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Factor Pricing in Commodity Futures and the Role of Liquidity

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Abstract
This paper empirically investigates the pricing factors and their associated risk premiums of commodity futures. Existing pricing factors in equity and bond markets, including market premium and term structure, are tested in commodity futures markets. Hedging pressure in commodity futures markets and momentum effects are also considered. While the literature has studied these factors separately, this study combines these factors to discuss their importance in explaining commodity future returns. One of the important pricing factors in equity and bond markets is liquidity, but its role as a pricing factor in commodity futures markets has not yet been proven. The risk premiums of two momentum factors and speculators' hedging pressure range from 2% to 3% per month and are greater than the risk premiums of roll yield (0.8%) and liquidity (0.5%). The result of a significant liquidity premium suggests that liquidity is priced in commodity futures.

Keywords: Commodity Futures; risk premium; liquidity; momentum; roll yield.
JEL Classifications: G12, G13, G15.

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1. Introduction

Commodity investment is increasingly popular among investors, as indicated by rapid innovations in related investment vehicles and rising trading volume (e.g., Dwyer et al. 2011; Basu & Miffre, 2013). The Goldman Sachs Commodity Index (GSCI) has been moving up over the past thirty years as shown in Figure 1. The popularity of commodity investment is attributed to increasing market demand for alternative asset classes that target aggressive returns and asset diversification. Commodity investment was further stimulated during the 2008 global financial crisis, in which stock markets shrank and bond markets offered historically low returns because of extensive expansionary monetary policies.

[Insert Figure 1]

The study of the determinants of commodity prices is an important area that has not yet been fully explored. In this paper, risk premiums for commodity futures are inferred using the following factors: market premium, momentum effects, term structure and hedging pressure. The factors are tested in turn to uncover their importance in explaining commodity futures returns.

Liquidity is a pricing factor in equity and bond markets, but its role in commodity futures markets remains ambiguous. This paper makes the first attempt to address this issue. In the equity literature, the positive relationship between stock returns and equity market illiquidity has been documented for decades. Amihud and Mendelson (1986) use bid-ask spread to measure stock liquidity. It is found that average stock returns increase with the spread, where a wider spread represents higher illiquidity. Their result remains significant when compared to the Fama-MacBeth (1973) benchmark. Brennan and Subrahmanyam (1996) discover a positive relationship between monthly stock returns and stock illiquidity measures constructed from intraday data, after controlling for the Fama and French factors and the stock price level. This relationship is attributed to the illiquidity cost for excess demand from uninformed investors, implying that the required rates of return are higher for illiquid stocks. Amihud (2002) proposes a new measure of liquidity, which is defined as the ratio of the absolute daily return of a stock to its daily dollar trading volume averaged over a period. This measure provides a convenient way of measuring liquidity for low frequency data. Amihud (2002) shows that this new measure is capable of explaining differences in excess returns across different stocks.

Recent studies find a positive relationship between returns and illiquidity in bond markets. Lin et al. (2011) use various liquidity measures, including the Amihud measure, to quantify market liquidity. They find that, after controlling for systematic and idiosyncratic factors, liquidity risk is priced in corporate bonds in both regression and portfolio-based tests. Their results support liquidity as an important determinant of expected corporate bond returns (Friewald et al. 2012). Furthermore, the effect of liquidity is magnified during financial crises, and that speculative grade bonds have greater reactions to liquidity changes.

Despite the importance of commodity investment in modern financial markets, its pricing factors are rarely explored. This paper empirically tests pricing factors in commodity futures. We find a significant liquidity premium in commodity futures using liquidity change instead of the liquidity level as pricing factor. The remainder of the paper is organized as follows. Section 2 provides a literature review on pricing factors. Section 3 describes the data and defines futures returns. Section 4 illustrates the multifactor models. Section 5 defines the risk factors, presents the factor sorted portfolios, and reports the results. Finally, Section 6 concludes the paper and provides suggestions for future research.

2. Literature Review

Commodity futures markets have received increasing attention in recent years. The pricing factors found in traditional asset classes, including market premium and term structure, have been tested in commodity futures. Hedging pressure is found to have an effect on returns, and momentum effects are documented for commodity futures. This paper combines these factors to assess their importance in explaining commodity futures returns. Apart from the existing factors, this paper also investigates the liquidity factor, a proven pricing factor in stock and bond markets, in commodity futures markets.

According to the classic capital asset pricing model (CAPM), market premium is an important factor in explaining asset returns. The excess return of a commodity futures market portfolio, which is usually represented by commodity indexes such as the GSCI or an equally weighted futures portfolio, has been used as the market premium in the literature (e.g., Miffre & Rallis, 2007; Fuertes et al. 2010; Hong & Yogo, 2012; Yang, 2013). However, it has been found that market premium alone cannot explain commodity futures returns. Introducing relevant pricing factors can improve the performance of the commodity CAPM.

Momentum is recognized in the literature (e.g., Fuertes et al., 2010; Basu & Miffre, 2013) as a signal for the generation of abnormal returns, because certain degrees of autocorrelation exist in commodity futures returns.[2] Returns tend to be positively autocorrelated in the short term. Thus, futures with high (low) returns in the past tend to continue to have high (low) returns. This short-term return continuation is followed by a long-term return reversal, wherein futures with high returns in the past tend to have low long-term returns. Momentum strategies with holding periods of less than a year tend to generate abnormal returns. Momentum is an effect observed in the markets, and certain factors drive momentum. Unfortunately, these factors remain ambiguous in commodity futures markets. A possible explanation is the sentiment theory, which suggests initial under-reaction and

[2] Momentum is an effect or a measure of the pricing factors, but momentum itself is not a real risk factor. Momentum is sometimes described as a pricing factor, but one should interpret the result with caution.

delayed over-reaction. Under-reaction and over-reaction hinder instantaneous price adjustments.

Moskowitz, Ooi and Pedersen (2012) identify two types of momentum, namely cross-sectional and time-series momentum. Cross-sectional momentum makes cross-futures comparisons. Futures that are outperforming in terms of previous returns will continue to outperform other futures. By contrast, time-series momentum focuses solely on the return of a particular future without cross-futures comparison. For cross-sectional momentum, Miffre and Rallis (2007) provide evidence for short-term continuation and long-term reversal in commodity futures prices. They identify thirteen profitable momentum strategies of longing futures with relatively high previous returns and shorting futures with relatively low previous returns. These strategies generate an average annual return of 9.38%. The results are robust after taking transaction costs into account. Moreover, their momentum strategies of longing backwardated futures and shorting contangoed futures indicate a relationship between momentum and term structure. Based on the 2007 findings, Fuertes et al. (2010) consider momentum and term structure jointly in forming profitable strategies. Following cross-momentum signals can generate an abnormal annual return of 10.14%. Their double-sort strategy, which utilizes momentum and term structure signals jointly, can further push the abnormal annual return up to 21.02%. However, Basu and Miffre (2013) find that momentum is not priced across commodity futures. Interestingly, the past-week return is significantly and positively serial correlated with the current return, implying that eliminating momentum as a factor may not be appropriate.

