Cross-Market Investor Sentiment in Commodity Exchange-Traded Funds

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March 18, 2015

* I am grateful to the referee for his or her comments. For their helpful comments, I thank the participants of the Annual Meetings of Midwest Finance Association held in Chicago, March 14-16, 2013, of the Bicentenary Conference of the Italian Academy of Management (AIDEA) held in Lecce, Italy, September, 19-21, 2013, of the workshop "Determinants and Impact of Commodity Price Dynamics" in Münster, Germany, June 26, 2014, and of seminars at University of Illinois at Chicago. I thank for data/information inquiry assistance provided by Eva Nelson at the Center for Research in Security Prices (CRSP). I also thank Chun Zhang, Jiayin Hou, and Saembyeol Park for research assistance. Address correspondence to Hsiu-lang Chen, Department of Finance, 601 South Morgan Street, Chicago, IL 60607, or e-mail: hsiulang@uic.edu.

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Abstract

This study shows how the investor sentiment in the stock market affects prices of commodity exchange-traded funds (ETFs). The study provides quantitative evidence that the tracking errors of commodity ETFs differ in the bullish versus the bearish stock market, and the aggregate tracking error of commodity ETFs is sensitive to the well-known sentiment measures. The study exploits a profitable trading strategy based on investor sentiment in the stock market and commodity market. The sentiment-driven demand for commodity ETFs could exist even after consideration of trading costs, and it is a short-term phenomenon. This unique evidence indicates investor sentiment affects asset valuation across markets.

I. Introduction

It is well known that liquid financial markets are not always as orderly as the efficient market advocates might suggest (see Grossman and Stiglitz, 1980). In a model of two types of investors, rational arbitrageurs who are sentiment-free and irrational traders prone to exogenous sentiment, DeLong, Shleifer, Summers, and Waldmann (1990) argue that rational arbitrageurs mainly face limits from short time horizons or from costs and risks of trading and short selling. Shleifer and Vishny (1997) show how agency problems between an arbitrageur and his or her source of capital can also hinder arbitrage. As a result, sentiment-based demands might drive prices away from their fundamental values. Empirically, examination of this issue is still contentious. The absence of precise valuation models for stocks makes measuring deviations from theoretical prices difficult. Similar problems arise from the difficulty in measuring investor sentiment. The study of passively managed commodity exchange-traded funds (ETFs) might be able to mitigate these issues.[1]

Most public statements by institutional investors emphasize the primary advantage of commodity investments as diversification, providing a return that has little correlation with core equity and bond holdings. Since their introduction in 2004, commodity ETFs have grown from just over $1 billion to $109 billion by the end of 2011, with total net assets almost tripling in the last two years. By construction, a passively managed commodity ETF tracks its underlying index.[2] Unlike the discounts on closed-end mutual funds, the market price of an ETF is close to

[1] An ETF is an investment company, typically an open-end investment company (open-end fund), whose shares are traded intraday on stock exchanges at market-determined prices. Investors may buy or sell ETF shares through a broker just as they would the shares of any publicly traded company. The first ETF—a broad-based domestic equity fund tracking the S&P 500 index—was introduced in 1993. Until 2008, the U.S. Securities and Exchange Commission's (SEC) exemptive relief was granted only to ETFs that tracked designated indexes. According to the 2012 Investment Company Fact Book, by the end of 2011, the total number of index-based and actively managed ETFs had grown to 1,134, and total net assets were $1.05 trillion.

[2] For example, United States Oil Fund, LP (USO), a commodity ETF, declared on its prospectus dated on April 10, 2006, that the price of USO's units on the American Stock Exchange would closely track the spot price of a barrel of WTI

the value of its underlying index assets net of the expense ratio, because its portfolio composition is transparent, and authorized participants (institutional investors) are allowed to assemble a basket of underlying index assets in exchange for shares of the ETF. The tracking error (TE) of an ETF can be defined as follows:

$$TE_j \equiv R_j - R_{BI} = F(\Lambda \mathrm{B}_j) - F(\Lambda \mathrm{B}_{BI}) \tag{1}$$

Where R_j is the gross return on an ETF j while R_{BI} is the total return on the ETF's benchmark index *BI*. *F(.)* is a valuation model. Λ is the risk premium vector of *1xK* associated with *K* factors while B is the factor loading vector of *Kx1*.

Because of investment mandates, a passively-managed ETF has to closely track the benchmark index and commonly hold the index underlying assets. Thus, a valuation model, whatever it is, as well as the same risk factors should apply to both the ETF and its benchmark index. As a result, the tracking errors of the ETF are free of any complex pattern of compensation for systematic risk. In examining tracking errors of ETFs, this study can put aside the concern of whether control variables are effective to separate investor sentiment from economic fundamentals in predicting stock returns in a regression framework commonly used in the literature.[3] Even though investor sentiment is taken into consideration, the sentiment will have a similar impact on the ETF and its index underlying assets as long as both are traded in the same market. For example, the tracking errors of S&P500 ETFs are unlikely influenced by investor sentiment in the stock market.

Commodity ETFs, however, are traded in a regular stock exchange. The fluctuations in the noise trader sentiment in the stock market likely affect many assets traded in the market,

light, sweet crude oil, less USO's expenses. USO sought to achieve its investment objective by investing in a mix of oil futures contracts and other oil interests such as options on oil futures contracts, forward contracts for oil, and over-the-counter transactions based on the price of oil and other petroleum-based fuels.

[3] See Brown and Cliff (2005), Lemmon and Portniaguina (2006), Baker and Wurgler (2006), and others.

including commodity ETFs.[4] It is labeled as the cross-market sentiment effect. Although arbitrage can be undertaken by market participants who can buy the inexpensive asset and short sell the more expensive one, commodity ETFs and their underlying securities are not traded in the same market. If arbitrageurs lack the capacity to engage in arbitrage across multiple markets, as Shleifer and Vishny (1997) point out that arbitrage markets are specialized, the tracking errors of commodity ETFs would be affected by investor sentiment in the stock market. Are investors investing in commodity ETFs likely to enjoy the exciting celebration as do stock investors for a bullish stock market? A psychology experiment conducted by Moreland and Beach (1992) supports this conjecture. With a controlled condition of no interaction, they show that students' mere exposure to the same classroom has strong effects on attraction and similarity to others. People also tend to conform to the judgments and behaviors of others. In a sequential decision model, Banerjee (1992) shows that people will do what others are doing rather than use their own information. This study empirically examines if the investor sentiment in the stock market affects prices of commodity ETFs.

Several studies have documented the interaction between the sentiment and the broad stock market returns. Brown and Cliff (2004) show that sentiment levels and changes are strongly correlated with contemporaneous market returns. Using a direct survey measure of investor sentiment, Brown and Cliff (2005) provide evidence that optimism is associated with overvaluation and low returns over the subsequent one to three years as the valuation level returns to its intrinsic value. Ben-Rephael, Kandel, and Wohl (2012) find that investor sentiment, proxied by net exchanges between equity funds and bond funds, creates noise in aggregate market prices. Others have used investor sentiment to explain anomalies in the asset pricing.

[4] This paper simply views investor sentiment as optimism or pessimism about stocks in general and thus assumes investor sentiment is positive (negative) in a bullish (bearish) stock market.

Lee, Shleifer, and Thaler (1991) argue that arbitrage against noise traders is risky because arbitrageurs do not have infinite horizons, and conclude that fluctuations in discounts of closed-end funds are mainly driven by changes in individual investor sentiment. Baker and Wurgler (2006, 2007) argue that investor sentiment drives the relative demand for speculative investments, which are typically hard to value and tend to be difficult to arbitrage and therefore possibly cause cross-sectional effects on stock returns.[5] They document that speculative and hard-to-arbitrage stocks have lower (higher) future returns on average than bond-like stocks when sentiment is measured to be high (low). Baker, Wurgler, and Yuan (2012) provide further international evidence for the forecasting power of investor sentiment.[6] In this study, I investigate whether investor sentiment in the stock market affects daily tracking errors of commodity ETFs. Ultimately, I explore whether I can quantify the cross-market sentiment effects by exploiting profits from a long-short investment strategy. The findings of this study complement the existing literature that asserts that investor sentiment affects the broad market returns and the cross-section of stock returns.

This study also contributes to the ETF literature. Elton, Gruber, Comer, and Li (2002) identify that both the management fee and the loss of return from dividend reinvestment cause the underperformance of Standard and Poor's Depository Receipts (commonly referred as Spider) relative to the S&P 500 Index, which Spider tracks. After correcting measurement errors in net asset value (NAV), Engle and Sarkar (2006) show the average premium of equity ETFs was less than 5 basis points (bps) and the standard deviation was less than 20 bps. Delcoure and Zhong

[5]D'Avolio (2002) documents that stocks that are young, small, unprofitable, or experiencing extreme growth tend to be more costly to buy and to sell short. Wurgler and Zhuravskaya (2002) also find such stocks have a high degree of idiosyncratic variation in their returns, which makes betting on them riskier.

