Is there smart money? How information in the futures market is priced into the cross-section of stock returns with delay

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Abstract

We document a new empirical phenomenon in which the positions of managed money (MM) traders, who are sophisticated speculators in the commodity futures market, as disclosed by the CFTC Disaggregated Commitments of Traders (DCOT) reports, can predict the cross-section of commodity producers' stock returns in the subsequent week. A trading strategy based on this finding generates a sizeable alpha that is robust to the Fama-French Five-Factor model, and the mispricing factor model. The results are more pronounced in firms with higher information asymmetry, proxied by analyst dispersion and historical volatility.

JEL codes: G11, G14

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1. Introduction

Is there smart money in the commodity futures market? We answer the question by studying the positions that Managed Money (MM) take in the weekly Disaggregated Commitments of Traders (DCOT) published by the Commodity Futures Trading Commission (CFTC), using a sample period from August 2006 to December 2017. The Managed Money (MM) category of traders in the DCOT reports consists of hedge funds, mutual funds, large ETFs, registered commodity trading advisers (CTAs), registered commodity pool advisers (CPOs), and unregistered funds identified by the CFTC.

Hong and Stein (1999) established that the gradual diffusion of information can explain a variety of predictability patterns of returns, as some investors can process only a subset of publicly available information. The theoretical work by van Nieuwerburgh and Veldkamp (2010) suggests that market participants cannot specialize in every asset as information acquisition and processing is costly. In addition, Menzly and Ozbas (2010) have found that due to investor specialization and market segmentation, value-relevant information diffuses gradually in financial markets; specifically, stocks that are in economically related supplier and customer industries cross-predict each other's returns. Thus, we posit our main conjecture as sophisticated investors who are specialized in commodities (specifically, MM) and who trade in the commodity futures market, would have their voices diluted in the stock market by investors who are not specialized in commodities. Therefore, one would expect that information extracted from the commodity futures market can predict stock returns of commodity producing firms of the same underlying commodity due to gradual information diffusion and market segmentation.

In addition, whether markets are efficient has long concerned academia.[1] If the efficient market hypothesis is true, then one cannot use the signals extracted from the commodity futures market to predict future stock returns in the cross-section, because arbitrageurs would

[1] See among others, Shleifer and Vishny (1997), Fama (1998), Schwert (2003), Chordia, Roll and Subrahmanyam (2008), Jegadeesh and Titman (1993) and Bondt and Thaler (1985)

exploit such predictability.

We find that the information contained in the commodity futures market, namely, the positions of MM traders[2], who are sophisticated speculators, can predict the cross-section of stock returns for commodity producers. In particular, if the DCOT reports an increase in long position, or a decrease in short position, or an increase in net position, or an increase in the ratio of long over short position of MM, then the stock price of producers of the same commodity would increase in the following week. This finding is robust to a variety of measures and weighting schemes. The fact that the commodity market is linked with other financial markets has been documented by Hong and Yogo (2012), in which they find that among other things, high commodity market activity, as measured by high open-interest growth, predicts low bond returns. In other words, Hong and Yogo find that information contained in the commodity futures market as measured by open interest growth, which is an informative signal of future inflation, is priced into the bond market with a delay. We are therefore not surprised that information contained in the positions of managed money in the commodity futures market is priced in the equity market with delay, in the cross-section of commodity producing firms.

We investigate why predictability arises by studying the relation of our results with measures of information asymmetry. We find that our results are stronger in firms with higher information asymmetry as measured by *ex ante* analyst dispersion and 60-day *historical* stock volatility. In addition to informational friction, trading friction can also be regarded as a form of market friction; thus we also investigate whether our predictability results arise due to trading friction, and liquidity in particular, by double-sorting our commodity futures market signal with Amihud's illiquidity measure (Amihud, 2002). We find no evidence that

[2]Our study is made possible with CFTC's decision to publish disaggregated Commitments of Traders (COT) reports for trades after June 13, 2006, which created the MM category of traders. We will elaborate more on this point in Section 3.1.2. According to the CFTC website, the transition from legacy COT reports to disaggregated COT reports was made because the new format provides greater market transparency by including more delineated trader classification categories beyond the two broad categories found in the legacy format. Per CFTC: the COT reports provide a breakdown of open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC.

predictability is stronger (weaker) in firms with higher trading friction. Therefore, we argue that informational, rather than trading friction, contribute to our predictability results.

In addition to finding abnormal return relative to the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model, we show that abnormal return remains even relative to the Stambaugh and Yuan (2016) model, which includes mispricing factors constructed from a broad set of well-known anomalies including momentum, net stock issues, asset growth, investment to assets, distress, O-score, and profitability, among others. However, some return anomalies generate abnormal returns mainly from short-selling overpriced stocks (Stambaugh et al., 2012), and such anomalies may be difficult to be arbitraged away due to short-selling constraints. This is not the case in our particular finding, as the abnormal return (alpha) in our long-short strategy is not solely due to the contribution of the short-leg of the Long-Short portfolio. We also employ a number of empirical methodologies in our analysis, including, single-sort, double-sort, and Fama-Macbeth regressions to confirm the robustness of our baseline results.

To the best of our knowledge, this is the first paper that shows the cross-sectional predictability of commodity producers' stock returns based on the information contained in the commodity futures market. Our contribution is mainly empirical rather than theoretical. We contribute to the literature by, firstly, introducing a robust return predictability phenomenon. Secondly, we report a robust trading strategy with a sizable alpha, that remains even relative to the Stambaugh and Yuan's (2016) mispricing factors model based on 11 prominent anomalies. Thirdly, we shed more light on the extent MM positions in the commodity futures market can predict future stock returns of commodity producers, in that our results are more pronounced in firms with higher information asymmetry, and by doing so we provide more empirical evidence to the literature on investor specialization, market segmentation, informational friction and gradual information diffusion. Our results are also stronger in non-NBER recession periods. Our empirical findings cast further doubts on the efficient market hypothesis.

The rest of the paper is organized as follows: Section 2 reviews the background and related literature. Section 3 discusses how information on traders' positions from the DCOT reports is extracted, matched to the sample of commodity producers stocks, and used as leading signal to form the Long-Short portfolio. We present our empirical results in Section 4, including results on portfolio alpha, single sorting, Fama-Macbeth cross-sectional regressions, and double-sorting. Finally, Section 5 concludes.

2. Background and Literature

Over the past 15 years, financial institutions have substantially increased their exposure to the commodities Ḃy studying the commodity-linked notes, Henderson et al. (2014) have found that financial investor flows have significant impacts on commodity futures prices. However, Sockin and Xiong (2015) have noticed that market participants of the commodity market face severe informational frictions and developed a theoretical model that illustrates the importance of feedback effects of commodity prices, in that a higher commodity price signals stronger economic growth and may motivate goods producers to produce more goods which leads to greater demand for the commodity as inputs. In addition, the paper also argues that the futures price is not merely a shadow of the spot price and instead may contain additional information.

By using monthly industry stock portfolio return data, Hong, Torous and Valkanov (2007) found that industry portfolios including retail, services, commercial real estate, metal, and petroleum, forecast the aggregate stock market by two months. The results support the hypothesis that investors who specialize in trading the broad market index, receive information originating from particular industries such as commercial real estate or commodities like metals and petroleum only with a lag, and therefore the returns of industry portfolios that are informative about macroeconomic fundamentals will lead the aggregate market. Our study, however, involves information for a number of commodities in the futures market, rather than the industry portfolios in stock market, in the construction of our leading signals.

Furthermore, we analyze predictability of firm-level stock return in contrast to aggregate stock return. In addition, we study predictability at the weekly frequency rather than at the monthly frequency, and we specifically find that information pertaining to the MM category in the commodity futures market, as opposed to other categories of traders, have predictive power at the weekly frequency.

Büyükşahin and Robe (2014) show that hedge funds' activity matters for the linkage between equity and commodity market. They also find that, after controlling for macroeconomic and commodity-market fundamentals, comovements in commodity-equity markets are positively related to greater commodity market participation by financial speculators and especially hedge funds, although no such effect exists for other kinds of traders. Their measure of commodity-equity market linkage is based on estimates of the dynamic conditional correlations between the weekly (daily) rates of return on two investable commodity indices (GSCI and DJ-UBS), versus, the unlevered rate of return on the S&P 500 equity index. In addition, Basak and Pavlova (2016) provides a theoretical model in which financialization of commodities would lead to increased correlation between the commodity and equity market returns. Rather than using aggregate indices, we instead investigate the cross-section of commodity-producing firms by using firm-level data, which allows us to employ specifically cross-sectional methodologies such as Jensen's alpha (abnormal return) analysis, single-sort, double-sort, and Fama-Macbeth regressions. Furthermore, we are more concerned with the lead-lag relationship between the two markets and whether the market linkage leads to stock return predictability.

Utilizing COT data in the old format published at bi-weekly or monthly frequency, in which the MM category is not established, Fernandez-Perez et al. (2017) find that the information contained in the commodity futures market can be used to construct two risk-factors useful for predicting long-horizon aggregate equity market return and for the business cycle.

An extensive body of literature relates expected futures returns to the net (long minus

short) positions of hedgers in the futures market, known as hedging pressure. Markets in which hedgers are net short (long) are found to have positive (negative) expected futures returns per Carter et al. (1983), Bessembinder and Seguin (1992), and De Roon et al. (2000). However, by exploring the COT reports in the energy market (including crude oil, unleaded gasoline, heating oil, and natural gas futures contracts), Sanders, Boris and Manfredo (2004) find that there is a positive contemporaneous correlation between commodity market returns and positions held by noncommercial traders and a negative contemporaneous correlation between commercial (commodity producers) positions and commodity market returns; yet, they find that traders' net positions, whether commercial or non-commercial, are generally not useful in predicting weekly energy futures returns; and Sanders et al. (2009) generally confirms the same result in the corn and live cattle futures market. On the other hand, Buchanan et al. (2001) find that non-commercial positions do provide information on the magnitude and direction of weekly price changes in the natural gas futures market. Wang (2003) find that a sentiment index based on positions of commercial and non-commercial traders are useful for predicting S&P 500 index future returns. In addition, by analyzing CFTC's COT reports of major currency futures, Tornell and Yuan (2012) find that the peaks and troughs of commercial traders and non-commercial traders' net positions are generally useful predictors to the evolution of spot exchange rates, and a simple trading strategy based on peaks/troughs proves to be quite profitable. Gorton, Hayashi and Rouwenhorst (2013) find no evidence that participants' positions in futures markets would predict risk premiums on commodity futures. We note that our paper, however, is studying the predictability of returns in the equity market rather than in the futures market.

Lastly, in the equity market, a number of studies have shown that investor sentiment related measures are useful to predict the future development of stock returns, such as trading volume, mutual fund flows, closed-end fund discounts, option implied volatility, and insider trading information (see survey by Baker and Wurgler, 2007). Especially relevant is the study by Han (2007), who find that a sentiment measure defined by the number of long

noncommercial contracts minus the number of short noncommercial contracts in S&P 500 futures (scaled by the total open interest), with data obtained from the COT reports, can help explain the shape of the S&P 500 index option volatility smile and risk-neutral skewness. Specifically, when investor sentiment is more bullish, the index risk-neutral skewness becomes less negative and the index option volatility smile is flatter; and vice versa.

3. Data and Estimation

3.1. Data on Stocks and Commodity Futures

3.1.1. Matching Futures Market Positions with Producers' Stocks

We utilize data from both the stock market and the commodity futures market. We use daily data from the Center for Research in Security Prices (CRSP) for ordinary common stocks (CRSP SHRCD= 10 or 11) traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ (CRSP EXCHCD= 1, 2, or 3).[3] Stock returns are based on the daily individual stock returns with dividends (CRSP RET) adjusted by the delisting returns (CRSP DLRET).