For time-series momentum, Moskowitz et al. (2012) document strategies that generate substantial abnormal returns in commodity futures markets. Time-series momentum is significantly and positively related to, but not fully captured by, cross-sectional momentum. They show a significant marginal effect of cross-sectional momentum on time-series momentum. The two types of momentum are not identical, so the two momentum factors should be priced separately. Furthermore, a link is found between time-series momentum and hedging pressure, which indicates that speculators profit from time-series momentum at the expense of hedgers. In contrast, Hong and Yogo (2012) argue that the last-month returns can partially predict futures returns, but the predictability is derived from open interest.

Term structure affects commodity futures returns. It describes the relationship between futures prices and the maturity of futures contracts and is captured by the futures curve. Futures in backwardation (a downward sloping futures curve) generally generate higher returns than futures in contango (an upward sloping futures curve). Prices of backwardated futures increase as time passes and future maturity reduces. This means positive returns for long positions of backwardated futures. A similar explanation applies to long positions of contangoed futures. Term structure refers to the slope of the futures curve, which can be measured by basis. The basis is the difference between the spot price and the futures price, scaled by the maturities of the futures contracts. Fuertes et al. (2010) identify term structure signals in basis from long backwardated and short contangoed futures. The term structure signals generate a substantial abnormal return of 12.66% annually. Hong and Yogo (2012) note that basis significantly predicts futures returns in all of their model specifications, in which futures in backwardation have relatively high returns. Yang (2013) sorts commodity futures into seven equally weighted portfolios by basis with a monthly rebalance. He discovers a statistically significant annual excess return difference between high- and low-basis portfolios. Basu and Miffre (2013) show that term structure remains a significant factor after controlling for hedging pressure and momentum. The structure is measured by roll yield, which is the natural log difference between the nearest and the second-nearest futures prices. The overwhelming returns associated with term structure strategies suggest that term structure is priced in commodity futures.

Hedging pressure, the relative sizes of hedging demand and supply in commodity futures markets, is another factor that determines futures returns. Hedgers use futures for hedging, whereas speculators provide hedging services for investment purposes. One measure of hedging pressure is the ratio of the number of long open interest to the total number of open interest. This measures the relative long and short positions of hedgers and speculators in the markets. If the hedging demand is larger than the supply, the hedgers should provide a higher risk premium to the speculators for taking opposite positions (Keynes, 1930; Hicks, 1939). Hong and Yogo (2012) find that the high hedging demand of hedgers predicts high returns from longing futures, but the predictability is derived from open interest. Basu and Miffre (2013) use hedgers' and speculators' hedging pressure as well as the single and double sorting methods to construct long and short commodity portfolios. Significant positive returns and low volatility are found for these portfolios. It is concluded that speculators' hedging pressure and term structure are independent drivers of futures returns.

Liquidity is generally viewed as the degree of the convenience of converting an asset into cash without significantly losing its asset value. Commodity pricing literature focuses less on liquidity, which is often treated as a control factor rather than a variable factor. Trading volume and open interest are commonly chosen controls related to liquidity, but are not good candidates. Hong and Yogo (2012) study commodity market open interest and find that movements in open interest predict commodity futures returns even after controlling for a number of predictors. In particular, they show that an increase in commodity market open interest by one standard deviation increases the expected commodity returns by 0.73% per month. Basu and Miffre (2013) control for the previous-week open interest in their cross-sectional pricing model, and find that the open interest is significant in explaining futures returns. However, the magnitude of the open interest coefficient is smaller than that of other factors. Fuertes et al. (2010) discover that trading volume and its percentage change fail to explain abnormal returns brought about by momentum and term structure. Recent papers including Belke et al. (2012), and Belke et al. (2010) link global financial liquidity and financialization to commodity price movements. However, the results are mixed. Sheldon and Chan (2016) show that the impact of financialization on realized volatility varies across commodity type. The analysis of index investment and speculator's positions in futures markets shows that financialization is generally negatively correlated with the realized volatility of non-energy commodities. The result for the energy commodities shows an opposite sign. Global liquidity and financialization require further investigation and beyond the scope of this paper. This paper focuses on the financial liquidity of specific markets.

Given the importance of liquidity as a pricing factor in equity and bond markets, its ambiguous role in commodity markets deserves further investigation. Marshall et al. (2012) show that the Amihud measure of liquidity based on return and trading volume is superior to other liquidity measures because it has the largest correlation with the liquidity benchmark. Therefore, the Amihud measure of liquidity is herein adopted.

Recent studies discover the important roles of the basis and momentum factors in pricing commodity futures (Bakshi et al. 2014, Szymanowska et al. 2014, and Yang 2013). Daskalaki et al. (2014) on the other hand find that none of the asset pricing models based on macroeconomic or equity-motivated tradable factors including the liquidity level is successful in explaining individual commodity's returns. As a robustness test, their commodity type portfolios also reveal the same deficiency in the asset pricing models. This paper tests the pricing factors in commodity futures using factor sorted portfolios. Our analysis differs from other studies by using liquidity change instead of the liquidity level as pricing factor. We also extend Daskalaki et al. (2014)'s data to incorporate other commodities from the energy sector including natural gas, coal, gasoline, and electricity.

3. Data

Commodity futures prices and open interest data are retrieved from Thomson Reuters Datastream (Datastream). The data used to measure hedging pressure are drawn from the United States Commodity Futures Trading Commission (CFTC). The CFTC dataset includes weekly quotes from October 1992 to December 2013, but only mid-month and month-end quotes are available from January 1986 to September 1992. Month-end observations are used to construct a comprehensive dataset covering February 1986 – December 2013. There are 335 monthly observations in total. Monthly data are selected to test asset pricing models, as the models describe medium- to long-term relationships between returns and risks.

The sample covers 26 commodities in total, with the commodities coming from the following four categories: energy, metal, agriculture and livestock. These commodities are widely traded on major exchanges, and hence serve as representatives of the markets. A commodity futures contract has a maturity date. To construct a time series of futures prices, we roll over the prices of consecutive contracts of the same commodity. The time series starts at the nearest contract month which forms the first and subsequent observations of the price series. It ends when the contract expires or on the first business day of the notional contract month, whichever comes first. The price from the second-nearest contract month is therefore used. This rolling-over method mitigates liquidity and market microstructure issues. Contract prices prior to the maturity date are subject to liquidity and market microstructure problems and are not used to test the asset pricing models.

A futures return is defined as the fully collateralized return of longing a futures contract. When opening a long position in a futures contract, an investor must deposit a cash amount equivalent to the notional amount of the futures contract as collateral. The deposit can earn interest at a risk-free rate of the Treasury bill $R_{f,t}$ at time t. The fully collateralized return is a sum of percentage change of futures prices and the risk-free rate. For commodity i, the futures price at time t with maturity T is denoted by $F_{i,t,T}$. Therefore, the futures return of longing a futures contract is

$$R_{i,t,T} = \ln(F_{i,t,T}) - \ln(F_{i,t-1,T}) + R_{f,t}. \tag{1}$$

The corresponding excess futures return is

$$R^{e}_{i,t,T} = \ln(F_{i,t,T}) - \ln(F_{i,t-1,T}). \tag{2}$$

The use of a margin account is common in futures trading. It allows the investment of a principal amount, known as the initial margin, to be less than the notional amount of the futures contract. Margin trading involves leverage. Therefore, futures returns can be exaggerated, and hence are not a proper measure. The fully collateralized return is not subject to the leverage effect or the involuntary liquidation of futures positions because collateral can be used to pay off margin calls.