[6]In addition to investor sentiments, several studies have addressed the interdependencies between consumer sentiments (consumer confidence), stock returns, and macroeconomic activities. See Lemmon and Portniaguina (2006) and Beckmann, Belke, and Kühl (2011).

(2007) and Levy and Lieberman (2013) analyze the "stale pricing" problem of securities traded in foreign country markets in generating a premium of country ETFs. Levy and Lieberman (2013) further find that whereas country ETF prices are mostly driven by their NAV returns during synchronized trading hours, the S&P 500 index has a dominant effect during non-synchronized trading hours. Because this study aims to determine whether investor sentiment in one market affects asset prices in another market, incorporating all possible channels through which investor sentiment might have influence is important. If the replication of an index a commodity ETF tracks is imperfect, investor sentiment could amplify the tracking errors. Therefore, I mainly confine this study to the ETF's price relative to its underlying index, not relative to its NAV. In addition, I use the underlying index to gauge the prospect of the commodity market relative to that of the stock market and to construct the index-adjusted performance measure for an investment strategy exploiting the sentiment effect. The result of this study suggests that in addition to the stale pricing problems, behavioral factors may account for some mispricing in ETFs.

In short, the first hypothesis I test is whether investor sentiment in the stock market affects the tracking errors of commodity ETFs after controlling the investor sentiment in the commodity market. If the cross-market sentiment effect exists, the tracking errors of commodity ETFs reflect investor sentiment in the stock market. Thus, the second hypothesis I investigate is whether the aggregate tracking errors of commodity ETFs load significantly on sentiment measures commonly used in the literature. The third hypothesis to be empirically tested is whether investor sentiment in the stock market can predict future returns on a long-short strategy involving commodity ETFs and the Spider.

The rest of the paper proceeds as follows. Section II describes the data. Section III presents statistics on tracking errors and tracking-error volatility for commodity ETFs. Section IV tests whether investor sentiment in the stock market affects prices of commodity ETFs. Section V exploits a profitable trading strategy based on investor sentiment in the stock market and commodity market. Section VI investigates the impact of transaction costs on the trading strategy. Section VII further performs a Fama-French risk-factor model for a robustness check, and section VIII concludes.

II. Data

The CRSP daily return files, CRSP Survivor-Bias-Free Mutual Fund database, and SEC's EDGAR database constitute the main data sources. I retrieve share returns, trading volumes, number of shares outstanding, closing prices, and closing bid/ask prices of all commodity ETFs as well as Spider (the ticker symbol: SPY) from CRSP return files.[7] I hand-collect all historical expense ratios for all commodity ETFs, and Spider from SEC's EDGAR database. I construct the daily gross returns by adding the expense ratios to the share returns for these ETFs. Daily net asset value (NAV) returns are directly retrieved from the CRSP Mutual Fund database. I only consider ETFs that have at least one-year daily returns, and have specified in the prospectus the underlying indexes that ETFs will track.[8] I retrieve the data of indexes tracked by ETFs from the web sites of the companies that publish the indexes, as well as the data service providers. The sample of this study includes 33 commodity ETFs from November 18, 2004, to December 31,

[7] An ETF is a security with a common share code of 73 in CRSP. There are six commodity ETFs in the sample, which are mistakenly classified as closed-end funds with a CRSP share code of 74. These include funds with ticker symbols of CORN, DNO, UNG, UNL, USCI, and USO.

[8] The criterion of requiring ETFs having at least one-year daily returns is to ensure that the test of cross-market sentiments based on individual ETFs has a reasonable number of sample observations. Only two newly-established commodity ETFs, AGOL (Inception: 2011/01/14) and NAGS (Inception: 2011/02/01), do not satisfy this criterion. In addition, I exclude four commodity ETFs (ticker symbols: BNO, UGA, WITE, and GLTR). I cannot have the complete data for the indexes the first two ETFs track. The last two ETFs track an index comprising a customized deposit of bullion metals.

2011 (see Appendix 1 for listing). An ETF's tracking error is the ETF's gross return minus its benchmark index return. I decompose daily ETF tracking errors into two components, mispricing component and imperfect index replication component. The mispricing component is the ETF's share returns minus its NAV returns while the imperfect index replication component is its NAV returns plus expense ratios minus its benchmark index returns.

The monthly data of Baker and Wurgler's measures of sentiment and discounts on closed-end equity fund are obtained from Jeffrey Wurgler's website at www.stern.nyu.edu/~jwurgler. The monthly data of the University of Michigan sentiment measure are obtained from the University of Michigan Surveys of Consumers at www.sca.isr.umich.edu. Data of daily VIX (Chicago Board Options Exchange Market Volatility Index) values are obtained from finance.yahoo.com.

III. Tracking Errors and Tracking-Error Volatility

I first present the quartile distribution of tracking errors of commodity ETFs over the entire sample period. The sample contains nine commodity ETFs designed to provide double returns, inverse returns, or double inverse returns of the indexes they track. For these leveraged/inverse ETFs, I define their tracking errors accordingly.[9] Panel A of Table 1 shows that commodity ETFs entail non-trivial tracking errors, whereas Spider tracks the S&P 500 Index nearly perfectly. The median commodity ETF trails its index by 0.8 basis points (bps) and on average a commodity ETF trails its index by 2.2 bps per day over the sample period. Given the underperformance of 2.2 bps, about one third of it is attributable to the commodity ETF's

[9] For example, the tracking error of ProShares Ultra Gold ETF (UGL) is its gross returns minus double returns on the daily performance of gold bullion as measured by the U.S. Dollar p.m. fixing price for delivery in London, the benchmark index UGL tracks. Similarly, the tracking error of ProShares UltraShort Gold ETF (GLL) is its gross returns minus inverse double returns on the benchmark index. According the description on page 21 of the initial prospectus on November 21, 2008, these two funds will not invest in bullion, but rather will use financial instruments to gain exposure to these precious metals. Not investing directly in bullion may introduce additional tracking errors.

mispricing and two third of it is attributable to ETF's imperfect index replication. To present the stability of an ETF in tracking its index, I calculate the volatility of the ETF's daily tracking errors over the sample period. Panel B of Table 1 shows the median tracking-error volatility (TEV) among these 33 commodity ETFs is about 1.905%. The median volatility of the mispricing components and imperfect index replication components is 0.875% and 1.202%, respectively. For a reference comparison, I also construct the quartile distribution of TEV for Spider in such a way that the volatility of Spider's tracking errors is calculated each time for a period in which TEV of a commodity ETF is calculated. Spider only entails a median tracking-error volatility of 0.164% and its mispricing component has the equivalent volatility. The standard deviation of the cross-sectional TEVs of commodity ETFs is about 1.731%. The big deviation might indicate the large variety of ways in which commodity ETFs implement tracking strategies—some investing in underlying assets directly whereas some using financial instruments to gain exposure to the underlying assets. This is also reflected in an even higher standard deviation of the cross-sectional volatilities of their components of imperfect index replication, which is 1.884%. One must take the large variation in tracking implementation into consideration when I empirically test whether the tracking errors of commodity ETFs can possibly indicate investor sentiment in the stock market.

Table 2 shows the quartile distribution of tracking errors over two contrast periods, bullish- and bearish-period. I define a bullish stock market versus a bearish stock market according to daily returns of RMRF, one of the Fama-French three factors. The bullish (bearish) stock markets include days that RMRF is positive (negative). Spider trails the S&P 500 Index in a bullish stock market, whereas overshoots the S&P 500 Index in a bearish market in an almost identical magnitude of about 2bps. However, commodity ETFs exhibit an opposite effect. The median commodity ETF overshoots its index by 8.4bps in a bullish stock market but trails its index by 11.3 bps in a bearish stock market. Investor sentiment in the stock market might affect traded securities regardless of whether or not the underlying assets of the securities are traded in the same market. Most one-sided tracking errors in either bullish or bearish periods are attributable to the mispricing component. Rather than contradicting the result of Panel A of Table 1, this indicates that individual commodity ETFs are selling at premium in the bullish period while at discount with a similar magnitude in the bearish period. Therefore, the mispricing component becomes smaller over the entire sample period as shown in Table 1. The component of imperfect index replication behaves differently—it is negative in a greater magnitude in the bearish period. This observation is also echoed by the result that the median mispricing (imperfect index replication) component of tracking errors is 7 bps (0.5 bps) in the bullish period while it is -8 bps (-1.7 bps) in the bearish period.

Brown and Cliff (2004) document that sentiment levels and changes are strongly correlated with contemporaneous market returns. Investors are likely more optimistic in a bullish stock market. These investors in turn are more likely excited about commodity ETFs that are also traded in the same market. The evidence shown in Table 2 that the daily tracking errors for commodity ETFs tend to be positive (negative) when the stock market is bullish (bearish) supports this conjecture. A similar behavior has been documented in a psychology experiment conducted by Moreland and Beach (1992) that shows students' mere exposure to the same classroom has strong effects on attraction and similarity to others. Banerjee (1992) also shows that people will do what others do rather than use their own information.