To match commodity-producing firms with the commodities for which the CFTC is collecting Commitments of Traders (COT) information, we follow the simple rule suggested by Gorton and Rouwenhorst (2006). For each commodity that can be associated with a four-digit U.S. Standard Industrial Classification (SIC) code,[4] we associate with that

[3]We exclude firms with SHRCD 12 in our baseline analysis since these corporations are incorporated outside of the United States, i.e., U.S.-listed foreign firms. Thus, their equity prices are subject to additional country-specific risk premia and country-specific shocks to asset prices (Foerster and Karolyi, 1999; Karolyi and Stulz, 2003; Ammer, Vega and Wongswan, 2010). We also exclude foreign firms trading on U.S. exchanges as ADRs (American depositary receipt, SHRCD 31 32). However, we will expand our scope in robustness checks and include SHRCD 12 in Table C.2.

[4]An obvious complication arises when a commodity and a publicly traded commodity producer may not be directly related. In the stock market, commodity-producing companies are not necessarily only involved in the production and processing of a commodity but are also involved in a number of sideline businesses. Hence, this methodology sacrifices precision for the simplicity necessary to build commodity equity-based portfolios. When the SIC code does not offer reliable identification of firms or yield a sufficient number of firms, we hand-pick firms by searching for U.S.-listed companies with their main line of business being the production of a commodity. The hand-picked firms' CRSP PERMNO are listed in the second column of Table B.1

commodity all publicly-traded companies with that same four-digit SIC code. Ultimately, 10 commodities are considered: 2 industrial metals—copper and steel; 3 precious metals—gold, silver and miscellaneous metals; 4 energy commodities—biofuel, oil & gas (crude oil and natural gas), petroleum (unleaded gas) and coal; and one soft commodity—lumber. Reasons for not selecting more soft commodities are twofold. First, based on their SIC codes, too few publicly-traded U.S. producers can be matched to a unique soft commodity, such as coffee, sugar, cattle, cocoa or cotton. Second, most of the listed producers in the soft category are highly diversified firms exposed to several agricultural goods simultaneously, rendering further analysis and construction of the Long-Short portfolio difficult.[5] Table B.1 in the appendix provides the details on the matching of commodities with producers' stocks.[6] Our panel sample consists of 127 firms, on average per week, from August 2006 to December 2017.

3.1.2. CFTC Data and Signal Measures

Our analysis is based on data from August 2006 to December 2017, due to data availability on commodities' disaggregated weekly reportable positions.[7] We use position data and the trader classification from the CFTC's Commitments of Traders (COT) reports. The publicly available Disaggregated Commitments of Traders (DCOT) report provides weekly information on traders' positions for 5 categories of market participants who are active in the commodity futures markets. The 5 trader categories are defined in Table 1. In the legacy format, however, the COT report divided reporting traders into the two broad categories of

[5]In the previous version of this paper, we had a 'Cattle' commodity which we have removed in this version because we think firms involved with cattle business are too diversified in other lines of businesses.

[6]Crude oil and natural gas are grouped together as firms engaged in crude oil production often also engage in natural gas production. For these firms, the signals in the commodities futures market are weighted yearly by the lagged U.S. oil segment and gas segment's total revenue (data retrieved from the U.S. Energy Information Administration). Miscellaneous metals comprise of platinum and palladium which are grouped together as firms engaged in platinum production often also engage in palladium production. In addition, price movements of these two rare metals exhibit a very high degree of correlation in the post 2006 sample.

[7]CFTC regulations require that clearing members, futures commission merchants, and foreign brokers file reports with power granted to the Commission under the Commodity Exchange Act. We use the Disaggregated Futures Only Reports. The CFTC also publishes reports combining traders' positions in futures and option markets. The CFTC began publishing the weekly Futures Only COT reports in a disaggregated format on September 4th, 2009 and provided historical data back to June of 2006 on October 20, 2009.

"commercial" and "non-commercial" traders. The "producer/merchant/processor/user" and "swap dealers" categories combined would equate to the commercial category in the legacy report. Additionally, the "managed money" and "other reporting" groups combined would equate the non-commercial (large speculator) category in the legacy report. DCOT reports have normally been released every Friday at 3:30 p.m. Eastern time with the open interest data as of the end-of-day on the Tuesday of the same week.

It should be noted that according to the CFTC Website: the actual trader category or classification is based on the predominant business purpose self-reported by traders on the CFTC Form 40 and is subject to review by CFTC staff for reasonableness, and failure to answer the form truthfully is a violation of the Commodity Exchange Act and CFTC regulations with violators subject to criminal or administrative sanctions. Furthermore, the traders are able to report business purpose by commodity and, therefore, can have different classifications in the COT reports for different commodities. Due to legal restraints however, the CFTC does not publish information on how individual traders are classified in the COT reports.

Traders' positions for a given market are aggregated across all contract expiration months. Managed money (MM), swap dealers (SW) and other reporting (OR) positions are divided into long (l), short (s) and spreading (sp)—which measures the extent to which a trader holds equal long and short futures positions;[8] whereas producer/merchant/processor/user (PM) and non-reporting (NR) positions are simply divided into long or short.[9] The following relation explains how the market's total open interest (TOI, i.e., the number of futures contracts outstanding) is disaggregated in the DCOT report, and the expressions above each

[8]For example, if a non-commercial trader holds 2,000 long contracts and 1,500 short contracts, 500 contracts will appear in the "long" category and 1,500 contracts will appear in the "spreading" category.

[9]In the legacy format, there was no spreading category for the commercial traders and there still is not one for PM, since spreading is not considered a commercial activity (Turner, 2009).

Table 1: CFTC Classification of Commodity Markets Participants from DCOT reports

Markets Participants	**Description**
Producers, Merchants, Processors, and Users (PM)	An entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities.
Swap Dealers (SW)	An entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions. The swap dealer counterparties may be speculative traders, such as hedge funds, or traditional commercial clients that are managing risk arising from their dealings in the physical commodity.
Money Managers (MM)	Entities that manage and conduct organized futures trading on behalf of their clients. This category includes registered commodity trading advisers (CTAs), registered commodity pool advisers (CPOs), and unregistered funds identified by the CFTC. Hedge funds and large ETFs are part of this category.
Other Reporting traders (OR)	Other reportable traders who are not placed into one of the above three categories.
Non-Reporting traders (NR)	Smaller traders who are not obliged to report their position.

brace represent the contribution of open interest accountable to each of the trader categories:

$$\left[\underbrace{(PM_l + PM_s)}_{\text{producer/merchants}} + \underbrace{(SW_l + SW_s + 2SW_{sp})}_{\text{swap dealers}} + \underbrace{(MM_l + MM_s + 2MM_{sp})}_{\text{managed money}} + \underbrace{(OR_l + OR_s + 2OR_{sp})}_{\text{other reporting traders}}\right] + \left[\underbrace{NR_s + NR_l}_{\text{non-reporting traders}}\right] = \underbrace{2 \times TOI}_{\text{total open interest}}$$

Figure B.I in the appendix shows the average market share held by each of the five trader categories over the sample period and across all 10 commodities. On average, 24.4% of the market share goes to MM, 29.9% to PM, 19.1% to SW, 17.2% to OR, and 9.4% to NR. Table B.2 in the appendix provides a summary of the net positions for the different DCOT trader categories in our sample of 10 commodities. For each commodity, we report the position by each trader category as measured by the average weekly net long position (long position - short position, and then scaled as a percentage of the open interest of that trader category), its standard deviation, the percentage of the weeks the position is long, and

the first-order autocorrelation coefficient of the position. First, we observe that MM and NR traders are on average net long in most markets, whereas PM positions are on average net short, consistent with the notion that they act as hedgers for the most part. In contrast, SW and OR positions are less clear-cut on average. MM traders can both long and short different commodities in a given week, and their average net long position across commodities is 26%. In addition, the table shows both a large time series variability in net positions over time and large cross-sectional differences across commodities. The average standard deviation of MM net position across commodities is approximatively 31% per week. While MM traders are almost equally likely to be long or short in copper, coal, lumber and steel, their positions are long more than 95% of the weeks for the other commodities (except for oil & gas). Finally, unsurprisingly for weekly positions, all traders' positions across all commodities exhibit a high degree of persistence. The first-order autocorrelation of MM positions ranges from 0.88 for biofuel to 0.99 for steel.

In this paper, we mainly focus on the positions of MM traders. These traders take speculative positions, invest others' money on a discretionary basis, may make use of leverage and usually do not intend on taking delivery of the underlying commodities they are trading. We mainly focus on MM in our paper since they are the category of traders who have the most incentive to seek out and process information related to changes in commodity markets and they are believed to have the expertise. Indeed, the theoretical model by van Nieuwerburgh and Veldkamp (2010) concludes that because information acquisition and processing is costly, the optimal learning strategy for investors is to concentrate on one or a small set of assets. In addition, MM may engage in a higher frequency of trading than commercial hedgers and thus are more sensitive to information related to the short-term. Later, we do find that MM positions in the commodity futures market can predict the cross-section of stock returns whereas the signal extracted from PM positions are less robust. To investigate the informativeness of MM positions in commodity futures markets, we form four different, albeit closely related, measures. The results for all four measures usually

agree with each other. Prior studies have used CFTC open interest data to explore market effects caused by trader categories, although they generally either focus on the returns within the commodity futures market or on the equity market as measured by aggregate market indices rather than on a cross-section of firms.[10] However, the disparity of results suggests that multiple position indicators should be utilized to understand the robustness of the results. The first signal measure we use is the "Net Change" in MM positions, defined as the percentage change in long MM positions minus the percentage change in short MM positions ($\frac{(MM_l+MM_{sp})_t}{(MM_l+MM_{sp})_{t-1}} - \frac{(MM_s+MM_{sp})_t}{(MM_s+MM_{sp})_{t-1}}$); incidentally in this measure the spreading positions held by long and short traders cancel out. We also compute the signal measure: "Long Short Ratio Growth", which is defined as the long positions of MM traders divided by their short positions, (growth in $\frac{MM_l+MM_{sp}}{MM_s+MM_{sp}}$). We also utilize the "Long Proportion Growth", which is calculated as the growth rate in the long positions of MM traders divided by the total positions held by MM: (growth in $\frac{MM_l+MM_{sp}}{MM_l+MM_s+2MM_{sp}}$). Similarly, we also use the signal measure "Short Proportion Growth" (growth in $\frac{MM_s+MM_{sp}}{MM_l+MM_s+2MM_{sp}}$). In addition, although not directly linked to our main hypothesis nor is it a measure of MM's position *per se*, we also examine the growth of total open interest (TOI) held by all trader categories, i.e., the total amount of futures contracts outstanding, as in Hong and Yogo (2012). Furthermore, we also investigate the four analogous measures based on PM positions.