Table 1 summarizes the statistics of commodity futures in the sample. The returns are fully collateralized returns. Futures returns are positively correlated across commodities over time. The average correlation of the returns of one commodity with other commodities, presented in the last column, ranges from 0.06 to 0.36.

[Insert Table 1]

4. Methodology

4.1 Risk Factors and Portfolios Sorted by Factors

This paper tests five pricing factors, namely cross-sectional momentum, time-series momentum, speculators' hedging pressure, roll yield, and liquidity. The factors are defined and their single-sorted portfolios are presented. The first step in observing the correlation between risk premiums and the factors is through single-sorted portfolios. If a factor is related to the average return, an average return spread should be presented across factor-sorted portfolios. Portfolios sorted by a factor can also be viewed as trading strategies, with these factors being treated as trading signals.

Commodity futures are sorted into two portfolios by time-series momentum and five portfolios by each of the other four factors individually. Available commodity futures are sorted by a factor at the end of month *t*, and the futures then grouped by four percentiles. Futures between two percentiles are grouped into one of five portfolios, namely <20th, ≧20th and <40th, ≧40th and <60th, ≧60th and <80th, and ≧80th. At the end of month *t+1*, the returns of these futures from *t* to *t+1* are compiled. The return of a portfolio is the equally weighted return of all the futures within the portfolio. Portfolio rebalancing is done monthly. Available commodity futures are again sorted by the factor at the end of month *t+1* by repeating the same procedures. Portfolios sorted by time-series momentum are constructed using similar procedures. Available commodity futures are grouped into two portfolios according to whether the sign of their previous 12-month returns is positive or negative.

Factor-based long-short strategies are formed. The long-short strategy is a combination of fully collateralized long and short strategies with equal investment capital in each strategy. The return of longing the portfolio with the largest factor and shorting the portfolio with the smallest factor is the return spread between the two extreme portfolios. The excess return of a long-short strategy lends support to the usage of a particular factor in factor pricing models. The excess return of a long-short strategy of longing portfolio *i* and shorting portfolio *j* is

$$R^e_{LS,t} = {}^1\!/_2(R_{i,t} - R_{j,t}). \tag{3}$$

4.2 Multifactor Models

This paper studies the rationale underlying the variation in average returns across commodity futures. Average returns are products of two components: degree of futures exposure to systematic risks, and risk premiums associated with systematic risks. A commodity futures contract, which either has a large degree of risk exposure or is exposed to risks that offer high premiums, has a high average return. Futures returns are illustrated by multifactor models with a two-stage regression (Cochrane, 2005) to identify the degree of risk exposure of futures and the risk premiums.

A two-stage regression, as the name suggests, consists of two stages in which excess returns of factor sorted portfolios, instead of individual commodity futures, are the explained variables. Factor sorting can reduce portfolio variance and facilitate the detection of average return differences. Betas of futures portfolios are usually more stable than those of individual futures.

The first stage is a time-series regression for quantifying the exposure of futures portfolios to risk factors. Excess returns of futures portfolios sorted by factors, including cross-sectional momentum, time-series momentum, speculators' hedging pressure, and roll yield, are regressed on factors as

$$R^e_{j,t} = a_j + \beta'_j f_t + \varepsilon_{j,t} \tag{4}$$

where *j* = 1,2,…, m. m is the number of commodity futures portfolios and it equals 17. The time *t* starts in February 1986 and ends in December 2013. f_t is a vector of factors that are the excess returns of the long-short strategies. β_j' is a vector of parameters that capture the degree of risk exposure of futures.

The second stage is a cross-sectional regression for estimating the risk premiums of risk factors. Average excess returns of futures portfolios are regressed on risk exposure measured by β_j as

$$\mathrm{E}[R_{j,t}^{e}] = \lambda'\beta_j + \alpha_j, \tag{5}$$

where j = 1,2,…, m. λ' is a vector of factor risk premiums that are not portfolio-specific. Five equations are estimated. Equation 6 is the commodity CAPM. Equations 9 and 10 including all factors are compared to the models without liquidity factor in Equations 7 and 8. If the insertion of liquidity factor improves estimation performance, it supports that liquidity is a key factor.

$$\mathrm{E}[R_{j,t}^{e}] = \lambda^{GSCI}\beta_j^{GSCI} + \alpha_j \tag{6}$$

$$\mathrm{E}[R_{j,t}^{e}] = \lambda^{GSCI}\beta_j^{GSCI} + \lambda^{CSMOM}\beta_j^{CSMOM} + \lambda^{HP}\beta_j^{HP} + \lambda^{RY}\beta_j^{RY} + \alpha_j \tag{7}$$

$$\mathrm{E}[R_{j,t}^{e}] = \lambda^{GSCI}\beta_j^{GSCI} + \lambda^{TSMOM}\beta_j^{TSMOM} + \lambda^{HP}\beta_j^{HP} + \lambda^{RY}\beta_j^{RY} + \alpha_j \tag{8}$$

$$\mathrm{E}[R_{j,t}^{e}] = \lambda^{GSCI}\beta_j^{GSCI} + \lambda^{CSMOM}\beta_j^{CSMOM} + \lambda^{HP}\beta_j^{HP} + \lambda^{RY}\beta_j^{RY} + \lambda^{LIQCH}\beta_j^{LIQCH} + \alpha_j \tag{9}$$

$$\mathrm{E}[R_{j,t}^{e}] = \lambda^{GSCI}\beta_j^{GSCI} + \lambda^{TSMOM}\beta_j^{TSMOM} + \lambda^{HP}\beta_j^{HP} + \lambda^{RY}\beta_j^{RY} + \lambda^{LIQCH}\beta_j^{LIQCH} + \alpha_j \tag{10}$$

The regression error α_j is an abnormal return that the identified risk factors are not able to explain. If the model is correct in explaining returns, the abnormal returns cannot deviate significantly from zero. Asset pricing theory suggests that the zero-beta excess return should be zero. This restriction is imposed, so there is no intercept in the cross-sectional regression.

5. Results

5.1 Risk Factors and Portfolios Sorted by Factors

The five pricing factors examined in this paper generate return spreads in sorted portfolios and significant returns in their long-short strategies. Therefore, it is likely that the factors are important pricing factors in commodity futures.

5.1.1 Cross-Sectional Momentum

Cross-sectional momentum is an effective strategy that leads to abnormal returns in stock, bond and commodity futures markets. Capturing cross-sectional momentum in asset pricing models can account for a part of unexplained abnormal returns. Cross-sectional momentum is the relative return performance of commodity futures in the cross-section. Fuertes et al. (2010), Moskowitz et al. (2012), and Basu and Miffre (2013) find commodity futures that performed well in generating returns in the past (generally the past three to twelve months) continue to outperform other futures in subsequent months.