IV. Do commodity ETFs' tracking errors reflect investor sentiment in the stock market?

The literature has well documented that investor sentiment affects the broad market and the cross-section of stock returns. However, whether aggregate investor sentiment in one market affects asset prices in another market is still unknown. In other words, can investor sentiment in the stock market affect all securities traded in the market, including securities whose underlying assets are commodities? I simply view investor sentiment as optimism or pessimism about stocks in general and thus assume investor sentiment is positive (negative) in a bullish (bearish) stock market. I define a bullish and a bearish stock market according to daily returns of RMRF. Similarly, a day for an ETF is classified as a bullish (bearish) market in a commodity market if the daily return on an index tracked by the ETF minus daily one-month T-bill rate is positive (negative). For each ETF since its inception, I classify trading days into four periods: (1) bullish stock market and bullish commodity market (BullSBullC), (2)bullish stock market and bearish commodity market (BullSBearC), (3) bearish stock market and bullish commodity market (BearSBullC), and (4) bearish stock market and bearish commodity market (BearSBearC). I examine whether investor sentiment in the stock market affects the commodity ETFs' tracking errors after controlling for sentiment in the commodity.

Because of the concern that commodity ETFs engage in quite different index tracking strategies in addition to commodity types varying from oil to bullion, I conduct a test on the basis of individual commodity ETFs in Table 3. I first test for whether the mean of daily tracking errors (TEs) of an ETF is identical in two contrast periods defined by the stock market, BullSBullC versus BearSBullC as well as BullSBearC versus BearSBearC. For a reference comparison, I also test for whether the mean of daily TEs of Spider is the same in two contrast periods defined by the underlying index of each commodity ETF, BullSBullC versus

BullSBearC as well as BearSBullC versus BearSBearC. Panel A shows that the tracking errors of 29 out of 33 commodity ETFs differ significantly in the bullish stock market versus the bearish stock market, after controlling for bullish sentiment in the commodity market. Similarly, Panel B shows that investor sentiment in the stock market affects the tracking errors of 31 commodity ETFs after controlling for bearish sentiment in the commodity market. After controlling for investor sentiment in the stock market, by contrast, Spider shows little evidence that sentiment in the commodity market significantly affects its tracking errors. This result is expected because there is no cross-market sentiment effect—both Spider and its underlying assets are traded in the stock market. For a robustness check, I conduct the same test based on the mispricing components of tracking errors and obtain the similar result.[10]

If the tracking errors of commodity ETFs really reflect investor sentiment in the stock market in which the ETFs are traded, the aggregate tracking errors are anticipated to be more sensitive to the sentiment, in the sense that the aggregate tracking errors of commodity ETFs will have higher sentiment betas after controlling for other factors that might affect the tracking errors. The other factors I consider are stock market returns and liquidity measures. The market returns incorporate investors' expectations regarding the general economy and reflect economic fundamentals. Two liquidity measures, Amihud illiquidity and turnover, are used for this study. Amihud (2002) illiquidity is the absolute return divided by the dollar volume.[11] It captures the daily price response associated with one dollar of trading volume. The turnover is the ratio of trading volume to the number of shares outstanding. Amihud and Mendelson (1986) document

[10] The mispricing components of 26 out of 33 commodity ETFs differ significantly in the bullish stock market versus the bearish stock market, after controlling for bullish sentiment in the commodity market. Similarly, investor sentiment in the stock market affects the mispricing components of 29 commodity ETFs after controlling for bearish sentiment in the commodity market. Still, Spider shows little evidence that sentiment in the commodity market significantly affects its mispricing components. For brevity, the result is not reported but available upon the request.
[11] The daily dollar volume is the trade volume times the daily closing price.

that turnover is negatively related to illiquidity costs. Investor sentiment measure (SENT) is constructed by Baker and Wurgler (2007) and directly retrieved from Wurgler's website.[12] Given that the sentiment measure is only available annually and monthly up to December 2010, daily tracking errors and liquidity measures are converted to monthly data first. Instead of retrieving monthly returns and liquidity variables directly, I average the daily data for each month for each ETF in the hopes that the averaging can reduce noises in the tracking-error calculation so the aggregate tracking errors of commodity ETFs can represent investor sentiment in the stock market. I calculate the cross-sectional average of monthly data in an equal weight for the portfolio of commodity ETFs. ETFs that use financial instruments to gain leverage exposure to their underlying assets may introduce additional tracking errors that are not necessarily related to investor sentiment. As a result, I exclude leveraged and inverse ETFs from the analysis.[13] I have 24 non-leveraged/non-inverse commodity ETFs in total and 74 months between November 2004 and December 2010.

I regress monthly tracking errors of the commodity ETF portfolio on the liquidity measures and sentiment measures with a control variable of the market excess returns, RMRF. Table 4 shows the aggregate tracking errors of commodity ETFs load positively and significantly on the sentiment regardless of whether or not I consider liquidity. In Model 4, a one standard deviation increase in the level of sentiment (0.301) is associated with a 1.7 bps increase in the average of daily tracking errors of commodity ETFs over a month, which represents 26% of the standard deviation of the dependent variable.[14] Because the tracking error has adjusted for any

[12] Baker and Wurgler (2006, 2007) construct their sentiment index based on six proxies: the trading volume; the dividend premium; the closed-end fund discount; the number and first-day returns on IPOs; and the equity share in new issues.

[13] The results, not reported but available upon the request, are basically the same even though leveraged and inverse ETFs are included. To avoid any confounding between the leverage effect and the sentiment effect, I decide to exclude them hereafter.

[14] (0.058*0.301)/0.066=0.2645.

fundamental influence associated with the economy by deducting returns on an index tracked by an ETF, I expect the aggregate tracking errors no longer strongly co-move with the stock market excess returns. An insignificant coefficient of RMRF in the regression confirms this expectation. When negative liquidity shocks hit, sentiment-driven demand, perhaps due to limits to arbitrage, will amplify the aggregate tracking errors as shown in the coefficients of two liquidity measures.

As a reference, I apply the same test to the tracking errors of Spider. As expected, the tracking errors of Spider are not sensitive to investor sentiment at all because sentiment, if any is present, affects both Spider and S&P 500 company stocks simultaneously and similarly. Shleifer and Vishny (1997) argue that markets in which fundamental uncertainty is high and slowly resolved are likely to deter arbitrage activity. Given that Spider and S&P 500 stocks are very liquid and are traded in the same market, and that Spider's NAV values are disseminated at a 15-second frequency throughout the trading days, arbitrage forces used to correct the mispricing on Spider are more effective. Therefore, sentiment-driven mispricing will wane much sooner on Spider than on commodity ETFs. This observation leads to consider both Spider and a commodity ETF for further testing the cross-market sentiment effect in Section V.

For a robustness check, I consider other three measures commonly used in the sentiment literature. The first one is discounts on closed-end equity funds (CEFD). CEFD widely used as an indicator of investor sentiment in the literature deserves a further consideration even though it is one of the six variables used for Baker and Wurgler's (2006, 2007) sentiment index. Lee, Shleifer, and Thaler (1991), Swaminathan (1996), and Neal and Wheatley (1998) all conclude that the discounts on closed-end funds reflect investor sentiment and can predict the size premium. The second one is the Michigan Consumer Sentiment Index (CSI) which is based on surveys. Lemmon and Portniaguina (2006) show that the sentiment component of CSI forecasts time-series variation in the size premium after allowing for time-series variation in market beta. Doms and Morin (2004) find, after controlling for economic fundamentals, that the measures of consumer confidence still respond to the sentiment. The third one is Chicago Board Options Exchange Market Volatility Index (VIX) which is the implied volatility of S&P 500 index options and is commonly termed as the investor fear gauge. Ben-Rephael, Kandel, and Wohl (2012) document that investor sentiment proxied by net exchanges between equity funds and bond funds is strongly negatively related to VIX while it is weakly positively related to the CSI. If the aggregate tracking errors of commodity ETFs proxy for investor sentiment in the stock market, it is expected that the tracking errors load positively on CSI while negatively on both CEFD and VIX. Panel C of Table 4 clearly shows that the loadings on the sentiments are significant and have the expected signs. The result still holds when daily tracking errors are compounded over a month and these monthly compounded tracking errors are used as the aggregate tracking errors of commodity ETFs.

If the tracking errors of commodity ETFs indeed reflect investor sentiment in the stock market, the daily tracking errors of commodity ETFs can serve as an indicator of daily sentiment for the stock market. Thus, the daily tracking errors of commodity ETFs complement indicators of annual and monthly sentiment measures provided by Baker and Wurgler (2006, 2007).

V. Using Sentiment to Predict Returns

So far I have shown investor sentiment in the stock market will likely swing the ETFs' tracking errors given that commodity ETFs are traded in the stock market. In other words, the positive sentiment in the stock market drives the prices of commodity ETFs above the intrinsic values of their underlying commodities. I follow the suggestion by Baker and Wurgler (2007) that the strongest tests of the effects of sentiment involve return predictability.