3.2. Data Manipulation and Portfolio Formation

3.2.1. Matching the Weekly Position Data with the Daily Stock Return Data

As previously described in Section 3.1.1, for each of the selected commodity, we identify the set of firms with the corresponding industry code. This procedure generates 10 baskets of equity portfolios each based on a commodity. Each commodity-equity portfolio has a daily return series, and is computed either as the value-weighted average of stocks' returns belonging to the same commodity (thereafter referred to as *V-Weight*) or as the equal-weighted average

[10] See, for instance, Büyükşahin and Robe (2014); Sanders et al. (2004); Cheng et al. (2014); Singleton (2013); Hamilton and Wu (2015)

(thereafter referred to as *E-Weight*). However, in either case, as will be described in Section 3.2.2, subsequently the 10 commodity-equity portfolios' returns are then weighted equally, or weighted according to the strength of the commodity signal, when calculating overall portfolio returns; and the *E-Weight* versus *V-Weight* dichotomy only refers to the weighting of firm returns within each commodity-equity portfolio. We will see depending on whether or not subsequently the individual commodity portfolios are weighted by the strength of the commodity signal measure, *E-Weight* will then give rise to the *No-Weight* and *Degree-Weight* weighting schemes; whereas *V-Weight* will give rise to the *Value-Weight* and *All-Weight* weighting schemes when calculating the returns of overall holdings.[11]

The DCOT reports are tabulated weekly from the beginning of trading on Wednesday to Tuesday's close (which is the compilation date). We match this time interval by computing weekly returns of portfolios of commodity-producing firms from Wednesday through the next compilation date. To be precise, the compilation date, which is usually a Tuesday unless it's a federal holiday, is considered the "signal generation date" for signals which we would utilize a day later beginning on Wednesday in determining whether to long or short each of the 10 commodity-equity portfolio, with details on how to match stocks with commodities as previously described in Section 3.1.2. The same portfolio is held from the beginning of the trading day right after the compilation date through the end of the next compilation date, and this process is henceforth referred to as the *Wednesday-to-Tuesday* convention.[12] The daily commodity-equity portfolio returns series are then further aggregated, with one of the weighting schemes to be described in Section 3.2.2, to generate the overall return of our Long-Short portfolio.

To summarize, and as will be made more precise with Equation 2 in Appendix A, here

[11] Following Fama and French (1993), for *V-Weight* we use the market capitalization measured at the end of December of the previous year as weights. While equal weighting will emphasize smaller stocks more, our sample is less prone to this bias because commodity producers are usually large firms (in terms of market capitalization). Nevertheless, one of the robustness checks we perform is to drop all micro-cap stocks, which will be shown in Table C.4.

[12] The CFTC is sometimes inconsistent with its handling of federal holidays, occasionally delaying the compilation date by one or two days. We adjust the aggregation step accordingly using CFTC's actual compilation dates (directly provided in the CFTC data).

we match weekly commodity position data with daily stock return data, and we begin by building commodity-equity portfolios and calculating daily returns of the portfolios, and then we compound the daily portfolio returns to obtain weekly returns for each of the commodity-equity portfolios (which will then be further aggregated to yield weekly returns for our Long-Short portfolio). Our empirical results are also robust compared to another method in which, instead of calculating daily returns for each of the commodity-equity portfolios and then compounding them to yield weekly returns, we calculate weekly returns for each of the stocks inside the portfolios and then construct and compute the weekly returns for the commodity-equity portfolios.

Although the CFTC does not release traders' positions as of Tuesday until Friday, we nevertheless use the Wednesday-to-Tuesday convention in our baseline analysis since MM positions are known by a number of parties, including the CFTC, MM traders themselves, market makers and clearing members. Since we are interested in the study of market efficiency and whether the equity prices (specifically, equity prices of commodity-producing firms) immediately reflect the information that lead the money managers to take the positions they do in the commodity futures market, the fact that the information contained in the signal is fixed already by Tuesday, even though it is released on Friday, does not impact our conclusion in that if we do find predictability, the result would still challenge market efficiency—more specifically, the strong-form efficient market hypothesis. Nevertheless, we also study whether our predictability results would persist, based on a *Monday-to-Friday* convention consistent with the actual release schedule of DCOT reports by the CFTC. In other words, in this convention the report release date, which is usually a Friday unless it's a federal holiday, is considered the "signal generation date" for signals which would determine the portfolio formation on the following Monday. The results are comparable with that of the Wednesday-to-Tuesday convention, as will be discussed in Section 4.4.1.

3.2.2. Long-Short Portfolio Formation

The *Long-Short portfolio* is constructed by sorting the commodity-equity portfolios weekly according to their *lagged* MM position signals by going long (short) on stocks of commodity-producing firms associated with a positive (negative) commodity signal if the signal we choose to utilize is Long Proportion Growth, Net Change or Long Short Ratio Growth; and vice versa if the signal is Short Proportion Growth. For example, if we are following the Wednesday-to-Tuesday convention as we will in our baseline analysis, we would form our weekly portfolio starting from Wednesday July 17th, 2013 utilizing the growth rate of MM's Long positions (or any one of the four signal measures) compiled by CFTC on Tuesday July 16th over that value compiled on Tuesday July 9th. We will subsequently refer to the timing of such signals as ‘‘lag1’’ or ‘‘1-week lag’’.[13] As will be shown later in Table 3, we also consider the case of utilizing J-week backward-looking moving averages of lagged signals to dictate our portfolio formation, to be denoted with timing convention MA(J).

The return series for both the Long and Short portfolios are computed from the commodity-level equity portfolios either according to the degree of the signals (the strength of the commodity signal measure, i.e., their distance from zero), thereafter referred to as the *D-Weight* as in Appendix A, or by averaging with equal-weight the returns of individual commodity-level equity portfolio in the Long (or Short) portfolio, thereafter referred to as the *N-Weight*. Combined with the two weighting schemes in the previous step as described on page 12, we finally form a zero-investment Long-Short portfolio by taking the difference between the Long and Short portfolio returns. Hence, we can then derive time-series of weekly returns for each of the 4 types of Long-Short portfolios, representing the following: (1) the *Value-Weight*, formed by applying *V-Weight* and then *N-Weight*; (2) the *Degree-Weight*, formed by applying *E-Weight* and then *D-Weight*; (3) the *All-Weight*, formed by applying *V-Weight* and then *D-Weight*; and (4) the *No-Weight*, formed by applying *E-Weight* and then *N-Weight*. Appendix A summarizes the procedure to compute the Long-Short portfolio

[13] For the Monday-to-Friday convention, we utilize an analogous procedure.

returns.

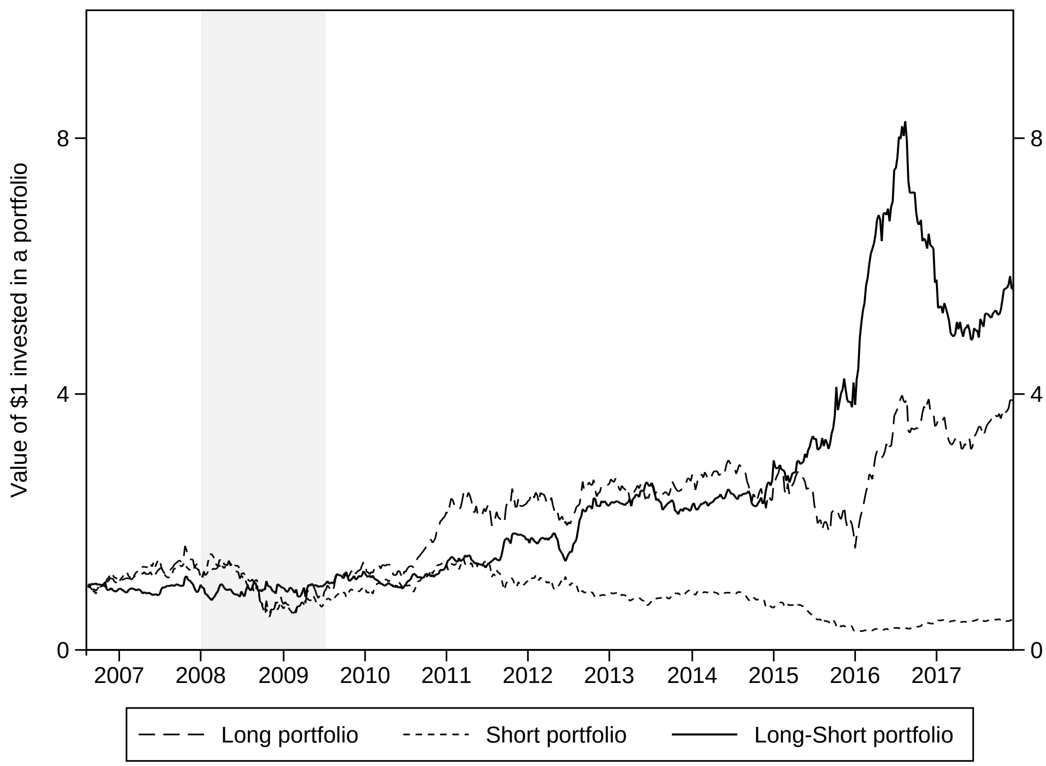
Figure B.II shows the total number stocks traded in the Long-Short portfolio each week from August 2006 to December 2017. It should be noted that the minor dips and spikes in the number of stocks traded are due to the fact that the commitments of traders data corresponding to the steel commodity are often missing in the CFTC DCOT reports for a number of weeks. The same problem occurs, although only occasionally, for coal prior to August 2012, though they are continuously reported from August 2012 onwards. In other words, two commodities sometimes experience data gaps due to the lack of positions information in the CFTC reports. Thus, to ensure that our results are not driven by these intermittent gaps in DCOT report, we also repeat our empirical analysis by removing steel from the whole sample and by removing coal prior to August 2012. The results remain largely the same and for sake of brevity, we do not report the results.

4. Empirical results

Our empirical analysis investigates the lead-lag relationship between the commodity futures and stock markets by exploiting the joint dynamics of commodity producers' equity price changes and MM position changes in the commodity futures market. First, we present the long-run performance of the Long-Short portfolios' as described in 3.2.2. Second, we examine the portfolios' abnormal returns by using the standard time-series regression calculation of Jensen's alpha relative to the Fama and French three-factor model augmented with the momentum factor, i.e., the Carhart four-factor model, and also other popular factor models as robustness checks. Our results are then confronted to a single-sorting procedure to study the price impacts of different signals and whether they exhibit a monotonic pattern according to the strength of the signal. In addition, we examine return predictability with Fama-Macbeth cross-sectional regressions across a range of time-lags. We also conduct a number of robustness checks. Finally, we discuss the relationship between our results and market frictions that could potentially contribute to our predictability results.

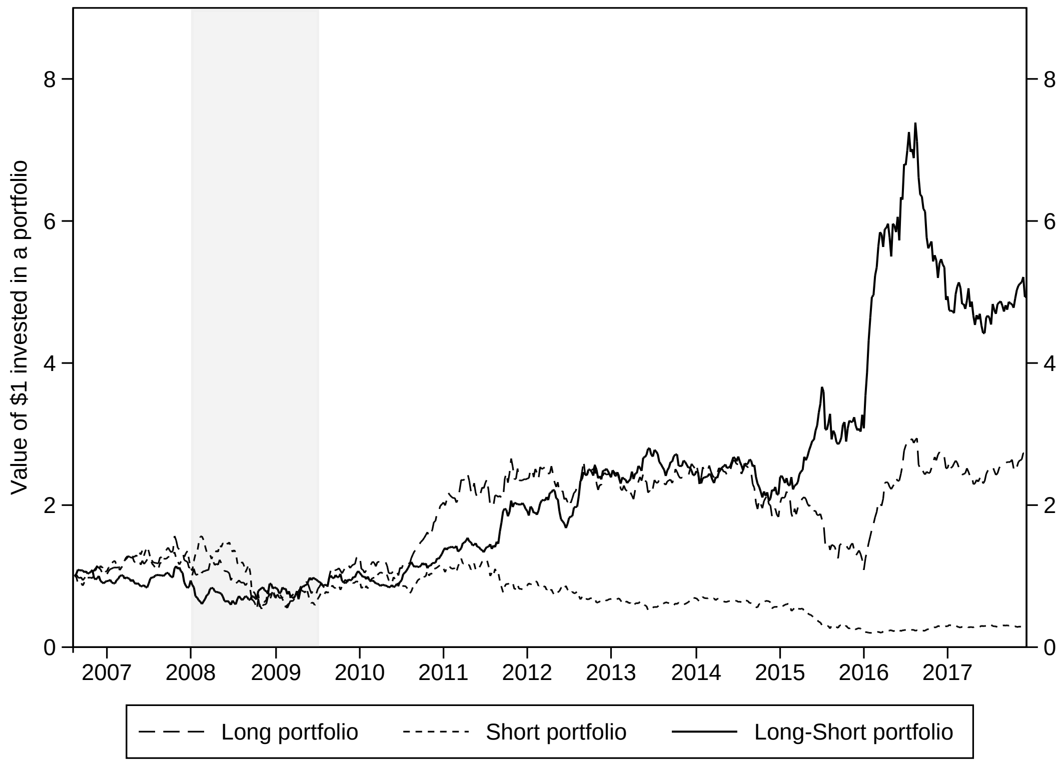
4.1. Portfolios' Long-run Performance

Figure 1: Cumulative Gains from Investments, Signaled by the MA(2) Managed Money Net Change (Value-Weight).