In order to have a cross-sectional momentum measure for factor construction, the momentum strategy of a 12-month ranking period and a 1-month holding period is chosen. At the end of month *t*, the futures returns for months *t* to *t-11* are observed and used to rank the futures. The futures are held for a month, and the returns for month *t+1* are realized at the end of month *t+1*. This choice of momentum strategy is based on the convention in the cross-sectional momentum literature (e.g., Miffre and Rallis, 2007).

Table 2 presents the key moments of five portfolios sorted by cross-sectional momentum. Portfolio returns increase with momentum, and the highest cross-sectional momentum portfolio (≧80th) produces about a 6% monthly return in excess of the lowest momentum portfolio (<20th), with statistical significance. The long-short strategy generates about 3% monthly returns, which are statistically significant. Futures with relatively high (low) returns for the previous twelve months (*t* to *t-11*) tend to have high (low) returns for the following month, *t+1*. Thus, cross-sectional momentum should be properly accounted for in modeling futures returns.

[Insert Table 2]

5.1.2 Time-Series Momentum

Time-series momentum is related to, but different from, cross-sectional momentum. Time-series momentum focuses on past futures returns without a cross-sectional comparison. Commodity futures with positive returns in the previous three to twelve months continue to generate positive returns in the subsequent months. The time series momentum may also capture the value effect in Asness et al. (2013) where the value effect is defined as the five-year difference of spot prices.

The momentum strategy of a 12-month ranking period and a 1-month holding period is again chosen to define time-series momentum. This choice is consistent with the choice of cross-sectional momentum. The strategy has been proved to generate significant returns—see, for example, the paper by Moskowitz et al. (2012). In some cases, there is no negative return from commodity futures in the last 12 months; therefore, no futures are shorted during these time periods.

The key moments of the two portfolios sorted by time-series momentum are presented in Table 3. Portfolio returns increase with the time-series momentum, and the portfolio with the positive time-series momentum offers an approximately 3.7% monthly return in excess of the portfolio with the negative momentum. The long-short strategy generates nearly 2% monthly returns, with statistical significance. Futures with positive returns for months *t* to *t-11* tend to have positive returns for month *t+1*. Similarly, futures with negative returns for months *t* to *t-11* tend to have negative returns for month *t+1*. These observations suggest that time-series momentum should be properly accounted for when modeling futures returns.

[Insert Table 3]

5.1.3 Speculators' Hedging Pressure

The CFTC classifies traders as reportable or non-reportable, based on the size of their position in each commodity. Reportable traders have relatively large trade positions and represent 70% to 90% of the total open interest in any given commodity market. Reportable traders are further classified into commercial and non-commercial traders, also known as hedgers and speculators. A commercial trader uses the futures of a particular commodity for hedging, as defined in the CFTC regulation; a non-commercial trader, on the other hand, does not have a hedging intention. Hedgers use futures for hedging, whereas speculators provide hedging services for investment; the former offer returns to the latter as compensation for their risk-taking activities. Based on the findings of Basu and Miffre (2013), the speculators' hedging pressure is more important than that of the hedgers in explaining futures returns—the impacts of hedger's hedging pressure is highly correlated with the influence of speculators. Therefore, this paper focuses only on speculators' hedging pressure.

Speculators' hedging pressure is defined as the number of speculators' long open interest divided by the total number of speculators' open interest. For instance, a speculators' hedging pressure of 0.7 implies that 70% of the speculators take long positions and 30% of them take short positions.

Table 4 reports similar results for speculators' hedging pressure. Portfolio returns increase with hedging pressure and the highest hedging pressure portfolio ($\geqq 80^{th}$) offers an approximately 6% monthly return in excess of the lowest hedging pressure portfolio ($<20^{th}$). The long-short strategy once again generates significant monthly returns of 3%. Thus, speculators' hedging pressure plays an important role in determining monthly futures returns.

[Insert Table 4]

5.1.4 Roll Yield

Roll yield is the natural log difference between the nearest and the second-nearest futures prices. Roll yield measures the slope of the front portion of the futures curve. Based on Basu and Miffre (2013), this paper uses roll yield to capture term structure: a positive roll yield indicates a downward sloping futures curve, and a negative roll yield denotes an upward sloping futures curve.

Table 5 shows that the highest roll yield portfolio ($\geqq 80^{th}$) produces a 1.5% monthly return in excess of the lowest roll yield portfolio ($< 20^{th}$), which is statistically significant. Backwardated futures have higher returns than contangoed futures. The long-short strategy generates approximately 1% of monthly returns, with statistical significance. The results lend support to using roll yield as one of the pricing factors in commodity futures.

[Insert Table 5]

5.1.5 Liquidity

The Amihud measure is defined as the absolute return of a commodity futures contract divided by the total open interest of all trading futures contracts of that commodity. A relatively liquid futures contract, which should have small changes in price and large open interest, has a relatively small measure. The higher the liquidity of the futures, the smaller the value of the Amihud measure is.

A cross-sectional comparison of liquidity may not be valid because open interest varies substantially across commodity futures. Table 6 presents the probabilities of the commodities in each of the five liquidity portfolios and the average open interest of the commodities. Commodity futures with large open interest, such as crude oil and corn, have small Amihud measures. If commodities are sorted by the liquidity level, these commodities will be included in liquid portfolios most of the time. Commodity futures with small open interest are usually added to illiquid portfolios. Note that liquidity, as indicated by the Amihud measure, is greatly affected by open interest, which is determined by the trading history and the popularity of a commodity. For this reason, the change of liquidity instead of the liquidity level is adopted for the portfolio sorting.

[Insert Table 6]

The key moments of the five portfolios sorted by liquidity change are presented in Table 7. The $\geqq$ 80th and <20th portfolios include commodity futures with the most positive and the most negative liquidity change, respectively. Portfolio returns increase steadily with liquidity change. The portfolio with the most positive liquidity change offers approximately 0.6% monthly returns in excess of the one with the most negative liquidity change. The long-short strategy generates approximately 0.6% monthly returns, with statistical significance, and its Sharpe ratio outperforms that of the GSCI market portfolio. This suggests that liquidity change is a potential pricing factor for futures returns.

[Insert Table 7]

Table 8 provides the correlation table of the factors. In the last column, the correlation figures between the liquidity factor and the other factors range from -0.055 to 0.042 with low significance. Liquidity is not highly correlated with the other factors, which suggests that liquidity may be an independent driver of returns. The high correlation between cross-sectional momentum and time-series momentum is expected because commodity futures outperforming the peer group tends to have positive returns in the past. However, such a high correlation between the two momentum factors suggests that the two factors should not be incorporated into the same regression simultaneously because of multicollinearity.