To possibly quantify the impact of sentiment in the stock market on commodity ETFs, I perform a long-short investment strategy involving a commodity ETF and Spider, depending on whether investor sentiment is simply positive or negative. A zero-cost investment in an efficient market should generate zero return after adjusting for risks. I investigate whether current investor-sentiment levels predict future returns on the long-short strategy as sentiment wanes differently on commodity ETFs and Spider, and as arbitrage forces accumulate to correct mispricing of these two securities at different paces. Additionally, using a commodity ETF and Spider, instead of a commodity ETF and its underlying assets, in the long-short investment strategy offers a practical advantage.

Unlike in equity ETFs, an authorized participant in the creation/redemption of a commodity ETF may have to deliver/receive a combination of cash and physical assets underlying the commodity ETF for a metal commodity ETF (e.g. SPDR Gold ETF [GLD]), or a combination of cash and Treasurys for a non-metal commodity ETF (e.g. United States Oil ETF [USO]). Types of assets for delivery in exchange for commodity ETF shares vary accordingly and may be illiquid or not available for short. A further impediment to arbitrage if a commodity ETF and its underlying assets are used in a long-short strategy is that both may not be traded in synchronized hours. For example, United States Commodity Index Fund (USCI) tracks the total return of the SummerHaven Dynamic Commodity Index, which is comprised of 14 futures contracts that will be selected on a monthly basis from a list of 27 possible futures contracts in the sectors of energy, livestock, grains, industry metals, precious metals, and softs. It might be challenging for retail investors engaging in arbitrage between USCI shares and its underlying securities—most are actively traded futures contracts with scheduled expirations. Not only are the open-outcry trading hours for these futures contracts varying and different from the trading hours of USCI shares at the NYSE Arca stock exchange, but futures contracts are also expiring constantly.[15] Shleifer and Vishny (1997) argue that arbitrage markets are specialized, and arbitrageurs typically lack the experience and reputation to engage in arbitrage across multiple markets. As a result, to avoid the criticism that the existence of mispricing in commodity ETFs might not be due to the investor sentiment but the difference in market structure between commodities and equities, I use a commodity ETF and Spider, instead of a commodity ETF and its underlying assets, in the long-short investment strategy to quantify the impact of sentiment in the stock market on commodity ETFs. I am mindful that the proposed long-short strategy is likely exposed to economic risk factors related to the fundamental difference between the commodity market and the stock market, and I have to take this into consideration.

In the single-market strategy, I explore an investment opportunity based on investor sentiment in the stock market. At the beginning of each day, I long an ETF and short SPY if the stock market was bullish the prior day, whereas I short an ETF and long SPY if the stock market was bearish the prior day. Note that sentiment-driven mispricing wanes sooner on Spider than on commodity ETFs shown in the previous section. In the cross-market strategy, I explore an investment opportunity based on investor sentiment in both stock and commodity markets. At the beginning of each day, I long an ETF and short SPY if the stock market was bullish and the ETF market was bearish the prior day (BullSBearC). I short an ETF and long SPY if the stock market was bearish and the ETF market was bullish the prior day (BearSBullC). Using ETFs' share returns, I calculate daily performance for each strategy for each ETF.

Table 5 shows that the proposed investment strategy is profitable. For example, the single-market strategy on the basis of individual ETFs generates 14.1 bps per day on average,

[15] A constant, scheduled expiration in futures contracts introduces an additional complexity for arbitrage because of uncertain "contango" and "backwardation" phenomena in describing the price relationship between the near month futures contracts and the next month futures contracts.

whereas the cross-market strategy results in about 19.9 bps. Both are significant at the level of 1%. As a reference, I perform a plain strategy of long ETF and short SPY constantly. Without relying on sentiment signals, the plain strategy results in zero performance. This result indicates that both commodity ETFs and Spider are exposed to systematic risk factors similarly during the sample period, and thus the profit from the proposed long-short strategy is not just compensation for bearing the systematic risk. Given it is costly to execute short selling, it is definitely subject to the argument of limits to arbitrage if most of profits of the proposed long-short strategy are from the short position. I attribute the strategy performance to each of the long and short position held by the strategy. The result shows that the long position generates significant returns and contributes more than 73% of the overall profits.

When I pool all performance of strategies across commodity ETFs, the average performance of sentiment strategies is significant and positive. The strong evidence also appears in a singular strategy under either single-market or cross-market sentiment consideration. For example, a sentiment strategy based on positive sentiment in the stock market generates 15.2 bps per day on average, whereas a strategy based on positive sentiment in the stock market and negative sentiment in the commodity market results in 24.5 bps. Both are significant at the 1% level. Again, the majority of strategy performance is generated from the long position in a long-short investment.

To test the sentiment effects further, I split the time series into extreme bullish (bearish) days depending on whether the daily market excess returns are ranked at the top (bottom) third over the entire bullish (bearish) market period.[16] If the sentiment effects indeed exist, I

[16] It is questionable if the strategy following the extreme sentiment signal is executable in practice, because ex ante I cannot identify if the prior market excess return is ranked as extreme or not. Alternatively, I can define extreme bullish (bearish) days depending on whether the daily market excess returns are greater (less) than a certain cutoff, for example, 1.5% (-1.5%). A sentiment strategy based on extreme positive sentiment with this certain cutoff of 1.5%

anticipate that investors are more excited in the extreme bullish market while more pessimistic in the extreme bearish market. As a result, a sentiment strategy based on these extreme signals is expected to generate higher returns, and Panel B of Table 5 confirms this expectation. For example, a sentiment strategy based on extreme positive sentiment in the stock market generates 23.3 bps per day on average, whereas a strategy based on extreme positive sentiment in the stock market and extreme negative sentiment in the commodity market results in 54.8 bps. Again, both are significant at the 1% level.

Although the proposed long-short strategy involves two liquid securities, a commodity ETF and Spider, performance of the strategy might still be exposed to economic risk factors related to the fundamental difference between the commodity market and the stock market. To take this possibility into consideration, I regress performance of long-short sentiment strategies on the return difference between the S&P 500 Index and the commodity index which the ETF tracks. According to the position of an ETF's trading signal in the timeline, I further classify each strategy into three mutually exclusive groups depending on whether a sentiment signal is fresh new, in the middle of a consecutive signal sequence, or at the tail of a consecutive signal sequence. I pool daily performance of each strategy across all ETFs in each group and perform a regression in Table 6. The strategy following the fresh positive sentiment in the stock market generates positive raw returns of 43 bps, and I can have such a strategy for 1,427 fund-days over the sample period. Although the fundamental difference between the stock and commodity markets explains about half of the returns, the strategy still delivers a significant alpha of 25.2 bps.

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in the stock market generates significant 36.8 bps per day on average and its long position contributes 24.2 bps. I can have such a strategy for 2,842 fund-days over the sample period. In short, the main result will not change if the alternative definition of extreme sentiment signals is used. The result is available upon the request.

Passively managed ETFs are neither difficult to value nor hard to arbitrage. As sentiment wanes (perhaps spurred by fundamental news or an absence thereof) or as arbitrage forces eventually accumulate to correct mispricing, I anticipate that the sentiment-driven demand for commodity ETFs is a short-term phenomenon and is likely to be corrected quickly. Table 6 confirms this conjecture. Only strategies following fresh positive sentiment in the stock market or following fresh positive sentiment in the stock market and fresh negative sentiment in the commodity market can generate significantly positive alphas.

To gauge the magnitude of the sentiment strategy performance and compare it to the existing literature, I focus on the single-market strategy which delivers a significant alpha of 9.7 bps per day or 1.94% per month. In a strategy based on the sentiment level in the preceding month, Baker and Wurgler (2007) show that monthly returns average about 1.25% for the equal-weighted market portfolio following the months when the sentiment level is within one standard deviation away from its historical average. In an out-of-sample strategy based on the normalized net exchange between equity funds and bond funds, a proxy for the sentiment, Ben-Rephael, Kandel, and Wohl (2012) show that monthly returns average about 1.37% for their "in the stock market" strategy. Although sentiment measures are not identical and investment strategies vary across studies, the alphas of strategies based on commodity ETFs and SPY in this study seem promising. However, the caution of performing daily investment strategies needs to be made and the concern of potential trading costs will be addressed next.

VI. Analyses of Trading Costs

Trading costs in a long-short investment that trades at the open and close of the day are not trivial. I investigate trading costs incurred in investment strategies following fresh new sentiment signals since only these strategies are profitable shown in Table 6. Given the fact that investors have different capital capacity and trading position, it is unlikely to have an accurate estimate about trading costs for each strategy. Instead, I calculate the highest trading cost (the cap of trading costs) such that raw returns or alphas of investment strategies after deducting the cap can still be positively different from zero at the significance level of 5% in a two-tail test.[17] By doing this way, I am able to take an important aspect—volatility of performance or the standard error of alpha estimate—into consideration. As a reference comparison, I also calculate the bid-ask spread, the ask price minus the bid price on an ETF at the end of the day divided by the ETF closing price, for each commodity ETF and SPY in each day. Since each strategy is a long-short investment strategy, I add the daily bid-ask spread of SPY to each commodity ETF's spread and report the aggregate bid-ask spread. I pool daily bid-ask spreads of all commodity ETFs in each strategy period and report the median and the average of aggregate bid-ask spreads for each investment strategy.