The cumulative return plots illustrate the cumulative weekly returns for investments in the zero-investment portfolio (''Long-Short portfolio'') that takes a long position in stocks with positive signal growth rates (''Long portfolio'') and a short position in equities with negative growth (''Short portfolio''), unless the signal measure used is Short Proportion growth in which case the long and short are flipped. Figure 1 presents the *Value-Weight* Long-Short portfolios' long-run performance signaled by the 2-week backward moving average of MM Net Change. There is considerable difference between the Long and Short portfolios' performance: an investment of $1 in the Long portfolio in August 2006, when our data begins, would have grown to $3.90 by December 2017; whereas a $1 investment in the Short portfolio would have declined to $0.47 over the same period. A dollar invested in the Long-Short

Figure 2: Cumulative Gains from Investments, Signaled by the MA(2) Managed Money Short Proportion Growth (All-Weight)



portfolio at start would have grown to $5.64 by December 2017, representing an annualized mean excess return of 18.81%. The long-short strategies' return pattern reveals a strong upward trend in profits over the entire sample period, with a sharp rise and heightened volatility from 2015 onwards. The shaded area corresponds to the NBER recession periods. In Figure 2, the *All-Weight* Long-Short portfolios' cumulative weekly returns based on the 2-week backward moving average of MM Short Proportion Growth (in which we long the commodity-equity portfolios with negative growth in this signal and vice versa) follows a similar pattern.

The cause of the heightened volatility lately can be partly attributed to the financial turmoil in China including a stock market crash and subsequent economic stimulus beginning in 2015, which spillovered to the commodity market, as well as uncertainties about the future

prospect of China's demand of commodities (Gross, 2017; Sada, 2016; Hutt, 2015). The 2015-2016 period saw large falls and subsequent recoveries in a number of commodity prices, in line with large swings in actual and expected demand from China, the world's largest commodity consumer. As an asset class, commodities appear to have made a significant bottom in late 2015, but the markets began to improve in the weeks and months that followed beginning in early 2016. Taken together, Figure H.I and Figure H.II in the appendix indicate, the large increase in the performance of the overall portfolio return beginning in 2015 as observed in Figures 1 and 2, which were steadily growing even before this period, can not be entirely attributed to any one commodity in particular. On closer inspection of the contributions of each commodity equity-based portfolios, the performance of the Long-Short portfolio in 2015 was mainly tied to returns from the Short portfolio—especially due to the contributions of the Miscellaneous Metal and Silver portfolios in early 2015 and the Copper and Coal portfolios in late 2015 according to Figure H.I. On the other hand, as the commodity markets began to recover in early 2016, the performance of the Long-Short strategy was driven by the outperformance of the Long portfolio—due to the contributions of Gold, Coal, Silver, Copper, Miscellaneous Metal and Steel commodities according to Figure H.II.

Table 2 presents the return moments and summary statistics of the Long-Short portfolios for each of the four weighting schemes as described in Section 3.2.2, that are constructed either with the 1-week lagged or the 2-week backward moving average of the four MM signal measures. Across all the different combinations of Long-Short portfolios and the signal measures, the annualized mean excess returns are generally statistically significant with t-statistics ranging from 1.76 to 3.54. The magnitude tends to be quite varied cross the weighting schemes used, with the No- and Degree-Weights generally yielding higher values than the Value- and All-Weights schemes. The risk-adjusted performances, as measured by the annualized Sharpe ratios, vary from 0.519 to 1.205, and for brevity we do not present the results for other MA(J) signals beyond J=2.

Table 2: Long-Short Portfolio Characteristics

Notes: Table 2 presents the return moments and summary statistics of the Long-Short portfolios for all four weighting schemes constructed either with the 1-week lagged or the 2-week backward moving average of the four Money Managers' (MM) signal variables. AW, DW, VW and NW stand for All-Weight, Degree-Weight, Value-Weight and No-Weight, respectively, as defined in Section 3.2.2. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth for the first three signal measures; and portfolios based on the Short Proportion Growth measure are constructed conversely. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1, and as usual in our baseline analysis, we follow the *Wednesday-to-Tuesday* convention.

	MA(2)				**1-week lag**			
	AW	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
MM Net Change								
Ann. Mean excess return (in %)	20.67	35.62	18.81	34.49	22.53	40.5	13.21	26.22
Ann. Standard deviation (in %)	29.52	35.11	26.06	29.19	30.9	36.51	25.46	29.58
t-stat	2.25	3.02	2.35	3.54	2.32	3.23	1.76	2.76
Ann. Sharpe Ratio	0.7	1.015	0.722	1.182	0.729	1.109	0.519	0.886
Cumulative return in \$ of \$1 invested (August 2006 - December 2017)	6.19	18.9	5.64	21.2	6.86	25.79	3.28	9.96
MM Long-Short Ratio Growth								
Ann. Mean excess return (in %)	18.63	32.7	18.33	31.6	22.67	40.77	13.61	26.16
Ann. Standard deviation (in %)	29.44	34.06	25.7	28.53	30.18	36.15	25.18	29.47
t-stat	2.06	2.9	2.33	3.36	2.39	3.29	1.83	2.77
Ann. Sharpe Ratio	0.633	0.96	0.713	1.108	0.751	1.128	0.541	0.888
Cumulative return in \$ of \$1 invested (August 2006 - December 2017)	5.15	15.43	5.45	16.86	7.15	26.8	3.45	9.94
MM Long Proportion Growth								
Ann. Mean excess return (in %)	20.34	36.04	18.57	28.74	22.49	39.08	13.71	28.5
Ann. Standard deviation (in %)	30.05	35.55	25.55	29.28	30.92	36.35	25.59	30.04
t-stat	2.18	3.01	2.37	3.02	2.31	3.15	1.81	2.92
Ann. Sharpe Ratio	0.677	1.014	0.727	0.981	0.727	1.075	0.536	0.949
Cumulative return in \$ of \$1 invested (August 2006 - December 2017)	5.73	18.82	5.59	12.77	6.64	22.74	3.29	11.43
MM Short Proportion Growth								
Ann. Mean excess return (in %)	18.34	36.4	17.1	34.68	21.4	38.68	13.75	26.53
Ann. Standard deviation (in %)	29.98	35.41	26.08	28.79	30.99	36.9	25.43	29.49
t-stat	1.99	3.05	2.16	3.6	2.21	3.08	1.82	2.8
Ann. Sharpe Ratio	0.612	1.028	0.656	1.205	0.691	1.048	0.541	0.9
Cumulative return in \$ of \$1 invested (August 2006 - December 2017)	4.93	20.11	4.78	21.86	6.19	21.88	3.47	10.28

Sample period : August 2006 - December 2017

4.2. Jensen's Alpha Analysis and Single Sorting

We have identified a significant mean return differential between the Long and Short stock portfolios. However, differences in portfolio characteristics and different exposures to risk factors could explain at least part of the return differential. To investigate the existence of abnormal returns, we regress the weekly returns of the Long-Short portfolios according to the Carhart (1997) four-factor model. The model consists of the momentum factor, which was documented by Jegadeesh and Titman (1993), combined with the Fama and French three-factor model. The α or Jensen's alpha is then calculated as the intercept of the regression.

Table 3 presents the baseline results for the Carhart four-factor α, together with its t-statistic. We investigate both the entire sample period (August 2006 to December 2017) and non-NBER recession periods only (panel B).[14] The table compiles results for the four MM signals and for the total open interest growth, where the signal from the futures market is either constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. We look beyond $J = 1$ since longer look-back horizons could capture any potential momentum or trend-following effects within the positions taken by MM traders. These effects have been documented to exist in a number of asset classes including equity index, currency, commodity, and bond futures (Moskowitz et al., 2012).

In Table 3, for simplicity we follow a strategy of buying the commodity producers' stocks with positive signal growth and selling short the stocks with negative signal growth for all of the four signals, including the Short Proportion Growth signal. Thus, we find that the alphas are all significantly positive except for the MM Short Proportion Growth case, which are all significantly negative, as expected. Focusing on the $J = 2$ look-back horizon, across the four MM sorting measures for the full sample period, the alphas are economically large, with magnitudes at above 33.7 basis points per week, and are statistically significant, with t-statistics ranging from 2.16 to 3.58. Importantly, the statistical significance is robust for all

[14]For non-NBER recession periods, we remove the samples from December 2007 to June 2009.

of the four weighting schemes used for all of the four MM signal measures used. However, for longer look-back horizons, the statistical significance varies more widely depending on the weighting scheme applied and the signal measure used, and in some cases the abnormal return can become statistically insignificant. In addition, the alpha's magnitude and significance in non-NBER recession periods remain consistent with the whole sample results. On the other hand, total open interest growth generally does not contain valuable information for predicting commodity producers' stock returns.[15]

Table C.1 of the appendix replicates the results of Table 3 using the Stambaugh and Yuan (2016) mispricing factor model that includes, in addition to the factors of market and size, two composite mispricing factors constructed based upon a set of 11 prominent anomalies. In particular, MGMT is a composite factor constructed on six anomaly proxies related to investment and financing, while the second cluster, labeled PERF, is based on five anomaly variables including return momentum and profitability. The sample period ends in December 2016 due to factors' availability. This exercise yield estimates of alphas qualitatively and quantitatively similar to our baseline findings.

In Table C.2 of the appendix, we find that the results presented in this section are robust even if we expand our scope and include the stocks of U.S.-listed foreign incorporated commodity producers (CRSP SHRCD=12) in our analysis. However, the statistical significance and economic magnitude decrease, consistent with the notion that the subsequent stock returns of foreign incorporated commodity producers are subject to additional market risk premium (Foerster and Karolyi, 1999; Karolyi and Stulz, 2003) and to country-specific foreign shocks; therefore they are more noisy. Standard practice in financial research is to restrict attention to SHRCD equal to 10 and 11, as in Lyon et al. (1999) and Cohen et al. (2008).

To ensure that our results are not driven by extreme observations, we also conduct a

[15]Hong and Yogo (2012) construct a predictor of commodity futures market returns (and of *aggregate* returns in currency, bond and stock markets) by taking a 12-month geometric average in the time series of monthly open interest growth. In contrast, we focus on a much shorter time horizon. The signal we use to predict the *cross-section* of commodity producers' stock returns is constructed at a weekly frequency and has a look-back horizon of, at most, 12 weeks.