[Insert Table 8]

5.2 Results of Multifactor Models

This section reports the test results of the two-stage regression. It is found that, in the time-series regression (Tables 9 to 12), the multifactor models outperform the commodity CAPM by improving the goodness of fit and reducing abnormal returns. The betas of the sorting factors are found to be significant in both the top and bottom percentiles. The liquidity change beta is always significant and positive after considering other factors. In other words, liquidity is an important risk factor in modeling commodity futures returns. The correlations between the liquidity factor and the other factors are below 0.1. As a result, liquidity may be a driving force of returns that is distinct from the other factors. In the cross-sectional regression (Table 13), multifactor models again outperform the commodity CAPM and the risk premiums of the discovered factors are significant. Moreover, the addition of the liquidity factor can improve models with cross-sectional momentum. Based on such evidence, liquidity may be a pricing factor in the cross-sectional regression.

5.2.1 Tests of Time-Series Regression

Tables 9 to 12 present the results of the time-series regressions with the explained variables as the excess returns of futures portfolios sorted by cross-sectional momentum, time-series momentum, speculators' hedging pressure, and roll yield, respectively. The GSCI is the proxy for the commodity market portfolio. The tests of the commodity CAPM are presented in the upper panels of the tables, whereas the tests of the multifactor models are in the lower panels.

The commodity CAPM cannot explain the returns because the excess returns of the GSCI portfolio are generally insignificant in explaining futures returns at the 5% level. The regression intercepts that represent abnormal returns are significant at the 1% level in more than half of the regressions. This implies that a certain portion of the excess returns of futures portfolios remains unexplained by the market premium. In addition, the adjusted R-squared ranges from -0.0021 to 0.0255 for the results of hedging pressure in Table 11. Relatively small values of adjusted R-squared suggest that the market premium alone is not sufficient to explain the commodity futures returns.

Given the inefficiency of the commodity CAPM, multifactor models are proposed. The multifactor model is used to study the importance of liquidity given the existing pricing factors. Compared with the commodity CAPM, the multifactor models perform better as the regression intercepts that represent abnormal returns are all insignificant at both the top and bottom percentiles. This finding suggests that excess returns of futures portfolios are well explained by the proposed factors. Moreover, the adjusted R-squared greatly improves in the multifactor models. The beta of the pricing factor in the multifactor models is generally significant in revealing the excess returns of the portfolios sorted by that corresponding factor. This result is predictable, since the factor used to sort portfolios should account for the excess returns of those portfolios.

The liquidity factor is always significant and positive in the multifactor models. This implies the existence of liquidity risks in commodity markets. If the commodity futures markets suffer from high liquidity risks because of economic downturns or unfavorable market sentiment, the return spread between illiquid and liquid futures widens. In such a situation, futures tend to offer higher returns because of higher liquidity premiums.

[Insert Table 9]

[Insert Table 10]

[Insert Table 11]

[Insert Table 12]

5.2.2 Tests of Cross-Sectional Regression

In the second stage, the expected excess returns of futures portfolios are regressed on the corresponding betas obtained from the first stage to estimate the risk premiums. If the beta of a factor does not exist in the second-stage model, that factor is excluded in the first stage. Test results of the commodity CAPM and the multifactor models are presented in Table 13. For the commodity CAPM, the adjusted R-squared is negative, and the root-mean-squared error (RMSE) approximating the average abnormal returns of the portfolios is 1.68% per month. These observations suggest that the commodity CAPM is not suitable for capturing the dynamics of futures returns.

Models (2) and (3) are multifactor models with the discovered pricing factors only. The two multifactor models greatly enhance the commodity CAPM by improving the adjusted R-squared to almost 0.9 and lowering the RMSE to approximately 0.5% per month. All the risk premiums in the two models are significant, which means that all discovered pricing factors are priced in the market, as reported in the literature. The two models are compared to models (4) and (5) to examine the importance of liquidity factors using an F-test, and its p-values are presented in the last column. For instance, model (2) is nested in model (4) so the F-test can be performed to compare the two models.

Comparing models (4) and (5), the cross-sectional momentum factor is superior to the time-series momentum factor according to the relatively high adjusted R-squared and the low RMSE. Comparing models (2) and (4), the addition of liquidity can improve the adjusted R-squared from 0.88 to 0.93 and reduce the RMSE from 0.5% to 0.37%. The liquidity risk premium is significant at the 10% level in model (4) with t-statistics of 1.68; the F-test has a p-value of 0.009, indicating the importance of the liquidity variable. These results suggest that liquidity is a pricing factor in determining commodity futures portfolio return.

The addition of the liquidity factor in models (2) and (4) with cross-sectional momentum can improve the models, but this improvement is not observed in models (3) and (5) with time-series momentum. Based on the individual t-test, liquidity risk premium with the time-series momentum is not significant as a factor. The estimated factor risk premiums in the models are close to the average excess returns of long-short strategies formed by the factors that are discussed in Section 4. The negative market premiums in models (4) and (5) are unexpected. The negative value, together with the insignificance of the market premiums, may empirically imply that market premium is not a constituent of commodity futures returns.

[Insert Table 13]

6. Conclusion

Significant betas and risk premiums are associated with momentum effects, term structure, and speculators' hedging pressure. However, our results show that market premium is not an important component in explaining commodity futures returns. The risk premiums of the two momentum factors and speculators' hedging pressure range from 2% to 3% per month. The risk premiums of roll yield and liquidity are smaller, with values of around 0.8% and 0.5% respectively.

Liquidity is important in equity and bond markets, but its role as a pricing factor in commodity futures markets has not yet been proven. In single-sorted portfolios based on the liquidity factor, expected portfolio returns increase with a reduction in liquidity. This suggests that liquidity change is a potential factor that affects returns. In periods of liquidity reduction, commodity futures portfolios offer higher liquidity premiums and higher returns. The long-short strategy of the liquidity factor produces a higher Sharpe ratio than the buy-and-hold strategy.

Multifactor models with a two-stage regression (Cochrane, 2005) are applied to model the degree of futures risk exposure and the risk premiums. The beta of liquidity change is significantly positive after considering other factors, thereby showing the importance of liquidity as a risk factor in modeling commodity futures returns. Low correlations between the liquidity factor and other factors indicate the unique contribution of liquidity as a driving force for futures returns. In the second-stage cross-sectional regression, the risk premiums of all factors including liquidity are significant. Therefore, our results conclude that liquidity is priced in commodity futures.

Various liquidity measures using high-frequency data, such as bid-ask spread and market depth, have been proposed in the literature by, for instance, Marshall et al. (2012). In this paper, we test the Amihud measure of liquidity in commodity futures using monthly data. Future research along this line can investigate a broader range of liquidity measures with the help of high-frequency data from futures exchanges. Last but not least, this paper uses relatively liquid and representative futures to study commodity futures pricing; future research may investigate a broader range of commodity futures to examine the importance of liquidity as a pricing factor in the markets. Considering multiple types of crude oil such as Dubai oil, Brent oil, and WTI oil is an example to broaden the oil category. Other avenues worthy of exploring include two-way sorts proposed by Patton and Timmermann (2010), global liquidity, and financialization of commodity markets (Belke et al. 2010).