Table 7 shows that only strategies following fresh positive (extreme positive) sentiment in the stock market are plausibly profitable as long as trading costs do not exceed 16.3 bps (19.1 bps) when I consider the alphas.[18] Over the fund-days when these two strategies are conducted, the median of closing bid-ask spreads is 12.1 bps and 13 bps, respectively. In an un-reported table, if the average of daily bid-ask spreads is calculated over the sample period for each ETF first, the median of daily bid-ask spreads among 24 non-leveraged/non-inverse commodity ETFs

[17] The cap of trading costs is defined as $\mu - TIN(0.975, n-1) \times \frac{\sigma}{\sqrt{n}}$ or $\hat{\alpha} - TIN(0.975, n-2) \times \sigma_{\hat{\alpha}}$, where n is the number of observations and *TIN(0.975, k)* is the critical value associated with the cumulative probability of 0.975 in the Student's t distribution with k degrees of freedom. The average performance is indicated by μ while σ is its sample standard deviation.

[18] If extreme bullish days are defined as the days that daily market excess returns are greater than a certain cutoff of 1.5% (see the discussion in Footnote 14), a sentiment strategy following fresh extreme positive sentiment in the stock market generates a significant alpha of 38 bps. The cap of trading costs for this strategy is 21.7 bps while the median of closing bid-ask spreads over 519 fund-days in which I have such a strategy is 13.8 bps.

is 13.9 bps. The median of daily bid-ask spreads of SPY during the sample period is 0.8 bps. The result seems to indicate that strategies following fresh positive (extreme positive) sentiment in the stock market offer attractive alphas which far exceed the cap of trading costs and are profitable in more than half of fund-days.

VII. Robustness Check

I have performed sentiment strategies based on fund-days individually. I further examine the effects of sentiment in predicting future returns on the basis of portfolios in Table 8. In each long-short sentiment strategy described in the previous section, at the beginning of each day, I form three portfolios by including ETFs that have consecutive trading signals over the prior 1-, 2-, and 3-day intervals. Each portfolio is composed of pairs of a commodity ETF and Spider in a long-short position according to the prior consecutive sentiment signals. Using ETFs' share returns, I calculate daily performance for each ETF for up to five days following the trading signal. To increase the power of the tests, I construct overlapping portfolios by following the methodology used in Jegadeesh and Titman (1993).[19] Each portfolio is equally weighted and held for up to five days following the portfolio formation. For each holding period, I regress the portfolio's daily performance on the 4-factor (Fama-French 3 factors plus a momentum) portfolios retrieved directly from the French website and report the intercept, which is in a percentage format.

[19]In any given day *t*, the strategies hold a series of portfolios that are selected in the current day as well as in the previous *K*-1 days, where *K* is the holding period. Specifically, a bull strategy that takes a long position on a commodity ETF and a short position on SPY on the basis of consecutive bullish signals over the past *J* days and holds them for *K* days. For instance, for a five-day holding strategy for positive sentiment in the stock market over the prior day, a Friday portfolio comprises commodity ETFs with the prior bullish stock signal on Thursday, Wednesday, and so on up to the previous Friday. Each day cohort is assigned an equal weight in this portfolio.

On average, there are about 14 commodity ETFs in a portfolio formed by an investor sentiment signal in the stock market. Over the sample period, 54% of the days are preceded by one-day bullish sentiment in the stock market and 45% of the days are preceded by one-day bearish sentiment. If a sentiment strategy cannot be performed on a regular basis, results from an overlapping portfolio strategy are less meaningful. In this regard, I focus only on the single-market and cross-market strategies based on sentiment in the prior day. On average, the portfolio in the single-market sentiment strategy based on the prior-day signal generates the 4-facor alpha of 17.2 bps, and its performance decays quickly to 4.4 bps in five days. A similar result is shown in the cross-market sentiment strategy.

VIII. Conclusion

This study explores how investor sentiment in the stock market affects prices of commodity ETFs. I provide quantitative evidence that the tracking errors of commodity ETFs differ in the bullish versus the bearish stock market, and thus the aggregate tracking error of commodity ETFs is sensitive to sentiment measures commonly used in the literature. I further exploit a profitable trading strategy based on investor sentiment in the stock market and commodity markets.

I use commodity ETFs and Spider in a long-short strategy according to the prior sentiment signals. The sentiment-driven demand for commodity ETFs exists and is a short-term phenomenon. Only strategies following fresh positive or extreme positive sentiment in the stock market can generate significantly positive index-adjusted alphas of 25.2 bps and 32.1 bps per day on average, respectively. These strategies indeed offer attractive alphas which far exceed the cap of trading costs and are profitable in more than half of fund-days. Following the methodology used in Jegadeesh and Titman (1993), I document that the portfolio in the single-market sentiment strategy based on the prior-day signal generates the 4-factor alpha of 17.2 bps, and its performance decays speedily to 4.4 bps in five days.

A recent study by Ben-David, Franzoni, and Moussawi (2014) documents that stocks owned by equity ETFs exhibit significantly higher intraday and daily volatility due to arbitrage activity between equity ETFs and the underlying stocks. Will such arbitrage trades still propagate the liquidity shocks from commodity ETF prices to the underlying securities, given that both are traded in different markets? I leave this interesting question for future research.

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Table 1 Summary Statistics

A tracking error of an ETF is its gross return minus its benchmark index return. To calculate gross returns, the table retrieves historical expense ratios of an ETF from SEC's EDGAR database and adds the ratios to the ETF's share returns on a daily basis. The benchmark index an ETF tracks is identified based on released prospectuses. This table calculates daily tracking errors for an ETF since its inception and record the quartile distribution of tracking errors (TEs) for each commodity ETF. The daily tracking errors are decomposed into mispricing component and imperfect index replication component. The mispricing component is the ETF's share returns minus its net asset value (NAV) returns while the imperfect index replication component is its NAV returns plus expense ratios minus its benchmark index returns. The sample period starts on November 18, 2004, the first inception date in commodity ETFs, and ends by December 31, 2011. In Panel A, the cross-sectional average of quartile distributions of TEs and the two components are reported. The table also reports the average (AVG) and standard deviation (STD) of the means of TEs/components across these 33 ETFs. For a reference comparison, this table reports the same statistics for Spider (symbol: SPY), an ETF tracking S&P 500 Index, over the same sample period. In Panel B, the table calculates volatility of tracking errors and components for each ETF over its lifetime, and reports the quartile distribution based on the volatilities of all commodity ETFs. A tracking-error (component) volatility of an ETF is the standard deviation of its tracking errors (components). The table also reports the average and standard deviation of the volatilities across these ETFs. To construct the quartile distribution of volatilities for SPY, the table first calculates the volatility of tracking errors and components of SPY over a period of each ETF's lifetime and then reports the statistics. All, except for number of ETFs, are in a percentage format.

	# of ETFs	**Quartile Distribution**					**AVG**	**STD**
		Lowest	**25%**	**50%**	**75%**	**Highest**		
				Panel A0. Tracking Errors				
Commodity	33	-15.653	-1.233	-0.008	1.190	14.267	-0.022	0.049
SPY		-1.621	-0.073	-0.001	0.070	2.939	0.000	0.217
				Panel A1. Component of Mispricing				
Commodity	33	-11.867	-0.710	0.003	0.701	8.015	-0.007	0.019
SPY		-1.627	-0.071	-0.002	0.069	2.959	0.000	0.218
				Panel A2. Component of Imperfect Index Replication				
Commodity	33	-12.563	-0.599	-0.003	0.576	13.425	-0.014	0.040
SPY		-0.527	-0.001	0.000	0.001	0.531	0.000	0.022
				Panel B0. Volatility of Tracking-Error				
Commodity	33	0.596	1.345	1.905	3.021	6.950	2.566	1.731
SPY		0.063	0.079	0.164	0.241	0.250	0.165	0.078
				Panel B1. Volatility of Mispricing Component				
Commodity	33	0.374	0.740	0.875	1.532	5.802	1.489	1.331
SPY		0.063	0.078	0.164	0.240	0.249	0.164	0.078
				Panel B2. Volatility of Imperfect Index Replication Component				
Commodity	33	0.080	0.407	1.202	1.867	7.170	1.746	1.884
SPY		0.004	0.005	0.006	0.006	0.022	0.007	0.004

Table 2 Statistics of Daily Tracking Errors in Contrast Periods

The calculation of daily tracking errors and the components for an ETF is described in Table 1. The table classifies the entire sample period into two contrast periods, bullish-and bearish-period, according to daily excess returns of the stock market. The bullish (bearish) period includes days when RMRF is positive (negative), where RMRF is one of the Fama-French three factors. In each period, the table constructs and reports the statistics of the quartile distribution in a way same as in Table 1.