Table 3: Baseline Carhart 4-Factor Alpha Results (%, per Week)

Notes: This table presents the Carhart (1997) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the MM category (as defined in Table 1) in the commodity futures market. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table report Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the whole sample period, from August 2006 to December 2017, while Panel B focuses on non-NBER recession periods only, without the January 2008-June 2009 period. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.431**	0.698***	0.282*	0.481***	0.478***	0.747***	0.279**	0.487***
	(2.42)	(3.31)	(1.93)	(2.8)	(2.92)	(3.42)	(2.12)	(2.73)
2	0.397**	0.626***	0.362**	0.604***	0.46***	0.654***	0.421***	0.602***
	(2.35)	(3.1)	(2.39)	(3.51)	(2.82)	(3.08)	(2.92)	(3.42)
3	0.451***	0.607***	0.291**	0.583***	0.468***	0.658***	0.342**	0.61***
	(2.61)	(2.95)	(1.96)	(3.39)	(2.8)	(3.08)	(2.42)	(3.55)
4	0.395**	0.588***	0.146	0.354**	0.494***	0.776***	0.261*	0.523***
	(2.26)	(2.94)	(0.99)	(2.06)	(2.98)	(3.71)	(1.89)	(2.95)
8	0.317*	0.481**	0.276*	0.39**	0.336**	0.498**	0.238*	0.326*
	(1.74)	(2.37)	(1.82)	(2.12)	(2.06)	(2.57)	(1.7)	(1.81)
12	0.632***	0.84***	0.657***	0.773***	0.562***	0.691***	0.588***	0.599***
	(3.5)	(4)	(4.12)	(4.19)	(3.44)	(3.47)	(4.13)	(3.57)

Money Managers' Long Short Ratio Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.437**	0.702***	0.289**	0.479***	0.464***	0.738***	0.254*	0.454**
	(2.53)	(3.37)	(2.01)	(2.8)	(2.84)	(3.37)	(1.92)	(2.54)
2	0.364**	0.575***	0.355**	0.555***	0.417**	0.651***	0.377***	0.572***
	(2.16)	(2.95)	(2.38)	(3.34)	(2.55)	(3.17)	(2.67)	(3.34)
3	0.387**	0.544***	0.325**	0.583***	0.356**	0.605***	0.326**	0.623***
	(2.25)	(2.75)	(2.17)	(3.4)	(2.16)	(2.9)	(2.31)	(3.52)
4	0.361**	0.647***	0.213	0.45***	0.421**	0.783***	0.293**	0.564***
	(2.05)	(3.04)	(1.45)	(2.62)	(2.48)	(3.31)	(2.07)	(3.1)
8	0.153	0.415**	0.147	0.384**	0.285*	0.54***	0.223	0.451**
	(0.87)	(2.14)	(0.98)	(2.11)	(1.75)	(2.63)	(1.57)	(2.3)
12	0.202	0.506**	0.146	0.454**	0.28*	0.484**	0.264*	0.45**
	(1.15)	(2.54)	(0.95)	(2.5)	(1.78)	(2.37)	(1.91)	(2.44)

Money Managers' Long Proportion Growth

	Panel A: Whole sample				Panel B: Without Recession			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.433**	0.674***	0.285*	0.513***	0.452***	0.702***	0.279**	0.5***
	(2.42)	(3.2)	(1.94)	(2.96)	(2.8)	(3.22)	(2.14)	(2.8)
2	0.388**	0.634***	0.36**	0.531***	0.408**	0.616***	0.385***	0.519***
	(2.24)	(3.1)	(2.43)	(3.13)	(2.45)	(2.89)	(2.75)	(2.91)
3	0.434**	0.649***	0.245*	0.541***	0.455***	0.694***	0.288**	0.562***
	(2.45)	(3.13)	(1.68)	(3.2)	(2.7)	(3.2)	(2.11)	(3.19)
4	0.407**	0.671***	0.201	0.414**	0.51***	0.831***	0.287**	0.575***
	(2.28)	(3.23)	(1.38)	(2.49)	(3.02)	(3.75)	(2.09)	(3.26)
8	0.307*	0.471**	0.235	0.473***	0.429***	0.622***	0.32**	0.539***
	(1.73)	(2.3)	(1.64)	(2.69)	(2.61)	(2.97)	(2.31)	(2.91)
12	0.481***	0.773***	0.321**	0.535***	0.448***	0.613***	0.361***	0.455***
	(2.59)	(3.53)	(2.05)	(2.9)	(2.86)	(3.02)	(2.75)	(2.65)

Money Managers' Short Proportion Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.412**	-0.674***	-0.29**	-0.483***	-0.469***	-0.755***	-0.286**	-0.49***
	(-2.3)	(-3.16)	(-1.99)	(-2.82)	(-2.83)	(-3.41)	(-2.18)	(-2.76)
2	-0.367**	-0.648***	-0.337**	-0.607***	-0.428***	-0.682***	-0.398***	-0.608***
	(-2.13)	(-3.18)	(-2.22)	(-3.58)	(-2.61)	(-3.19)	(-2.77)	(-3.51)
3	-0.385**	-0.608***	-0.258*	-0.534***	-0.379**	-0.653***	-0.329**	-0.602***
	(-2.24)	(-2.96)	(-1.76)	(-3.09)	(-2.32)	(-3.07)	(-2.35)	(-3.48)
4	-0.33*	-0.597***	-0.181	-0.384**	-0.404**	-0.789***	-0.285**	-0.554***
	(-1.91)	(-2.92)	(-1.23)	(-2.24)	(-2.42)	(-3.64)	(-2.07)	(-3.16)
8	-0.288	-0.567***	-0.319**	-0.522***	-0.289*	-0.553***	-0.297**	-0.466***
	(-1.6)	(-2.81)	(-2.15)	(-2.86)	(-1.78)	(-2.88)	(-2.18)	(-2.67)
12	-0.539***	-0.877***	-0.618***	-0.825***	-0.485***	-0.78***	-0.593***	-0.768***
	(-2.97)	(-4.2)	(-3.89)	(-4.62)	(-2.88)	(-3.91)	(-4.18)	(-4.78)

Open Interest Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.121	0.073	0.054	-0.025	0.125	0.086	-0.031	-0.083
	(0.8)	(0.42)	(0.41)	(-0.16)	(0.96)	(0.5)	(-0.27)	(-0.53)
2	0.024	0.057	0.017	-0.036	-0.026	0.046	-0.057	-0.071
	(0.16)	(0.33)	(0.13)	(-0.23)	(-0.19)	(0.27)	(-0.47)	(-0.47)
3	-0.069	0.029	0.062	0.095	-0.091	-0.042	0.002	0.025
	(-0.44)	(0.15)	(0.46)	(0.59)	(-0.61)	(-0.22)	(0.02)	(0.17)
4	-0.23	-0.11	-0.172	-0.109	-0.294*	-0.164	-0.238*	-0.163
	(-1.42)	(-0.6)	(-1.19)	(-0.66)	(-1.91)	(-0.86)	(-1.72)	(-0.97)
8	-0.085	-0.105	-0.116	-0.231	-0.172	-0.105	-0.156	-0.172
	(-0.54)	(-0.57)	(-0.82)	(-1.44)	(-1.17)	(-0.56)	(-1.21)	(-1.05)
12	0.111	0.355*	-0.003	0.171	-0.257*	-0.029	-0.333**	-0.184
	(0.65)	(1.84)	(-0.02)	(0.9)	(-1.78)	(-0.16)	(-2.49)	(-1.03)

robustness exercise in which we winsorize the individual stock's weekly return at 1st and 99th percentiles, using annually updated cutoffs calculated from our matched sample. Formal approaches to discriminate outliers include trimming and winsorizing data. For instance, Knez and Ready (1997) employ a trimmed least squares estimation method and find that outliers have a large influence on the cross-sectional regressions found in Fama and French (1993). Specifically, the size factor seems to be due to a small proportion of the small firms that do extraordinary well. We perform winsorization and present the results in Table C.3 in the appendix, which shows that outliers' behaviors do not have large influences on our estimated alphas, thus confirming our baseline findings reported in Table 3.

We next remove stocks in the bottom 25% of market capitalization using annually updated cutoffs calculated from the CRSP universe. Table C.4 in the appendix shows that our baseline results are not sensitive to dropping micro-cap stocks.

To summarize, these first findings show that economically large and statistically significant alphas can be attributed to signals extracted from MM's commodity futures market positions. Most importantly, our results are robust to a variety of choices of signal measures, weighting schemes and timing of lags. The results are also robust to the removal of micro-cap stocks, and to the removal of extreme return observations. These results reasonably suggest that MM traders have valuable information that predicts the returns of commodity-producers' stocks which is not captured by known predictors of equity returns.

To control for any potential non-linear relation between our signal measures and future stock returns that is not captured in a regression framework, we also adopt a single-sorting procedure as part of our analysis, in a way that differs in some respects from the method previously outlined. Each week, all stocks are sorted into three bins based on the signal's value, with bin 1 representing the lowest tercile and bin 3 representing the highest tercile.[16] In the next step, we compute the subsequent equal- or value-weighted returns for each portfolio

[16]In contrast to single-sorting, the Jensen's alpha estimation presented earlier was based on a zero-investment strategy by going long (short) on stocks simply according to the sign of the signal measure, and the strength of the signal measure was not ranked; although the *Degree-Weight* and *All-Weight* weighting schemes do take the strength of the signal into consideration.

bin, and the long-short returns of going long on the highest tercile and going short on the lowest tercile ("3-1"). The relevance of the signal variable is then assessed by evaluating Jensen's alpha relative to the Carhart four-factor model, as well as the Stambaugh and Yuan (2016) mispricing factor model. Additionally, we use the Fama and French five-factor model to control for the profitability and asset growth (i.e., investment) factors. With the single-sorting procedure, we are able to investigate the price impacts of different signal bins and to check if there is a monotonic relation between signal strength and subsequent portfolio returns.

Table 4 shows the results for both the equal-weighted (Panel A) and value-weighted (Panel B) returns for each portfolio bin. First, for all signal measures in both panels, the *mean* column confirms the monotonicity of the raw returns over the signal-ranked bins. Second, the return difference between the two extreme portfolios bins is economically large and statistically significant at 1% to 5%. The results are qualitatively similar to the findings reported in Table 3. These results further confirm that our MM signals can predict the commodity producers' stock returns in the one week following the DCOT report. Furthermore, notice that the sign of the α for the Short Proportion Growth measure is negative while the sign is positive for the other three signal measure, as expected, since for simplicity we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth for all of the four signals, including the Short Proportion Growth signal.