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Appendix

Figure 1 Goldman Sachs Commodity Index

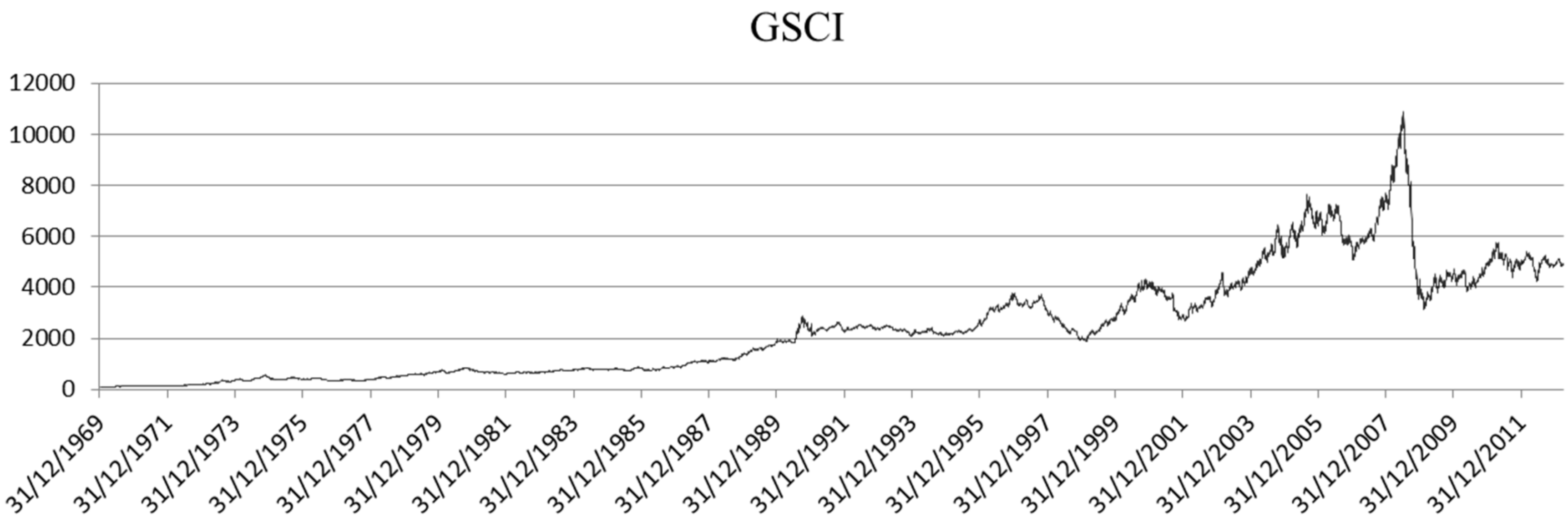

Table 1 Summary statistics of commodity futures in the sample

Category	Commodity	Exchange	Sample period of return	Expected return	SD of return	Avg. corr. of return to other commodities
Energy	Heating oil	NYMEX	1986/02 - 2013/12	0.00702	0.10589	0.19601
	Natural gas	NYMEX	1990/06 - 2012/12	0.00463	0.16735	0.08922
	Light crude oil	NYMEX	1986/02 - 2013/12	0.00685	0.10012	0.20669
	Coal	NYMEX	2004/05 - 2013/12	0.00178	0.08266	0.21242
	Unleaded gasoline	NYMEX	1986/02 - 2007/01	0.00695	0.11902	0.11959
	RBOB gasoline	NYMEX	2005/12 - 2013/12	0.00615	0.12178	0.36380
	Electricity	NYMEX	2004/05 - 2013/12	0.00007	0.15811	0.11063
Metal	Gold	CMX	1986/02 - 2013/12	0.00702	0.04327	0.13163
	Silver	CMX	1986/02 - 2013/12	0.00671	0.07941	0.17293
	Platinum	NYMEX	1986/02 - 2013/12	0.00721	0.06372	0.20131
	Copper	CMX	1988/09 - 2013/12	0.00726	0.07621	0.19213
	Palladium	NYMEX	1986/02 - 2013/12	0.00916	0.09052	0.16914
Agriculture	Cocoa	CSCE	1986/02 - 2013/12	0.00362	0.08204	0.11474
	Coffee	CSCE	1986/02 - 2013/12	0.00066	0.10195	0.10632
	Corn	CBT	1986/02 - 2013/12	0.00461	0.08039	0.19750
	Cotton	CSCE	1986/02 - 2013/12	0.00373	0.09780	0.09789
	Oats	CBT	1986/02 - 2013/12	0.00608	0.10285	0.17588
	Rough rice	CBT	2000/03 - 2013/12	0.00650	0.08689	0.11390
	Soybean meal	CBT	1986/02 - 2013/12	0.00637	0.07387	0.18069
	Soybean oil	CBT	1986/02 - 2013/12	0.00497	0.06822	0.20321
	Soybeans	CBT	1986/02 - 2013/12	0.00579	0.06612	0.22457
	Sugar	CSCE	1986/02 - 2013/12	0.00592	0.12105	0.06899
	Wheat	CBT	1986/02 - 2013/12	0.00495	0.08153	0.18179
Live stock	Feeder cattle	CME	1986/02 - 2013/12	0.00580	0.03890	0.01122
	Lean hogs	CME	1986/02 - 2013/12	0.00487	0.09512	0.05742
	Live cattle	CME	1986/02 - 2013/12	0.00535	0.04542	0.06096

Table 2 Key moments of the five portfolios sorted by cross-sectional momentum

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th	Long-short	GSCI	Risk-free
Mean	-0.02360 **	-0.00270	0.00537	0.01259 **	0.03525 **	0.03247 **	0.00689	0.00304
Standard deviation	0.06510	0.04770	0.04263	0.04832	0.06432	0.04216	0.05896	0.00201
Sharpe ratio	-0.40924	-0.12037	0.05469	0.19766	0.50083	0.69801	0.06534	NA
t-Statistics	-6.64782	-0.95217	1.90904	5.02740	10.25027	17.94441	1.89141	0.82489

The moments are based on monthly returns, which are fully collateralized returns. T-statistics are adjusted by Newey-West correction. The Goldman Sachs Commodity Index (GSCI) and the risk-free asset are included for benchmark reference. Figures with * and ** are significant at the 5% level and 1% level respectively.

Table 3 Key moments of the two portfolios sorted by time-series momentum

Sign of previous 12-month return	Positive	Negative	Long-short	GSCI	Risk-free
Mean	0.02265 **	-0.01476 **	0.02199 **	0.00689	0.00304
Standard deviation	0.04350	0.05006	0.02857	0.05896	0.00201
Sharpe ratio	0.45083	-0.35553	0.66318	0.06534	NA
t-Statistics	8.85549	-5.31941	20.23703	1.89141	0.82489

The moments are based on fully collateralized monthly returns. T-statistics are adjusted by Newey-West correction. The Goldman Sachs Commodity Index (GSCI) and the risk-free asset are included for benchmark reference. Figures with * and ** are significant at the 5% level and 1% level respectively.