	# of ETFs	Quartile Distribution					AVG	STD
		Lowest	**25%**	**50%**	**75%**	**Highest**		
				Bullish Period				
				Panel A0. Tracking Errors				
Commodity	33	-14.274	-1.089	0.084	1.236	12.772	0.096	0.584
SPY		-1.399	-0.093	-0.020	0.043	2.939	-0.025	0.206
				Panel A1. Component of Mispricing				
Commodity	33	-11.407	-0.603	0.070	0.741	7.786	0.078	0.294
SPY		-1.374	-0.091	-0.017	0.045	2.959	-0.023	0.206
				Panel A2. Component of Imperfect Index Replication				
Commodity	33	-11.014	-0.590	0.005	0.598	11.808	0.018	0.455
SPY		-0.364	-0.003	-0.001	0.000	0.362	-0.002	0.017
				Bearish Period				
				Panel A0. Tracking Errors				
Commodity	33	-12.219	-1.399	-0.113	1.067	12.167	-0.164	0.731
SPY		-1.621	-0.042	0.021	0.102	1.556	0.031	0.228
				Panel A1. Component of Mispricing				
Commodity	33	-6.838	-0.832	-0.080	0.610	6.125	-0.112	0.376
SPY		-1.627	-0.045	0.018	0.100	1.555	0.028	0.229
				Panel A2. Component of Imperfect Index Replication				
Commodity	33	-9.601	-0.654	-0.017	0.558	9.739	-0.052	0.562
SPY		-0.527	0.000	0.001	0.004	0.531	0.003	0.027

Table 3 Cross-Market Tests on Individual Tracking Errors

This table tests for whether the mean of daily tracking errors (TEs) of an ETF differs in two markets, the stock market and the commodity market. In the stock market, a bullish (bearish) day is the day when the daily RMRF, one of the Fama-French three factors, is positive (negative). In a commodity market, a bullish (bearish) day for an ETF is the day when the daily return on an index tracked by the ETF minus daily one-month T-bill rate is positive (negative). For each ETF since its inception, the cross-market classification results in four periods: (1) bullish stock market and bullish commodity market (BullSBullC), (2) bullish stock market and bearish commodity market (BullSBearC), (3) bearish stock market and bullish commodity market (BearSBullC), and (4) bearish stock market and bearish commodity market (BearSBearC). For each ETF, the table tests for whether the mean of the TEs is identical in two contrast periods: BullSBullC versus BearSBullC as well as BullSBearC versus BearSBearC. For Spider (SPY) as a reference, the table calculates the means and variances of its TEs in a period defined by each ETF and test for whether the mean of SPY's TEs is identical in two contrast periods: BullSBullC versus BullSBearC as well as BearSBullC versus BearSBearC. The table lists ETFs that have the significant difference and classify them according to the p-value (1%, 5%, or 10%) of the tests. For SPY, the table lists ETFs for which the period is defined and SPY has the significant difference in the tests. To consider that the population variances may not be equal in two periods, the table uses the modified t-test according to Satterthwaite's procedure described by Anderson and Bancroft (1952, p. 83).

p-value	**#**	**Ticker Symbols of Commodity ETFs**
Panel A: H_0: The mean of TEs of an ETF is identical in both **BullSBullC** and **BearSBullC**.		
$p \leq 1\%$	25	USCI,GLD,IAU,DBC,SLV,USO,GSG,DBE,DBP,DBS,DBA,DBO,DGL, DBB,UCD,CMD,UCO,SCO,GLL,ZSL,AGQ,SIVR,DNO,PPLT,PALL
$p \leq 5\%$	2	USL,UGL
$p \leq 10\%$	2	SGOL,UNL
Panel B: H_0: The mean of TEs of an ETF is identical in both **BullSBearC** and **BearSBearC**.		
$p \leq 1\%$	22	USCI,GLD,IAU,DBC,SLV,USO,GSG,DBE,DBO,DBB,UNG,GCC,UCD, CMD,UCO,SCO,ZSL,AGQ,SIVR,DNO,PPLT,PALL
$p \leq 5\%$	6	DBS,DBA,UGL,GLL,SGOL,UNL
$p \leq 10\%$	3	DBP,USL,CORN
Panel C: H_0: The mean of SPY's TEs is identical in both **BullSBullC** and **BullSBearC**.		
$p \leq 1\%$	0	
$p \leq 5\%$	2	SIVR, PPLT
$p \leq 10\%$	0	
Panel D: H_0: The mean of SPY's TEs is identical in both **BearSBullC** and **BearSBearC**.		
$p \leq 1\%$	2	UGL,GLL
$p \leq 5\%$	3	ZSL,AGQ,CORN
$p \leq 10\%$	4	SLV,USO,DBB,SIVR

Table 4 The Link between Aggregate Tracking Errors and Investor Sentiments

The calculation of daily tracking errors for an ETF is described in Table 1. This table calculates two daily liquidity measures, Amihud illiquidity and turnover, for each ETF. Amihud (2002) illiquidity is the absolute return divided by the dollar volume. The turnover is the ratio of trading volume to the number of shares outstanding. The investor sentiment measure (SENT) is constructed by Baker and Wurgler (2007) and directly retrieved from Wurgler's website. The sentiment measure is only available annually and monthly up to December 2010. Thus daily tracking errors and liquidity measures are converted to monthly data. The table averages the daily data for each month for each ETF and then calculates the cross-sectional average of monthly data for the entire commodity ETF. To avoiding the confounding, the table excludes leveraged and inversed ETFs from the analysis for this table. There are 24 non-leveraged/non-inversed commodity ETFs in total and 74 months between November 2004 and December 2010. Monthly tracking errors of the commodity ETF portfolio are regressed against the liquidity measures and sentiment measures. To control the conditions of the general economy and the stock market, the table adds monthly RMRF, one of the Fama-French three factors, to the independent variables. Both tracking errors and RMRF are in a percentage format. The t-value associated with a coefficient estimate is in parentheses. As a reference, the tracking errors (TEs) of Spider are regressed against the same variables. TEs and liquidity measures for Spider are constructed in the same way to obtain monthly data. For brevity, the table only reports results of two models for SPY in the last two columns. Note that Amihud illiquidity is defined as 10^6 |r| / \$Vol for commodity ETFs and as 10^8 |r| / \$Vol for Spider. Panel A presents regression results while Panel B presents statistics for the regression variables. In Panel C, the analysis is extended to other investor sentiment measures, which include monthly closed-end equity fund discounts (CEFD), monthly Michigan Consumer Sentiment Index (CSI), and daily Chicago Board Options Exchange Market Volatility Index (VIX). Daily VIX values are converted to monthly data by simply averaging daily values over a month. In Panel C, the dependent variable of compounded tracking errors is added. For each commodity ETF in each month, the compounded tracking error is the compounded daily returns on the ETF minus the compounded daily returns on its benchmark over the month. The dependent variable is the cross-sectional average of monthly data for the entire commodity ETF. The data of CEFD end at February 2011 while the data of CSI and VIX end at December 2011.

Panel A. Regression Results

Independent Variable	Dependent Variable					
	Tracking Errors of Commodity ETFs				TEs of SPY	
	Model 1	Model 2	Model 3	Model 4	Ref 1	Ref 2
Constant	-0.015	0.007	-0.028	-0.005	0.0002	0.002
	(-2.02)	(0.52)	(-2.81)	(-0.39)	(0.10)	(0.32)
RMRF	0.002	0.001	0.003	0.002	-0.0003	-0.0004
	(1.06)	(0.68)	(1.71)	(1.43)	(-1.03)	(-1.10)
Turnover		-0.308		-0.341		-0.008
		(-2.06)		(-2.33)		(-0.65)
Amihud Illiquidity			0.746	0.836		5.994
			(1.91)	(2.20)		(0.07)
SENT	0.064	0.058	0.065	0.058	-0.0009	-0.0008
	(2.53)	(2.33)	(2.59)	(2.37)	(-0.17)	(-0.14)
Adjusted R^2	6.058	10.153	9.440	14.809	0.00	0.00
# Observations (Months)	74	74	74	74	74	74

Table 4—*Continued*

Panel B. Statistics for the Regression Variables in Panel A over 74 Months

			Commodity ETFs			Spider (SPY)		
Variable	SENT	RMRF	TE	Turnover	Amihud	TE	Turnover	Amihud
AVG	-0.027	0.320	-0.016	0.070	0.016	0.00007	0.289	0.00005
STD	0.301	4.851	0.066	0.050	0.020	0.012	0.150	0.00002