4.3. Fama-MacBeth Analysis

We run Fama-Macbeth cross-sectional regression to investigate whether—conditional on controls such as firm size, book-to-market ratio, short-term reversal, momentum and past change in commodity spot price—our signal can predict the stock returns of commodity producers in the week following the DCOT report. The Fama-Macbeth regressions is performed at the daily frequency, that is, for each of the 5 trading days (the first is a

Table 4: Single Sorting Results

Notes: Each week, all producers' stocks are sorted into three bins based on the signal value, with bin 1 representing the lowest tercile and bin 3 representing the highest tercile. The signal from the futures market is constructed as a 1-week lag. Subsequent equal-weighed (Panel A) or value-weighted (Panel B) returns for each portfolio bin are computed. The long-short returns of going long for the highest third portfolio and going short for the lowest third portfolio ("3-1") are also shown. From the long-short returns, we then calculate the abnormal return (α) relative to the Carhart four-factor model (C4 α), to the Fama and French five-factor model (FF5 α) as well as to the Stambaugh and Yuan mispricing factor model (SY4 α). The table reports average returns and differences in returns, together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. The returns have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Equal-Weight				**Panel B: Value-Weight**			
rank	Mean	C4 α	FF5 α	SY4 α	Mean	C4 α	FF5 α	SY4 α
1	-0.275 (-1.13)				-0.096 (-0.46)			
2	0.179 (0.85)				0.222 (1.30)			
3	0.469** (2.13)				0.43** (2.13)			
(3-1)	0.744*** (3.83)	0.743*** (3.77)	0.729*** (3.66)	0.761*** (3.60)	0.527*** (3.08)	0.538*** (3.07)	0.459*** (2.66)	0.553*** (2.87)

Money Managers' Long-Short Ratio Growth

rank	Mean	C4 α	FF5 α	SY4 α	Mean	C4 α	FF5 α	SY4 α
1	-0.207 (-0.86)				-0.062 (-0.30)			
2	0.162 (0.76)				0.241 (1.43)			
3	0.407* (1.83)				0.358* (1.76)			
(3-1)	0.614*** (3.20)	0.618*** (3.19)	0.603*** (3.09)	0.624*** (2.99)	0.42** (2.49)	0.432** (2.51)	0.361** (2.13)	0.441** (2.32)

Money Managers' Long Proportion Growth

rank	Mean	C4 α	FF5 α	SY4 α	Mean	C4 α	FF5 α	SY4 α
1	-0.227 (-0.96)				-0.055 (-0.27)			
2	0.164 (0.77)				0.218 (1.24)			
3	0.456** (2.01)				0.432** (2.16)			
(3-1)	0.683*** (3.66)	0.681*** (3.59)	0.672*** (3.54)	0.689*** (3.36)	0.488*** (2.95)	0.5*** (2.97)	0.414** (2.50)	0.51*** (2.75)

Money Managers' Short Proportion Growth

rank	Mean	C4 α	FF5 α	SY4 α	Mean	C4 α	FF5 α	SY4 α
1	0.434* (1.95)				0.391* (1.95)			
2	0.197 (0.90)				0.264 (1.46)			
3	-0.236 (-1.02)				-0.069 (-0.35)			
(3-1)	-0.67*** (-3.50)	-0.673*** (-3.42)	-0.673*** (-3.26)	-0.691*** (-3.21)	-0.459*** (-2.72)	-0.46*** (-2.67)	-0.409** (-2.36)	-0.478** (-2.50)

Wednesday and the last is the Tuesday of next week, unless it is a trading holiday) following a new DCOT report on a Tuesday, even though the value of the signal does not change for these five subsequent trading days (although its value will change for the observations in the next Wednesday-to-Tuesday cycle, as the signal is updated weekly). We then report average slopes and Newey-West corrected t-statistics with five lags as there are five trading days in a week in case one is concerned with auto-correlation in firm returns in a week. The signal from the futures market is constructed as a 1-week lag or as a J-week backward moving average, where J is equal to 2, 3, 4, 8, or 12. As usual in our baseline analysis, we restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers.

The regression specification is as follows:

$$R_{i,t+K} = \alpha_{t+K} + \beta Signal_{i,t}^{J} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t+K}, \tag{1}$$

where K can be 1, 2, 3, 4 or 5 trading days ahead of the Tuesday this week which is denoted time t, and $R_{i,t+K}$ is the daily return of the firm's stock in the five trading days (from Wednesday this week to Tuesday next week) following a new signal generation of $Signal_{i,t}^{J}$ at the Tuesday of this week; and $\mathbf{X}_{i,t}$ represents control variables. The coefficient β in Equation (1) is our focus.

Control variables include ret_{-1}, which is the stock return over the previous month; $ret_{-2,-12}$, which is the stock return over the 11 months preceding the previous month; ln(BE/ME) which denotes the log of the ratio of the book value of equity to the market value of equity; and ln(ME), which denotes the log of the market value of equity. We also include the change in spot price of the commodity in the previous week as an additional control. Following Henderson et al. (2014), we use the prices of the front-month futures contracts as proxies for spot prices. If our signals are significant in the presence of this control, then it would indicate that the positions of MM do have predictive power in addition to the

information already contained in commodity prices.

We present the results using the MM Net Change signal measure in Table 5. We perform the analysis for the full sample period (August 2006 to December 2017), and for the non-NBER recession sample period. We find a 1-week lag of our signal in the commodity futures market can predict future stock returns with a t-statistic of 3.037, and an even higher t-statistic of 3.753 if we focus only on non-NBER recession periods. We present the full Fama-Macbeth regression results in Appendix F.

In addition to MM Net Change, in Appendix F we also use MM Long Short Ratio Growth, MM Long Proportion Growth, and MM Short Proportion Growth as our signals. In each table, the top panel shows the results using the 1-week lag and the 2- and 3-week moving averages of our commodity futures market signals, while the lower panel presents the results using the signals' 4-, 8-, and 12-week moving averages. Columns (1), (3), (5), (7), (9) and (11) show the results when the signal alone acts as the regressor. In terms of the values of the adjusted R^2's of the Fama-Macbeth regressions, which are the averages of the cross-sectional adjusted goodness-of-fit, the values at a little less than 7% are comparable in magnitude as the values found in recent studies in the finance literature. For example, our R^2 are actually much larger than those reported in table II of Tetlock et al. (2008). It should be noted that we are running the Fama-Macbeth regressions at daily frequency using firm-level daily returns for each of the subsequent five trading days as dependent variables on weekly-updated commodity signals among other low-frequency controls, whereas higher R^2 are expected for returns at longer horizons (Fama, 2014).

We find that the coefficients on signals are all positive except in the case of MM short proportion growth, which are negative as predicted. For the 1-week lag and the 2-week moving averages, the statistical significance of the signal variables varies from the 1% to the 5% level, according to columns (1) and (3). However, for the 3-, 4-, 8-, and 12-week moving averages, our signal can become statistically insignificant. According to columns (2), and (4), even in the presence of control variables, our signal's coefficients remain statistically

Table 5: Fama-Macbeth Regressions: Managed Money Net Change

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1% 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

All Observations	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	$+0.003^{*}$	$+0.006^{***}$	$+0.005^{***}$	$+0.005^{**}$	$+0.005^{**}$	$+0.005^{**}$
Net Change	(+1.820)	(+3.037)	(+3.193)	(+2.492)	(+2.385)	(+1.988)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.278)		(+0.210)		(+0.141)
$ln(ME)$		-0.000^{*}		-0.000^{*}		-0.000^{*}
		(-1.807)		(-1.865)		(-1.862)
ret_{-1}		+0.000		+0.001		+0.000
		(+0.412)		(+0.464)		(+0.427)
$ret_{-2,-12}$		$+0.001^{*}$		+0.001		+0.001
		(+1.645)		(+1.624)		(+1.530)
$\Delta CPrice_{-1}$		+0.004		+0.009		+0.008
		(+0.582)		(+1.384)		(+1.192)
N–Companies	197	190	197	189	193	189
N–Observations	299457	284810	298202	284032	297332	283370
$Adj.R^2$		0.06806		0.06823		0.06807

Non-Recession Periods Only	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	$+0.004^{***}$	$+0.006^{***}$	$+0.004^{***}$	$+0.004^{***}$	$+0.004^{***}$	$+0.005^{***}$
Net Change	(+3.373)	(+3.753)	(+2.740)	(+2.884)	(+2.648)	(+2.970)
$ln(BE/ME)$		+0.000		−0.000		−0.000
		(+0.001)		(-0.042)		(-0.061)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.647)		(-0.698)		(-0.678)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.597)		(+0.657)		(+0.602)
$ret_{-2,-12}$		$+0.001^{*}$		$+0.001^{*}$		$+0.001^{*}$
		(+1.935)		(+1.900)		(+1.811)
$\Delta CPrice_{-1}$		+0.004		+0.011		+0.009
		(+0.519)		(+1.561)		(+1.366)
N–Companies	196	189	196	188	192	188
N–Observations	255877	242138	254670	241360	253800	240698
$Adj.R^2$		0.06718		0.06726		0.06729

significant, with statistical significance consistently at the 1% level. For example, during non-recession periods, the MM long-short ratio growth is a statistically significant predictor of future firm returns in the following 5 trading days with a t-statistic of 3.629, and the signal's coefficient is 0.006. The results from these multivariate regressions suggest that signals in the commodity futures market can indeed predict subsequent stock returns, and this effect cannot be absorbed by a set of existing determinants of stock returns.

Furthermore, we have also conducted the Fama-Macbeth regressions while excluding the previous week's change in commodity spot price as an control variable. The results are robust though we do not present these results for brevity.

As another robustness test, we have also conducted the Fama-Macbeth regressions on samples that first underwent winsorization of stock returns at the 1st and 99th percentile (based on the distribution of stock returns in the cross-section in our sample in a given year). The results remain qualitatively the same and we again omit the results in presentation.

4.4. Further Discussions

4.4.1. Jensen's Alpha Analysis for the Monday-to-Friday Convention

Our baseline results are based on the Wednesday-to-Tuesday convention, which uses the CFTC report compilation date as the signal generation date and the portfolio formations are made starting at the beginning of the next trading day (on a Wednesday).

We now apply a different method to aggregate the daily commodity-equity based portfolios' return series into a weekly frequency, by computing the weekly return from one trading day after the actual release date through the end of the next release date, referred as the *Monday-to-Friday* convention.[17]

Our main objectives with this new convention is to study whether the time lag for

[17]The DCOT reports are usually released on Friday, but federal holidays may delay release by one or two days. Similarly to our treatment of the compilation dates in Section 3.2.1, we adjust the convention accordingly by using CFTC's actual release dates (which is available on CFTC website for only the last 12 months, but older actual historical release dates can be obtained using archived cache of the website).

incorporating information contained in MM's futures markets positions into producers' equity prices is longer than what was captured by the Wednesday-to-Tuesday convention and whether we our predictability results remain even in the Monday-to-Friday convention which corresponds to actual release schedules although it forgoes the Wednesday, Thursday and Friday immediately following the compilation of DCOT reports on Tuesday. Figure B.III in the appendix plots the portfolios' cumulative weekly returns, signaled by the MA(2) MM short proportion growth, which documents an overall upward trend in the cumulative return of the Long-Short portfolio over the sample period.

The results shown in Table D indicate that although the strategy based on the CFTC's information release schedule can still generate statistically significant returns, the findings are however more sensitive to the choices of signal measures, weighting schemes, timing of lags and sample periods. For example, focusing on the ''Without Recession'' sample, in which restrict our attention to the non-NBER recession periods by removing the January 2008-June 2009 period, a trading strategy based on the 4-week moving average MM Net Change measure can generate alphas with t-statistics from 2.36 to 3.31 across the four weighting schemes. On the other hand, as shown in Table D, signals based on total open interest growth generally does not yield significant alphas that are robust across the signal measures, the weighting schemes, and economic cycles.

4.5. Additional Results

In addition, we investigate whether MM traders are the only smart money in the commodity futures market by studying whether we can also construct a profitable trading strategy based on the commodity futures market positions of the PM category, which includes commodity producers, merchants, processors and users. Per the CFTC definition in Section 3.1.2, ''PM'' here means an entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities. As Table E.1 indicates, utilizing PM signals instead of MM

signals generally does not yield significant Jensen's alphas for lag1 and moving averages of the immediate past, however, the signals calculated using moving averages of the past 8- or 12-weeks do lead to marginally significant predictability, although the results are less robust than that of the MM category of traders. Notice that as commercial hedgers, naturally, the signs on these Jensen's alphas are flipped when comparing with the results of speculators (MM) in Table 3. To the extent that PM's MA(8) signal is statistically significant in the whole sample but not in the non-NBER recession sample, this can be rationalized by the notion that as hedgers, PM activity in the futures market, especially to the extent that the PM category captures the activity of commodity producers who are worried about commodity price drops in recessions, are perhaps more potent predictors during the recession periods but much less so during normal times.