Table 4 Key moments of the five portfolios sorted by speculators' hedging pressure

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th	Long-short	GSCI	Risk-free
Mean	-0.02322 **	-0.00877 **	0.00508	0.02120 **	0.03284 **	0.03107 **	0.00689	0.00304
Standard deviation	0.04970	0.05130	0.05117	0.05261	0.05111	0.03222	0.05896	0.00201
Sharpe ratio	-0.52838	-0.23014	0.03985	0.34530	0.58312	0.87007	0.06534	NA
t-Statistics	-7.48036	-2.93092	1.64471	7.27611	10.59185	15.63665	1.89141	0.82489

All moments are based on fully collateralized monthly returns. T-statistics are adjusted by Newey-West correction. The Goldman Sachs Commodity Index (GSCI) and the risk-free asset are included for benchmark reference. Figures with * and ** are significant at the 5% level and 1% level respectively.

Table 5 Key moments of the five portfolios sorted by roll yield

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th	Long-short	GSCI	Risk-free
Mean	-0.00436	0.00369	0.00682 *	0.01035 **	0.01069 **	0.01056 **	0.00689	0.00304
Standard deviation	0.05786	0.05196	0.04648	0.04795	0.05727	0.03488	0.05896	0.00201
Sharpe ratio	-0.12781	0.01247	0.08131	0.15251	0.13360	0.21572	0.06534	NA
t-Statistics	-1.33434	1.18428	2.16413	3.66169	3.52922	5.48406	1.89141	0.82489

The moments are based on fully collateralized monthly returns. T-statistics are adjusted by Newey-West correction. The Goldman Sachs Commodity Index (GSCI) and the risk-free asset are included for benchmark reference. Figures with * and ** are significant at the 5% level and 1% level respectively.

Table 6 Probabilities of the commodities in each of the five liquidity portfolios and the average open interest of the commodities

Category	Commodity	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th	Average OI
Energy	Heating oil	0.19	0.22	0.38	0.18	0.03	164,796
	Natural gas	0.20	0.32	0.21	0.16	0.11	469,569
	Light crude oil	0.67	0.24	0.07	0.02	0.01	666,740
	Coal	0.01	0.02	0.03	0.05	0.89	**6,728**
	Unleaded gasoline	0.13	0.14	0.25	0.29	0.20	85,855
	RBOB gasoline	0.09	0.16	0.40	0.26	0.08	217,497
	Electricity	0.03	0.03	0.08	0.28	0.58	46,329
Metal	Gold	0.56	0.33	0.11	0.00	0.00	241,483
	Silver	0.20	0.18	0.26	0.31	0.06	97,964
	Platinum	0.05	0.03	0.10	0.26	0.55	19,705
	Copper	0.10	0.14	0.30	0.30	0.16	78,086
	Palladium	0.02	0.01	0.04	0.10	0.84	**9,973**
Agriculture	Cocoa	0.13	0.18	0.28	0.31	0.10	97,329
	Coffee	0.10	0.08	0.17	0.38	0.28	71,354
	Corn	0.68	0.26	0.05	0.00	0.00	587,603
	Cotton	0.09	0.16	0.28	0.32	0.15	92,812
	Oats	0.02	0.02	0.04	0.09	0.84	**12,194**
	Rough rice	0.01	0.01	0.04	0.13	0.82	**10,811**
	Soybean meal	0.21	0.26	0.28	0.22	0.03	129,238
	Soybean oil	0.23	0.30	0.33	0.13	0.01	157,139
	Soybeans	0.41	0.37	0.20	0.03	0.00	253,723
	Sugar	0.28	0.30	0.27	0.12	0.03	313,805
	Wheat	0.17	0.29	0.25	0.26	0.04	182,136
Livestock	Feeder cattle	0.06	0.09	0.13	0.38	0.34	**20,419**
	Lean hogs	0.05	0.13	0.21	0.28	0.33	87,528
	Live cattle	0.32	0.33	0.25	0.09	0.00	146,094

The third to seventh columns present the probabilities of the commodities in each of the five liquidity portfolios. The last column shows the time-series average open interest of the commodities and the five smallest figures are in bold.

Table 7 Key moments of the five portfolios sorted by liquidity change

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th	Long-short	GSCI	Risk-free
Mean	0.00194	0.00271	0.00677 *	0.00792 *	0.00787	0.00601 **	0.00689	0.00304
Standard deviation	0.01806	0.03663	0.05227	0.06578	0.07449	0.03572	0.05896	0.00201
Sharpe ratio	-0.06109	-0.00909	0.07143	0.07420	0.06487	0.08308	0.06534	NA
t-Statistics	1.61388	1.21516	2.24529	2.06134	1.75494	3.03289	1.89141	0.82489

The moments are based on fully collateralized monthly returns. T-statistics are adjusted by Newey-West correction. The Goldman Sachs Commodity Index (GSCI) and the risk-free asset are included for benchmark reference. Figures with * and ** are significant at the 5% level and 1% level respectively.

Table 8 Correlation table of factors

	GSCI	CSMOM	HP	RY	TSMOM	LIQCH
GSCI	1.00000	-0.00256	-0.04067	-0.02031	0.01593	0.03388
CSMOM		1.00000	0.33149*	0.18206*	0.77683*	0.00007
HP			1.00000	0.03687	0.29709*	0.00637
RY				1.00000	0.13206*	0.04210
TSMOM					1.00000	-0.05481
LIQCH						1.00000

The correlation figures with * are significant at the 10% level.

Table 9 Time-series tests of the commodity CAPM and the multifactor model on the five portfolios sorted by cross-sectional momentum

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th
			Commodity CAPM		
Alpha	-0.02704**	-0.00593*	0.00199	0.00931**	0.03183**
	(-7.606)	(-2.266)	(0.856)	(3.527)	(9.060)
GSCI	0.10287	0.04778	0.08887*	0.06394	0.09921
	(1.707)	(1.078)	(2.257)	(1.430)	(1.666)
Adj. R-squared	0.0057	0.0005	0.0121	0.0031	0.0053
			Multifactor Models		
Alpha	-0.00170	0.00141	0.00405	-0.00305	-0.00170
	(-0.587)	(0.442)	(1.381)	(-1.001)	(-0.587)
GSCI	0.08043*	0.03389	0.07486*	0.04871	0.08043*
	(2.319)	(0.885)	(2.126)	(1.330)	(2.319)
CSMOM	-1.16502**	0.09813	-0.15905*	-0.28817**	0.83498**
	(-14.780)	(1.127)	(-1.988)	(-3.463)	(10.593)
HP	0.06088	-0.17513*	-0.10696	0.11196	0.06088
	(0.893)	(-2.326)	(-1.546)	(1.555)	(0.893)
RY	-0.09763	-0.03581	0.07903	0.18142**	-0.09763
	(-1.624)	(-0.539)	(1.295)	(2.858)	(-1.624)
TSMOM	0.28533*	-0.35969**	0.18448	0.76248**	0.28533*
	(2.502)	(-2.856)	(1.594)	(6.333)	(2.502)
LIQCH	0.89356**	0.61483**	0.53237**	0.65653**	0.89356**
	(15.504)	(9.659)	(9.100)	(10.789)	(15.504)
Adj. R-squared	0.6723	0.2571	0.2142	0.3349	0.6643

The upper panel reports the tests of the commodity CAPM and the lower panel reports the tests of the multifactor model. T-statistics are in parentheses. Estimates with * and ** are significant at the 5% level and 1% level respectively.

