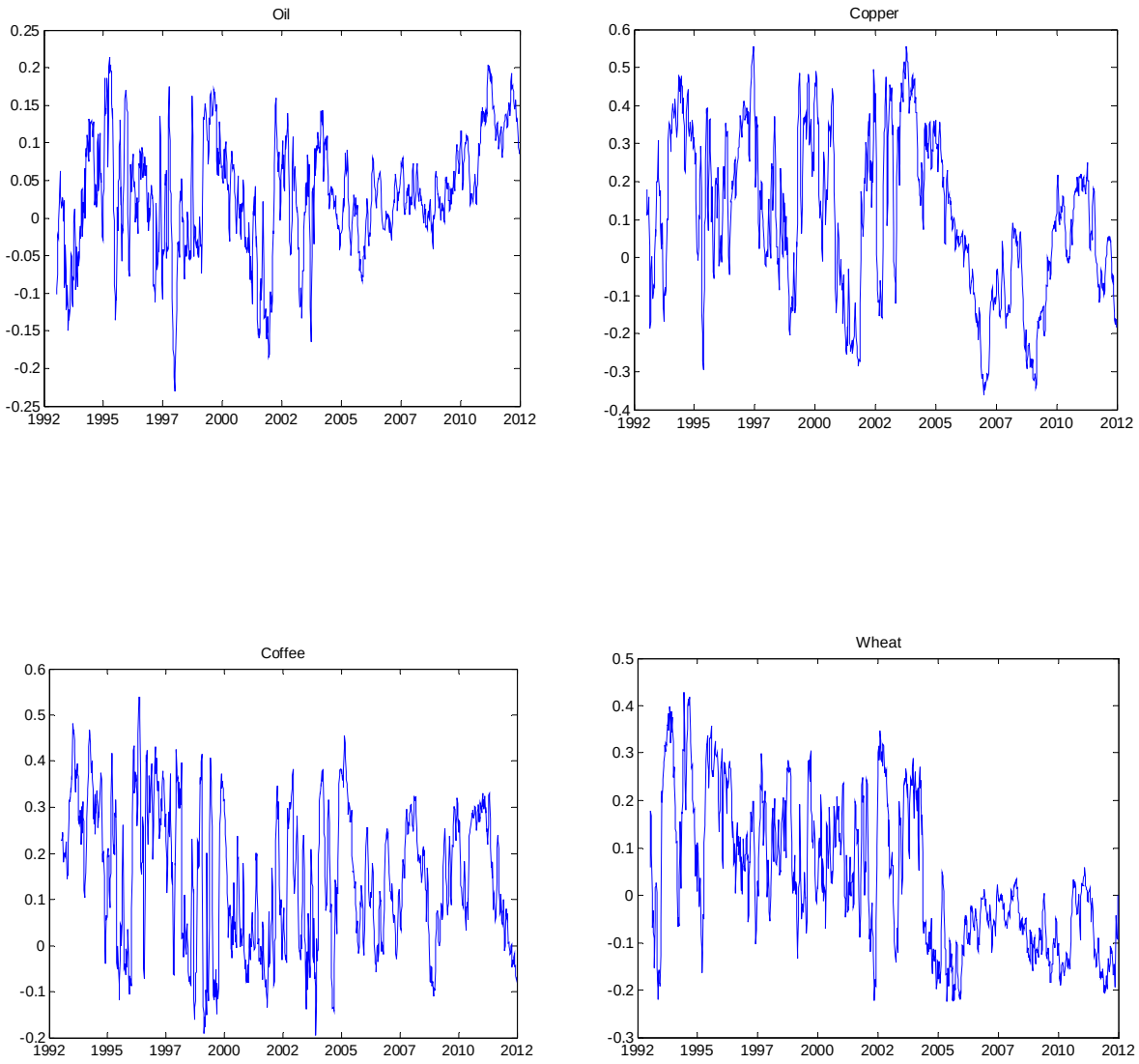
$R_{i,t+1} = a_0 + a_1 Q_{i,t} + a_2 R_{i,t} + a_3 B_{i,t} + a_4 S_{i,t}\hat{v}_{i,t} + \varepsilon_{i,t+1}$

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.

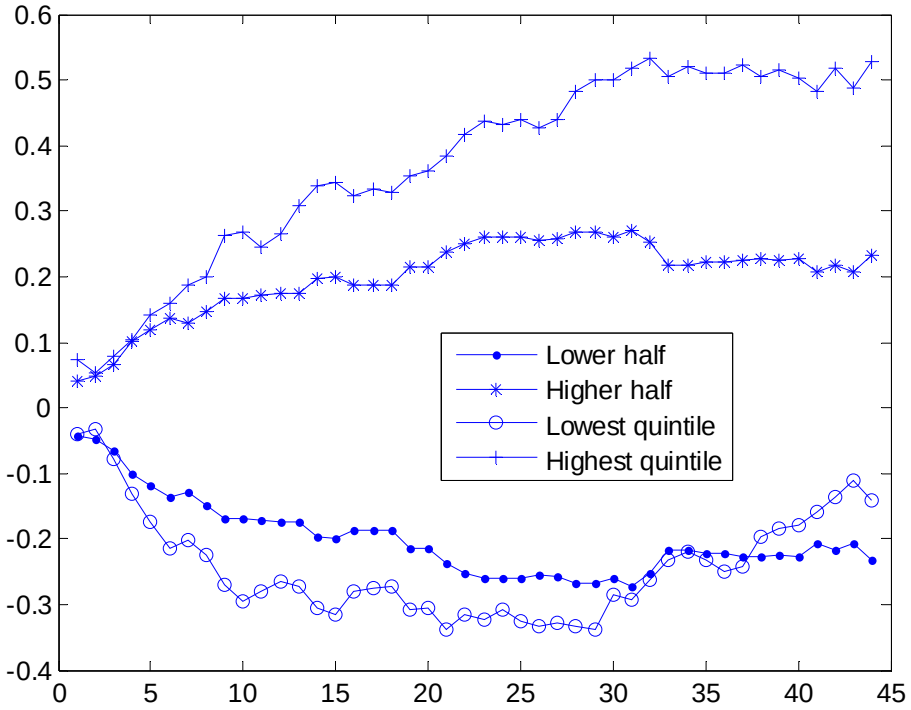
	All Sample Period			Sub Sample Period: 1994~2003			Sub Sample Period: 2004~2012		
Trader's Type	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others	Hedgers	Specu-lators	Others
$\boldsymbol{Q_{i,t}}$	3.459	-4.221	-0.887	3.043	-3.453	-0.710	4.028	-5.296	-0.921
	(4.87)	*(-5.52)*	*(-0.60)*	*(4.52)*	*(-4.55)*	*(-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 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).