Overall, the results are consistent with the notion that MM traders are sophisticated speculators, who are often levered, and who have the most incentive to process and acquire information related to movements in the fundamentals of the commodity market; whereas PM are not necessarily as short-term focused as the MM traders. In addition, Cheng and Xiong (2014) have found that the PM category traders have significantly engaged in trades for reasons other than hedging, since they frequently change their futures positions for reasons unrelated to output fluctuations, possibly due to speculation. As hedging versus speculation trades mandate opposite (long versus short) positions to be taken, this limits the usefulness of the PM data as a signal. The fact that users, processors, merchants and producers are grouped together in the DCOT reports further limits the usefulness of the signal as they are a diverse group with varying incentives to trade in the commodity futures market. All in all, the positions on the PM category of traders, as a whole, do not contain information that is robustly conducive towards predictability of equity returns in the short-term.

We omit here the results for the Wednesday-to-Tuesday convention in which we remove one commodity at a time from our analysis as robustness checks. In general, removing any one commodity do not change our results qualitatively for our baseline analysis. However, we

note here we should not remove too many commodities from our sample as it is a well-known fact in the empirical literature of commodities, that an empirical phenomenon which may hold for a diversified portfolio of commodities does not necessarily hold when one restricts the sample size to only one particular commodity.[18]

4.6. Double-Sorting Results and Relationship with Market Frictions

Our analysis revealed the existence of sizable and significant abnormal returns for commodity producing stocks in the equity market based on information extracted from the commodity futures market. In this section, we examine why this predictability arises. Due to legal and privacy reasons, the CFTC does not publish information on how individual traders are classified in the COT reports and information are always aggregated to protect the identity of any individual reportable trader; though we can still use the double-sort methodology to focus our investigation on two sets of market frictions that could potential contribute to our predictability results, namely, informational frictions and trading frictions.

Informational friction is at the center of a number of consistent findings in the literature of return anomalies. Firms with higher analyst dispersion have been found by Sadka and Scherbina (2007) to earn lower subsequent returns, which is believed to be because these firms have higher information asymmetry. We proxy informational friction based on two measures, *ex ante* analyst dispersion and 60-day *historical* stock volatility.[19]

We proxy trading friction with the illiquidity measure proposed by Amihud (2002).

[18]For example, to quote Fabozzi et al. (2008): ‘‘Thus, while individual (commodity futures) markets did not appear to provide consistent risk premiums, a portfolio of futures did appear to provide significant premiums. One explanation for this finding (Fama and French, 1987) is that diversification across commodities reduces portfolio risk without reducing return.’’ See also, Erb and Harvey (2005).

[19]One can draw an analogy between these two measures and two similar stock volatility measures, namely, historical volatility and option implied volatility of stocks. These two measures do not necessarily coincide with each other (Bollerslev et al., 2009). The former is a backward-looking measure, calculated *ex post*, based on realized historical data. On the other hand, the later is a forward-looking measure based on market participants' expectations of future return variation, like analyst dispersion.

Liquidity captures the ease of trading a security. Exogenous transaction costs, demand pressure, inventory and search friction risk are all possible sources of illiquidity.

Ultimately, we aim to explore the relationship between market friction and our stock return predictability results. To do so, we utilize double-sorting as our main methodology. Specifically, each week, all producers stocks are first sorted into three friction portfolios using one of the three aforementioned firm-level proxies for market friction, with the requirement that each commodity appears across those three portfolios. Then, two signal portfolios are formed dependently within each friction portfolio based on one of the four MM signal variables. The 3-by-2 double-sorting method produces six portfolios. Finally, we calculate equal- and value-weighted returns of the sorted portfolios in a similar fashion as the single-sorted portfolios presented in Section 4.2.

Table 6 presents the results for the returns utilizing the (lag1) MM Net Change signal measure and double-sorted with the three friction proxies.[20] We pay special attention to the Long-Short portfolio returns and whether the 4- or 5-factor alphas arise in the difference between the high- and low-friction bins. By double-sorting our commodity futures market signal with Amihud's illiquidity measure (LIQ), we find no evidence that predictability is stronger (or weaker) in firms with higher trading friction. However, we find that our results are significantly stronger in firms with higher information asymmetry as measured by 60-day *historical* stock volatility (VOL) and *ex ante* analyst dispersion (AD) as compared to the firms with lower information asymmetry. For instance, if we focus on the Value-Weight column, the difference in the Long-Short portfolio's FF5 α between the highest tercile and lowest tercile of 60-day *historical* stock volatility (VOL) is in itself a significant difference with t-statistic of 3.05, and the statistical significance of the differences remain if we use alternative factor model such as the Carhart's four-factor model (C4) or the mispricing factor model (SY4).

[20]As a technical detail, unlike the single-sorting exercise in which we applied the method of first build the commodity-equity portfolios from stocks and then compound the daily portfolios returns into weekly returns for each of the commodity-equity portfolios, in the double-sorting exercise we first compute weekly returns for each stock and then build the commodity-equity portfolios.

Table 6: Double Sorting: Money Managers' Net Change (%, per Week)

Notes: This table presents results from our double-sorted cross-sectional exercise. Specifically, each week, all the producer stocks are first sorted into three friction portfolios using one of the three firm-level proxies of friction (LIQ, VOL, and AD), with the requirement that each commodity appears across those three portfolios. LIQ, VOL and AD stand for the Amihud's illiquidity measure, the 60-day *historical* stock volatility and the *ex ante* analyst dispersion, respectively. Then, the two signal portfolios are formed dependently within each of the three friction portfolios, based on the MM Net Change signal. The signal from the futures market is constructed with a 1-week lag, and the same is true for the three proxies of market friction. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. This 3-by-2 double-sorting procedure produces six portfolios.Finally, we both equally weight (Panel A) or value-weight (Panel B) the sorts. The significance of the sorting variable is assessed by calculating the Jensen's alpha relative to the Carhart (1997) four-factor model (C4 α) and the Fama and French (2015) five-factor model (FF5 α). The table reports average returns, together with t-statistics reported in parentheses, and the t-statistics for the Jensen's alphas are based on Newey-West adjusted standard errors. The returns and Jensen's alphas, per week, have been multiplied by 100. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

	Panel A: Equal-Weight				Panel B: Value-Weight			
Signal \ AD	1	2	3	(3 − 1)	1	2	3	(3 − 1)
1	0.245	0.022	-0.296	-0.53***	0.245	0.016	-0.31	-0.543***
	(1.20)	(0.11)	(-1.06)	(-2.70)	(1.27)	(0.08)	(-1.13)	(-2.77)
2	0.315	0.402*	0.31	-0.014	0.266	0.362*	0.302	0.023
	(1.56)	(1.96)	(1.15)	(-0.07)	(1.43)	(1.82)	(1.14)	(0.12)
(2-1)	0.071	0.38**	0.613**	0.523**	0.032	0.361**	0.636***	0.589**
	(0.38)	(2.32)	(2.55)	(2.07)	(0.18)	(2.19)	(2.70)	(2.38)
C4 α	0.077	0.361**	0.645***	0.551**	0.058	0.348**	0.66***	0.586**
	(0.41)	(2.20)	(2.62)	(2.12)	(0.31)	(2.10)	(2.75)	(2.34)
FF5 α	0.03	0.327**	0.691***	0.646**	-0.017	0.317*	0.691***	0.696***
	(0.16)	(1.99)	(2.76)	(2.43)	(-0.09)	(1.91)	(2.91)	(2.76)
SY4 α	0.121	0.446***	0.667**	0.546**	0.093	0.425**	0.681***	0.591**
	(0.63)	(2.59)	(2.58)	(2.03)	(0.47)	(2.46)	(2.71)	(2.25)
Signal \ VOL	1	2	3	(3 − 1)	1	2	3	(3 − 1)
1	0.163	0.042	-0.373	-0.536***	0.086	0.038	-0.379	-0.464**
	(1.02)	(0.19)	(-1.33)	(-2.80)	(0.56)	(0.16)	(-1.35)	(-2.37)
2	0.31*	0.347	0.426	0.116	0.265	0.375*	0.496*	0.231
	(1.86)	(1.65)	(1.48)	(0.54)	(1.61)	(1.71)	(1.74)	(1.08)
(2-1)	0.147	0.305*	0.799***	0.652***	0.179	0.337**	0.881***	0.701***
	(1.07)	(1.90)	(3.21)	(2.63)	(1.31)	(2.11)	(3.44)	(2.75)
C4 α	0.14	0.332**	0.799***	0.66***	0.183	0.365**	0.87***	0.686***
	(1.00)	(2.06)	(3.11)	(2.58)	(1.33)	(2.27)	(3.35)	(2.66)
FF5 α	0.108	0.319**	0.88***	0.772***	0.134	0.342**	0.946***	0.81***
	(0.78)	(2.00)	(3.28)	(2.90)	(0.99)	(2.12)	(3.54)	(3.05)
SY4 α	0.176	0.334*	0.929***	0.753***	0.24	0.368**	1.013***	0.77***
	(1.14)	(1.87)	(3.33)	(2.70)	(1.56)	(2.08)	(3.59)	(2.70)

Signal \ LIQ	Panel A: Equal-Weight				Panel B: Value-Weight			
	1	2	3	$(3-1)$	1	2	3	$(3-1)$
1	-0.014	-0.033	-0.071	-0.057	-0.016	0.047	-0.168	-0.152
	(-0.07)	(-0.14)	(-0.29)	(-0.32)	(-0.09)	(0.20)	(-0.68)	(-0.82)
2	0.294	0.418*	0.432*	0.138	0.289*	0.479**	0.393	0.104
	(1.58)	(1.90)	(1.68)	(0.75)	(1.67)	(2.19)	(1.52)	(0.57)
(2-1)	0.307**	0.451**	0.503**	0.195	0.305**	0.431**	0.561**	0.256
	(2.10)	(2.44)	(2.14)	(0.79)	(2.10)	(2.47)	(2.33)	(1.02)
C4 α	0.323**	0.467**	0.492**	0.17	0.334**	0.448**	0.547**	0.213
	(2.17)	(2.53)	(2.02)	(0.66)	(2.27)	(2.54)	(2.21)	(0.82)
FF5 α	0.28*	0.49***	0.537**	0.257	0.288*	0.456**	0.591**	0.302
	(1.84)	(2.61)	(2.19)	(1.00)	(1.94)	(2.55)	(2.38)	(1.17)
SY4 α	0.321**	0.501**	0.599**	0.278	0.359**	0.459**	0.65**	0.291
	(2.01)	(2.46)	(2.29)	(1.01)	(2.24)	(2.37)	(2.40)	(1.04)

Similar results are observed when we use alternative signal measures—MM Long-Short Ratio Growth, MM Long Proportion Growth, and MM Short Proportion Growth, which are presented in Appendix G. Based on the results, we posit that the lead-lag relationship is due to informational friction rather than trading friction such as stock liquidity.

Because the results suggest that predictability is more pronounced in firms with higher information asymmetry, our results suggest that MM traders may view trading on the commodity futures market as a first choice instead of dealing with a non-transparent firm in the equity market, contributing to the time lag of pricing information in the equity market.