Panel C. Regression Results Based on Other Investor Sentiment Measures

Independent Variable	**Dependent Variable: Commodity ETFs**							
	Average Tracking Errors				**Compounded Tracking Errors**			
Constant	-0.005	0.004	-0.094	0.022	-0.242	-0.068	-1.795	0.225
	(-0.39)	(0.33)	(-1.82)	(1.27)	(-0.94)	(-0.27)	(-1.84)	(0.70)
RMRF	0.002	0.002	0.002	0.001	0.063	0.060	0.046	0.039
	(1.43)	(1.33)	(1.12)	(0.81)	(2.05)	(2.00)	(1.75)	(1.47)
Turnover	-0.341	-0.321	-0.327	-0.341	-4.036	-3.652	-3.976	-4.277
	(-2.33)	(-2.23)	(-2.37)	(-2.52)	(-1.46)	(-1.35)	(-1.53)	(-1.67)
Amihud Illiquidity	0.836	1.262	1.113	1.512	16.681	24.358	21.235	27.211
	(2.20)	(3.11)	(2.84)	(3.14)	(2.32)	(3.18)	(2.88)	(2.98)
SENT	0.058				1.000			
	(2.37)				(2.17)			
SENT_CEFD		-0.004				-0.068		
		(-2.60)				(-2.48)		
SENT_CSI			0.001				0.019	
			(1.78)				(1.68)	
SENT_VIX				-0.002				-0.029
				(-2.10)				(-1.79)
Adjusted R^2	14.809	15.953	11.706	12.986	11.655	13.270	9.213	9.627
# Observations (Months)	74	76	86	86	74	76	86	86

Table 5 Investment Strategies Based on Cross-Market Investor Sentiments

In the stock market, a bullish (bearish) day is the day when the daily RMRF, one of the Fama-French three factors, is positive (negative). In a commodity market, a bullish (bearish) day for an ETF is the day when the daily return on an index tracked by the ETF minus daily one-month T-bill rate is positive (negative). The table further classifies the extreme bullish (bearish) market for which the daily excess returns on the market are ranked at the top (bottom) third over the entire bullish (bearish) market period. For each commodity ETF, two long-short investment strategies are performed depending on signals in a single market or cross-markets. In the single-market strategy, at the beginning of each day, the table longs an ETF and shorts SPY if the stock market was bullish the prior day, whereas the table shorts an ETF and longs SPY if the stock market was bearish the prior day. In the cross-market strategy, at the beginning of each day, the longs an ETF and shorts SPY if the stock market was bullish and the ETF market was bearish the prior day (BullSBearC). The table shorts an ETF and longs SPY if the stock market was bearish and the ETF market was bullish the prior day (BearSBullC). Using ETFs' share returns, the table calculates daily performance for each strategy for each ETF. Panel A reports the distribution of average performance of each strategy on the basis of individual commodity ETFs. Panel B pools daily performance of each strategy across all commodity ETFs and reports the performance distribution based on all fund-days. Numbers in performance are in a percentage format. The table reports the t-value associated with the test if the average performance is zero. As a reference, the table also reports the performance of a plain strategy, simply longing an ETF and shorting SPY daily, without relying on any investment signal. The average performance of each strategy is further split into performance attributed to each of the long and short position by the strategy. The significance level of returns equaling to 0in either long or short position is indicated by *** (1%), ** (5%), and * (10%).To avoid the confounding, leveraged and inverse ETFs are excluded from the analysis for this table. The sample period from November 18, 2004, to December 31, 2011, contains 24 non-leveraged/non-inverse commodity ETFs.

Strategy	**#Obs**	**Quartile Distribution**			**AVG**	**STD**	**t**	**AVG**	
		25%	**50%**	**75%**				**Long**	**Short**
			Panel A. On the basis of individual ETFs						
Without Signals	24	-0.031	0.013	0.061	0.007	0.074	0.48	0.032**	-0.025***
With Signals									
Single-Market	24	0.109	0.150	0.182	0.141	0.097	7.10	0.103***	0.038***
Cross-Market	24	0.147	0.166	0.262	0.199	0.112	8.68	0.190***	0.010
			Panel B. On the basis of pooling observations across all ETFs						
Without Signals	25690	-1.023	0.020	1.095	0.010	2.102	0.80	0.031**	-0.020**
With Signals									
Single-market	25525	-0.981	0.069	1.142	0.156	2.097	11.91	0.107***	0.049***
Bullish	13861	-0.888	0.076	1.089	0.152	1.950	9.18	0.115***	0.037***
Extreme Bullish	5337	-0.909	0.123	1.256	0.233	2.212	7.69	0.169***	0.064***
Bearish	11664	-1.101	0.061	1.206	0.161	2.260	7.71	0.098***	0.064***
Extreme Bearish	4669	-1.027	0.269	1.533	0.391	2.541	10.50	0.220***	0.171***
Cross-Market	11068	-1.000	0.125	1.216	0.200	2.125	9.92	0.181***	0.019
BullSBearC	5839	-0.883	0.163	1.263	0.245	2.041	9.18	0.228***	0.017
Extreme BullSBearC	684	-1.159	0.414	2.040	0.548	2.749	5.22	0.584***	-0.036
BearSBullC	5229	-1.120	0.075	1.176	0.151	2.215	4.92	0.129***	0.021
Extreme BearSBullC	691	-1.238	0.127	1.658	0.375	2.840	3.47	0.209**	0.166*

Table 6 Alphas of Investment Strategies

Table 5 defines investment strategies. For each commodity ETF, at the beginning of each day, the table performs long-short investment strategies depending on the prior-day bull/bear signals of the stock and commodity markets. According to the position of an ETF's trading signal in the timeline, the table further classifies each strategy into three mutually exclusive groups. Strategies following signals that are fresh new are labeled as the "1st Signal" group. Strategies following the signals that are 2nd or 3rd in the sequence of consecutive same signals are labeled as the group of "2≤ #Consecutive Signals ≤3." Strategies following the signals preceded by at least three consecutive same signals are labeled as the group of " #Consecutive Signals >3." Using ETFs' share returns, the table calculates daily performance for each strategy for each ETF. The table pools daily performance of each strategy across all ETFs in each group and performs a regression. The strategy performance is regressed against the return difference between the S&P 500 index and the underlying index the ETF tracks. Note that when the strategy longs SPY and shorts an ETF in the Y variable, the X variable will be the S&P 500 index returns minus returns on the index that the ETF tracks. When the strategy longs an ETF and shorts SPY in the Y variable, the X variable will be returns on the index the ETF tracks minus the S&P 500 index returns. In the brackets, the table reports the average of raw returns in strategies and numbers of observations for each group. Alphas, returns, and Adjusted R^2 ($AdjR^2$) are all in a percentage format. This table only analyzes non-leveraged/non-inverse commodity ETFs over the sample period from November 18, 2004, to December 31, 2011. The significance level of returns/alphas equaling to 0 or betas equaling to 1 is indicated by *** (1%), ** (5%), and * (10%).

$$\tilde{Y} = \alpha + \beta\tilde{X} + \tilde{\varepsilon}$$

$$Where\ \tilde{X} = \tilde{R}_{Index\ tracked\ by\ the\ ETF} - \tilde{R}_{S\&P500} \quad if \quad \tilde{Y} = \tilde{R}_{ETF} - \tilde{R}_{SPY}$$

$$\tilde{X} = \tilde{R}_{S\&P500} - \tilde{R}_{Index\ tracked\ by\ the\ ETF} \quad if \quad \tilde{Y} = \tilde{R}_{SPY} - \tilde{R}_{ETF}$$

Strategy	1st Signal			2≤ #Consecutive Signals ≤3			#Consecutive Signals >3		
	α	β	$AdjR^2$	A	B	$AdjR^2$	α	β	$AdjR^2$
Single-market	0.097***	0.514***	37.46	0.008	0.506***	35.21	-0.047	0.583***	42.32
	[0.237***	/ 3428]		[0.146***	/19398]		[0.130***	/ 2699]	
Bullish	0.252***	0.558***	44.57	-0.003	0.477***	31.45	-0.042	0.451***	25.44
	[0.430***	/ 1427]		[0.126***	/10689]		[0.083**	/ 1745]	
Ex Bullish	0.321***	0.574***	43.11	0.004	0.473***	31.94	0.052	0.572***	33.23
	[0.659***	/ 712]		[0.157***	/ 4198]		[0.270**	/ 427]	
Bearish	-0.011	0.458***	29.77	0.024	0.532***	38.88	-0.014	0.648***	52.07
	[0.099**	/ 2001]		[0.169***	/ 8709]		[0.218**	/ 954]	
Ex Bearish	-0.060	0.474***	35.30	0.079**	0.510***	38.63	-0.006	0.746***	53.53
	[0.229***	/ 617]		[0.462***	/ 3598]		[0.047	/ 454]	
Cross-Market	0.075***	0.537***	38.44	-0.006	0.474***	31.80	0.218	0.646***	41.71
	[0.214***	/ 5414]		[0.180***	/ 5580]		[0.759***	/ 74]	
BullSBearC	0.113***	0.532***	39.34	0.041	0.384***	24.22	0.170	0.562***	37.56
	[0.284***	/ 2723]		[0.205***	/ 3067]		[0.583***	/ 49]	
Ex BullSBearC	0.197	0.526***	35.20	0.161	0.335***	27.66	0.036	0.646***	94.89
	[0.711***	/ 336]		[0.387***	/ 343]		[0.711	/ 5]	
BearSBullC	0.037	0.544***	37.35	-0.049	0.573***	40.35	0.413	0.666**	40.87
	[0.143***	/ 2691]		[0.149***	/ 2513]		[1.105	/ 25]	
Ex BearSBullC	0.201*	0.635***	51.31	0.061	0.496***	31.09	2.694***	0.498***	99.98
	[0.407**	/ 310]		[0.301**	/ 378]		[6.419***	/ 3]	