Table 10 Time-series tests of the commodity CAPM and the multifactor model on the two portfolios sorted by time-series momentum

Sign of previous 12-month return	Positive	Negative
Commodity CAPM		
Alpha	0.01921**	-0.01863**
	(8.128)	(-6.734)
GSCI	0.10520**	0.08975
	(2.626)	(1.914)
Adj. R-squared	0.0173	0.0079
Multifactor Models		
Alpha	-0.00130	-0.00130
	(-0.607)	(-0.607)
GSCI	0.08808**	0.08808**
	(3.419)	(3.419)
CSMOM	-0.04269	-0.04269
	(-0.729)	(-0.729)
HP	0.13693**	0.13693**
	(2.704)	(2.704)
RY	0.01883	0.01883
	(0.422)	(0.422)
TSMOM	0.83652**	-1.16348**
	(9.874)	(-13.734)
LIQCH	0.67495**	0.67495**
	(15.764)	(15.764)
Adj. R-squared	0.5955	0.7020

The upper panel reports the tests of the commodity CAPM and the lower panel reports the tests of the multifactor model. T-statistics are in parentheses. Estimates with * and ** are significant at the 5% level and 1% level respectively.

Table 11 Time-series tests of the commodity CAPM and the multifactor model on the five portfolios sorted by speculators' hedging pressure

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th
			Commodity CAPM		
Alpha	-0.02681**	-0.01202**	0.00158	0.01807**	0.02942**
	(-9.955)	(-4.258)	(0.569)	(6.270)	(10.629)
GSCI	0.14252**	0.05588	0.11876*	0.02628	0.09861*
	(3.122)	(1.167)	(2.519)	(0.538)	(2.101)
Adj. R-squared	0.0255	0.0011	0.0158	-0.0021	0.0101
			Multifactor Models		
Alpha	-0.00152	-0.00884**	-0.00156	0.01070**	-0.00152
	(-0.654)	(-2.637)	(-0.455)	(3.148)	(-0.654)
GSCI	0.10664**	0.03284	0.10195*	0.00672	0.10664**
	(3.819)	(0.816)	(2.472)	(0.165)	(3.819)
CSMOM	-0.06561	-0.17956	-0.08240	-0.18873*	-0.06561
	(-1.034)	(-1.964)	(-0.879)	(-2.037)	(-1.034)
HP	-0.96963**	-0.21257**	0.02135	0.04689	1.03038**
	(-17.665)	(-2.688)	(0.263)	(0.585)	(18.772)
RY	0.01581	0.01880	-0.09124	0.00458	0.01581
	(0.327)	(0.270)	(-1.276)	(0.065)	(0.327)
TSMOM	0.09620	0.30039*	0.19041	0.48830**	0.09620
	(1.048)	(2.271)	(1.404)	(3.643)	(1.048)
LIQCH	0.68067**	0.77999**	0.71228**	0.80834**	0.68067**
	(14.669)	(11.668)	(10.391)	(11.933)	(14.669)
Adj. R-squared	0.6371	0.2981	0.2503	0.3053	0.6512

The upper panel reports the tests of the commodity CAPM and the lower panel reports the tests of the multifactor model. T-statistics are in parentheses. Estimates with * and ** are significant at the 5% level and 1% level respectively.

Table 12 Time-series tests of the commodity CAPM and the multifactor model on the five portfolios sorted by roll yield

Percentile	<20th	≧20th and <40th	≧40th and <60th	≧60th and <80th	≧80th
			Commodity CAPM		
Alpha	-0.00777*	0.00030	0.00354	0.00694**	0.00737*
	(-2.450)	(0.105)	(1.392)	(2.662)	(2.355)
GSCI	0.09722	0.09137	0.06281	0.09562*	0.07341
	(1.808)	(1.904)	(1.458)	(2.162)	(1.384)
Adj. R-squared	0.0067	0.0078	0.0034	0.0109	0.0027
			Multifactor Models		
Alpha	0.00010	-0.00467	0.00039	-0.00094	0.00010
	(0.038)	(-1.320)	(0.119)	(-0.291)	(0.038)
GSCI	0.06441*	0.07496	0.05061	0.08213*	0.06441*
	(2.059)	(1.764)	(1.278)	(2.123)	(2.059)
CSMOM	-0.20038**	-0.06005	-0.01045	-0.11195	-0.20038**
	(-2.819)	(-0.622)	(-0.116)	(-1.274)	(-2.819)
HP	-0.02094	0.04558	-0.04960	0.10464	-0.02094
	(-0.341)	(0.546)	(-0.637)	(1.376)	(-0.341)
RY	-1.03520**	-0.12063	0.06927	0.01306	0.96480**
	(-19.096)	(-1.638)	(1.009)	(0.195)	(17.797)
TSMOM	0.20621*	0.23158	0.14803	0.33179**	0.20621*
	(2.005)	(1.657)	(1.136)	(2.609)	(2.005)
LIQCH	0.88329**	0.68797**	0.52635**	0.64421**	0.88329**
	(16.994)	(9.743)	(7.996)	(10.023)	(16.994)
Adj. R-squared	0.6655	0.2254	0.1611	0.2469	0.6548

The upper panel reports the tests of the commodity CAPM and the lower panel reports the tests of the multifactor model. T-statistics are in parentheses. Estimates with * and ** are significant at the 5% level and 1% level respectively.

Table 13 Cross-sectional tests of the commodity CAPM and the multifactor models with and without the liquidity factors

		GSCI	CSMOM	TSMOM	HP	RY	LIQCH	Adj. R-squared	RMSE	F-test
(1)	Risk premium	0.01130						-0.05861	0.01679	
	t-statistics	(0.243)								
(2)	Risk premium	0.02325	0.03026**		0.02788**	0.00851*		0.88250	0.00504	
	t-statistics	(1.498)	(8.482)		(7.103)	(2.117)				
(3)	Risk premium	0.01283		0.02058**	0.02855**	0.00791*		0.92210	0.00411	
	t-statistics	(1.015)		(9.541)	(8.949)	(2.433)				
(4)	Risk premium	-0.03610	0.03079**		0.02884**	0.00786*	0.00665	0.92850	0.00378	0.00993
	t-statistics	(-0.966)	(11.044)		(9.393)	(2.524)	(1.680)			(2) and (4)
(5)	Risk premium	-0.03420		0.02011**	0.02892**	0.00788*	0.00497	0.92620	0.00384	0.21420
	t-statistics	(-0.902)		(9.449)	(9.275)	(2.490)	(1.247)			(3) and (5)

The risk premiums of the factors are presented and their corresponding t-statistics are in parentheses. Risk premia with * and ** are significant at the 5% level and 1% level respectively. The RMSE and the p-values of the F-tests are presented in the last two columns.