Table 7 Trading Costs of Investment Strategies

Extending analyses on investment strategies following fresh new signals as defined in Table 6, This table calculates the cap of trading costs such that raw returns or alphas of the investment strategies after deducting the cap can still be positively different from zero at the significance level of 5% in a two-tail test. The label of NA indicates that such a cap does not exist. The table calculates the bid-ask spread,(closing ask - closing bid)/closing price, for each commodity ETF and SPY in each day. Since each strategy is a long-short investment strategy, the table adds the daily bid-ask spread of SPY to each commodity ETF's spread in the reported column. The table pools daily bid-ask spreads of all commodity ETFs in each strategy period and reports the median and the average of bid-ask spreads for each investment strategy. The regression used in strategy performance analysis is re-stated below. Alphas, returns, adjusted R^2 (AdjR^2), and bid-ask spreads are all in a percentage format. This table only analyzes non-leveraged/non-inverse commodity ETFs over the sample period from November 18, 2004, to December 31, 2011. The significance level of returns/alphas equaling to 0 or betas equaling to 1 is indicated by *** (1%), ** (5%), and * (10%).

$$\tilde{Y} = \alpha + \beta\tilde{X} + \tilde{\varepsilon}$$
$$Where\ \tilde{X} = \tilde{R}_{Index\ tracked\ by\ the\ ETF} - \tilde{R}_{S\&P500} \quad if \quad \tilde{Y} = \tilde{R}_{ETF} - \tilde{R}_{SPY}$$
$$\tilde{X} = \tilde{R}_{S\&P500} - \tilde{R}_{Index\ tracked\ by\ the\ ETF} \quad if \quad \tilde{Y} = \tilde{R}_{SPY} - \tilde{R}_{ETF}$$

Strategy	# Fund-Days	Raw Returns $E(\tilde{Y})$	α	β	AdjR^2	Cap of Trading Costs		Closing Bid-Ask Spreads	
						Raw Returns	α	Median	AVG
Single-market	3428	0.237***	0.097***	0.514***	37.46	0.170	0.044	0.115	0.209
Bullish	1427	0.430***	0.252***	0.558***	44.57	0.311	0.163	0.121	0.218
Extreme Bullish	712	0.659***	0.321***	0.574***	43.11	0.489	0.191	0.130	0.246
Bearish	2001	0.099**	-0.011	0.458***	29.77	0.023	N.A.	0.111	0.203
Extreme Bearish	617	0.229***	-0.060	0.474***	35.30	0.071	N.A.	0.116	0.294
Cross-Market	5414	0.214***	0.075***	0.537***	38.44	0.158	0.031	0.122	0.245
BullSBearC	2723	0.284***	0.113***	0.532***	39.34	0.203	0.050	0.125	0.262
Extreme BullSBearC	336	0.711***	0.197	0.526***	35.20	0.391	N.A.	0.158	0.548
BearSBullC	2691	0.143***	0.037	0.544***	37.35	0.066	N.A.	0.119	0.227
Extreme BearSBullC	310	0.407**	0.201*	0.635***	51.31	0.090	N.A.	0.149	0.364

Table 8 The 4-Factor Alphas of Investment Strategies

Table 5 defines investment strategies. In each strategy, at the beginning of each day, this table forms three portfolios by including ETFs that have consecutive trading signals over the prior 1-, 2-, and 3-day intervals. Using ETFs' share returns, the table calculates daily performance for each ETF for up to five days following the trading signal. To increase the power of the tests, the table constructs overlapping portfolios by following the methodology used in Jegadeesh and Titman (1993). Each portfolio is equally weighted and held for up to five days following the portfolio formation. For each holding period, the portfolio's daily performance is regressed against the 4-factor (Fama-French 3 factors plus a momentum) portfolios retrieved directly from the French website and the intercept in a percentage is reported. This table only analyzes non-leveraged/non-inverse commodity ETFs. The significance level of alphas equaling to zero is indicated by *** (1%), ** (5%), and * (10%). The table also reports the average number of ETFs in each portfolio and the percentage of days for which a strategy is executed over the entire sample period from November 18, 2004, to December 31, 2011.

Strategy	# prior consecutive signals	# ETFs	% days covered	Holding Days				
				+1	+2	+3	+4	+5
Single-market	1	14	99	0.172***	0.116***	0.072***	0.048**	0.044**
	2	15	47	0.260***	0.257***	0.220***	0.189***	0.172***
	3	15	22	0.316***	0.309***	0.309***	0.237***	0.212***
Bull	1	14	54	0.141***	0.140***	0.140***	0.141***	0.140***
	2	14	28	0.158***	0.156***	0.156***	0.156***	0.155***
	3	15	14	0.083	0.081	0.080	0.081	0.081
Bear	1	14	45	0.110**	0.110**	0.110**	0.110**	0.110**
	2	15	19	0.218***	0.218***	0.218***	0.218***	0.218***
	3	15	8	0.305**	0.305**	0.305**	0.305**	0.305**
Cross-Market	1	7	87	0.187***	0.133***	0.086***	0.048**	0.052**
	2	4	29	0.344***	0.320***	0.239***	0.213***	0.200***
	3	3	8	0.346*	0.359*	0.363*	0.337*	0.257
BullSBearC	1	7	46	0.166***	0.151***	0.142***	0.126***	0.132***
	2	4	17	0.239**	0.201**	0.188**	0.185**	0.184**
	3	3	5	-0.138	-0.158	-0.160	-0.160	-0.160
BearSBullC	1	7	40	0.108*	0.114**	0.127**	0.126**	0.120**
	2	4	13	0.261**	0.250**	0.266**	0.295**	0.293**
	3	3	3	0.444	0.478	0.487	0.487	0.363

Appendix 1 List of Commodity ETFs

The sample period in this study starts on November 18, 2004, the first inception date in commodity ETFs, and ends by December 31, 2011. Commodity ETFs investing in underlying physical assets directly are indicated by "P" while some using financial instruments to gain exposure to the underlying assets are indicated by "F" in the last column.

Ticker	Name	Inception Date	Type of Assets
AGQ	PROSHARES ULTRA SILVER	20081201	F
CMD	PROSHARE U/S DJ-UBS(AIG) COMMODITY	20081124	F
CORN	TEUCRIUM CORN FUND	20100608	F
DBA	POWERSHARES DB AGRICULTURE FUND	20070105	F
DBB	POWERSHARES DB BASE METALS FUND	20070105	F
DBC	POWERSHARES DB COMMODITY INDEX TRACKING FUND	20060203	F
DBE	POWERSHARES DB ENERGY FUND	20070105	F
DBO	POWERSHARES DB OIL FUND	20070105	F
DBP	POWERSHARES DB PREC METALS FUND	20070105	F
DBS	POWERSHARES DB SILVER FUND	20070105	F
DGL	POWERSHARES DB GOLD FUND	20070105	F
DNO	UNITED STATES SHORT OIL FUND	20090924	F
GCC	GREENHAVEN CONTINUOUS CMDTY	20080124	F
GLD	SPDR GOLD TRUST	20041118	P
GLL	PROSHARES ULTRASHORT GOLD	20081201	F
GSG	ISHARES S&P GSCI COMMODITY-INDEXED TRUST ETF	20060710	F
IAU	ISHARES GOLD TRUST	20050121	P
PALL	ETFS PALLADIUM TRUST	20100108	P
PPLT	ETFS PLATINUM TRUST	20100108	P
SCO	PROSHARE U/S DJ-UBS(AIG) CRUDE OIL	20081124	F
SGOL	ETFS GOLD TRUST	20090909	P
SIVR	ETFS SILVER TRUST	20090724	P
SLV	ISHARES SILVER TRUST	20060421	P
UCD	PROSHARE ULT DJ-UBS(AIG) COMMODITY	20081124	F
UCO	PROSHARE ULT DJ-UBS(AIG) CRUDE OIL	20081124	F
UGL	PROSHARES ULTRA GOLD	20081201	F
UHN	UNITED STATES HEATING OIL LP	20080409	F
UNG	UNITED STATES NATURAL GAS FUND, LP	20070418	F
UNL	UNITED STATES 12 MONTH NATURAL GAS FUND	20091118	F
USCI	UNITED STATES COMMODITY INDEX FUND	20100810	F
USL	UNITED STATES 12 MONTH OIL	20071206	F
USO	UNITED STATES OIL FUND LP	20060410	F
ZSL	PROSHARES ULTRASHORT SILVER	20081201	F