In addition to the usual limits-to-arbitrage arguments such as the fact that MM cannot infinitely lever-up, we can rationalize our finding through a number of angles, all of which involve asset pricing under imperfect information.

Firstly, our empirical results are in line with the theoretical model developed by Sockin and Xiong (2015), who find that market participants of the commodity market face severe informational frictions (i.e., market participants do not have perfect information on supply and demand shocks affecting a commodity) and emphasized the informational role and feedback effect of commodity prices, in that a higher commodity price signals stronger economic growth and may motivate goods producers to produce more goods which leads to

greater demand for the commodity as inputs. Thus, in our context, if the market participants believe MM's increased positions in a certain commodity signal stronger growth in economic demand requiring that commodity, that is good news for the commodity producers.

In addition, van Nieuwerburgh and Veldkamp (2010) have developed a model assuming information processing and information acquisition in the financial market is costly, as at a minimum it costs time ; and their results suggest it's optimal for agents to be under-diversified, and to hold one well-diversified portfolio plus one specialized portfolio which contains only one or very few (specialized) assets, and that agents cannot learn everything about all risks which would be too costly. In other words, MM may find learning about the company fundamentals of the commodity producing firms, many of which can influence company stock price in addition to the general prospects of the commodity, of each of stocks (especially those stocks with higher information frictions) in the commodity-equity based portfolio to be too costly; and thus MM do not trade on these stocks in the equity market, which leads to the stronger predictability results in subsequent stock returns especially amongst the stocks that have higher information asymmetry, leading to price inefficiency in these stocks at least in the short-term.

The lead-lag results in the equity and futures market can also be rationalized by a model involving Bayesian learning, through noisy signals, of correlated fundamentals that are not directly observable (Ho, 2013). Specifically, the fundamental of a commodity and the fundamental of a commodity-producing firm are clearly correlated, though the fundamental of the commodity-producing firm has components other than commodity prices as at a minimum it involves its capital structure, local cost of production, CEO ability among other things. If an equity investor sees an increased MM position, which is a noisy signal but nevertheless contains some information about the fundamental of a commodity, she will now have a more optimistic posterior probability on the fundamental of the firm, whether or not the signal is really caused by a true change in the fundamental of the commodity. In other words, there can be a contagion effect from the futures market to the equity market, and

Bayesian learning can generate comovements beyond what is mandated by true innovation in fundamentals (Ho, 2013). To put differently, through learning, the equity investor will have beliefs correlated with that of MM, similar to the mechanism in Simonovska et al. (2016).

5. Conclusion

Using the CFTC Disaggregated Commitments of Traders (DCOT) reports from August 2006 to December 2017, we document a new empirical phenomenon in which the positions of managed money (MM) in the commodity futures market can predict the stock returns of commodity producers in subsequent weeks. This predictability is established by a number of methodologies including single-sort and Fama-Macbeth cross-sectional regressions across a range of measures and time-lags. Specifically, if the DCOT reports an increase in long position, or a decrease in short position, or an increase in net position, or an increase in the ratio of long over short position of MM, then the stock price of producers of the same commodity would increase in the following week. Across the different measures, 1-week lag and 2-week moving averages usually produce the best predictability results. A trading strategy based on this finding can generate a significant and sizable alpha relative to the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Stambaugh and Yuan (2016) mispricing factor model.

Since money managers, speculators and hedge funds can trade on the stock market as well, why do we find predictability results? We argue that predictability arises due to informational frictions. Our double-sorting exercises indicate that our results are more pronounced with firms with higher *ex ante* analyst dispersion and higher *historical* stock volatility. We do not find predictability arises as a result of trading friction, as indicated in our double-sorting results with regards to Amihud's illiquidity measure. Our finding further challenges the efficient market hypothesis.

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Appendices

A. Procedure to compute the Long-Short portfolio returns

This appendix supplements the description of the procedure to compute the Long-Short portfolio returns in Section 3.2.

First, we compute the daily stock returns for each of the 10 commodity-equity portfolios:

$$r_t^C = \frac{1}{\sum_{i \in C} W_i^V} \sum_{i \in C} W_i^V r_{it}^C \tag{2}$$

where r_{it}^C is the stock return at day t of producer i belonging to commodity C, and

$$W_i^V = \begin{cases} marketcap_{i,year-1} & \text{if V-Weight is applied} \\ 1 & \text{if E-Weight is applied} \end{cases}$$

Then, we compound r_t^C to obtain weekly returns R_w^C, where the week w in the Wednesday-Tuesday convention runs from the beginning-of-day of Wednesday ($t = 1$) till the end-of-day of next Tuesday ($t = T$):

$$R_w^C = \prod_{t=1}^{T} (1 + r_t^C) - 1 \tag{3}$$

For a signal with a J-week *look-back horizon*, $J \geq 1$, the weekly signal s of the futures market are aggregated over the *look-back horizon* as: $\frac{1}{J} \sum_{k=1}^{J} s_{w-k}^C$. If the signal is positive, then the commodity-equity portfolio C belongs to the Long portfolio (L) in week w. If the signal is negative, then it belongs to the Short portfolio (S).

Finally, we compute the Long (R_w^L), Short (R_w^S) and Long-Short (R_w^{LS}) portfolio returns at week w, as follows:

$$R_w^L = \frac{1}{\sum_{C \in L} W_C^D} \sum_{C \in L} W_C^D R_w^C \tag{4}$$

$$R_w^S = \frac{1}{\sum_{C \in S} W_C^D} \sum_{C \in S} W_C^D R_w^C \tag{5}$$

$$R_w^{LS} = R_w^L - R_w^S \tag{6}$$

where,

$$W_C^D = \begin{cases} |\frac{1}{J} \sum_{k=1}^{J} s_{w-k}^C| & \text{if D-Weight is applied} \\ 1 & \text{if N-Weight is applied} \end{cases}$$

B. Data

Table B.1: Sample of Commodity Producers

Notes: The number of companies and the four-digit SIC codes (plus, whenever we hand-pick a firm in addition to SIC code matching, its five-digit permno) reported in the table correspond to the cases where we select ordinary common stocks with CRSP SHRCD=(10 or 11) or CRSP SHRCD=(10, 11 or 12). [1] Oil & Gas comprises crude oil [067651] and natural gas [23651], weighted yearly by the lagged U.S. oil and gas industry's total revenue (data retrieved from the U.S. Energy Information Administration) [2] Petroleum Refining comprises unleaded gas [111659]. [3] Miscellaneous metals comprises platinum [076651], and palladium [075651], weighted equally.

			Number of stocks where SHRCD:			
			(10 or 11)		**(10, 11 or 12)**	
Commodity [Contract Code]	Matching SIC codes (and permno)	SIC description	Avg. per week	Total	Avg. per week	Total
Copper [85692]	1020; 1021; 3331 (91418)	Copper Ores; Primary Smelting and Refining of Copper	3	4	7	12
Oil & Gas[1]	1310; 1311	Crude Petroleum and Gas Extraction	68	118	83	145
Petroleum Refining[2]	2910; 2911	Petroleum refining Extraction	11	16	13	19
Gold [88691]	1041, 1040	Gold ores; Gold and silver ores	5	9	40	72
Silver [84691]	1044; 1040	Silver Ores	3	4	10	14
Biofuel [25601]	2869; 2860	Industrial organic chemicals	10	16	11	19
Steel [192651]	3312 (37402, 80375)	Steel works, blast furnaces and rolling mills	11	19	13	22
Lumber [58643]	(21186, 39917, 56143, 56223, 79878, 84365)	n.a.	4	6	4	6
MiscMetal[3]	1099	Miscellaneous Metal Ores	4	5	5	7
Coal [24651,24658]	1220; 1221; 1222	Bituminous Coal and Lignite mining	8	16	8	16
		Total	= 127	= 213	= 194	= 332

Sample period : August 2006 - December 2017

Table B.2: Summary of positions held by DCOT's traders categories, August 2006-December 2017

Notes: The table summarizes the positions of traders in commodity futures markets according to the classification employed in the Disaggregated Commitments of Traders (DCOT) reports. For each category of traders, as described in Table 1, positions are measured as Net Long (long position - short position)and scaled by the open interest of that trader category. The columns report the sample average position, the standard deviation of the position, the fraction of the weeks the position is long, and the first order autocorrelation (ρ) of the position. The end of the sample period is December 2017 for all commodities. The starting date of the sample period is indicated in parenthesis below each commodity. While the first month of the sample period for coal is June 2007, the series shows many missing gaps, but becomes continuous from August 2012 onwards. Open interests extracted from CFTC on steel show similar time gaps. The average and standard deviation of the position have been multiplied by 100 so that they can be interpreted as percentages.

	Net Long position of traders as percent of open interest																			
	Money Managers				**Producers, Merchants, Processors & Users**				**Swap Dealers**				**Other Reporting**				**Non-Reporting**			
Commodity (Start)	Avg	Std. dev.	Long (%)	ρ	Avg	Std. dev.	Long (%)	ρ	Avg	Std. dev.	Long (%)	ρ	Avg	Std. dev.	Long (%)	ρ	Avg	Std. dev.	Long (%)	ρ
Copper (2006m8)	5.1	28.2	54.3	0.96	-47.3	22.8	0.7	0.97	58.4	14.2	100	0.97	-18.7	16	12.1	0.93	-7.2	12.8	29.6	0.92
Steel (2012m12)	2	70.1	48.5	0.99	5.7	52.1	57.3	0.99	84	32.3	94.9	0.98	-22.7	10.4	1.3	0.96	45.3	58.5	80.3	0.86
Gold (2006m8)	46.9	23.3	97.8	0.96	-52.7	19.1	1.5	0.98	-24.9	14.5	5.7	0.95	25	12	96.1	0.93	31.4	19.4	92.9	0.95
Silver (2006m8)	33	19.4	94.6	0.94	-60.9	13.9	0	0.97	-4.8	22.2	40.7	0.98	23.6	14.8	98.5	0.95	35.5	12.4	100	0.93
MiscMetal (2006m8)	61.2	20.9	100	0.97	-75.3	11.6	0	0.96	-32.3	19	7.4	0.94	43.4	14.6	98.7	0.88	41.8	17	99.8	0.93
Biofuel (2009m11)	55.9	31.6	96.6	0.88	-17.3	23.6	21.6	0.97	-20.1	40.3	29.3	0.9	13.6	30.5	66.4	0.92	21.9	17.6	89.3	0.77
Oil&Gas (2006m8)	8.5	9.4	82.9	0.98	-18.7	11.1	5.9	0.99	-0.9	17.1	53.9	1	-0.4	8	56.5	0.97	12.4	6.5	98.8	0.85
Petroleum (2006m8)	38.5	19.7	97.1	0.96	-34.7	6.3	0	0.88	50.2	14.8	100	0.97	18.9	15.4	87.9	0.94	14.5	12.7	86.2	0.89
Coal (2007m6)	-3.2	55.5	45.5	0.96	-8.6	34	38.4	0.99	-38.6	37.3	16.4	0.97	30.5	47.4	63.3	1	3.6	27.8	55.7	0.9
Lumber (2006m8)	5.9	39.9	50.8	0.97	-43	38.7	13.6	0.96	97.3	5.7	100	0.86	-3	18	38	0.91	3.4	12.1	59.5	0.89

Figure B.I: Breakdown of Total Open Interest (TOI) by Trader Category

Notes: This figure shows the average market share, for the commodities considered in our analysis, held by each of the five trader categories in the commodity futures market over the whole sample period from August 2006 to December 2017. The definitions of the trader categories are described in Table 1.

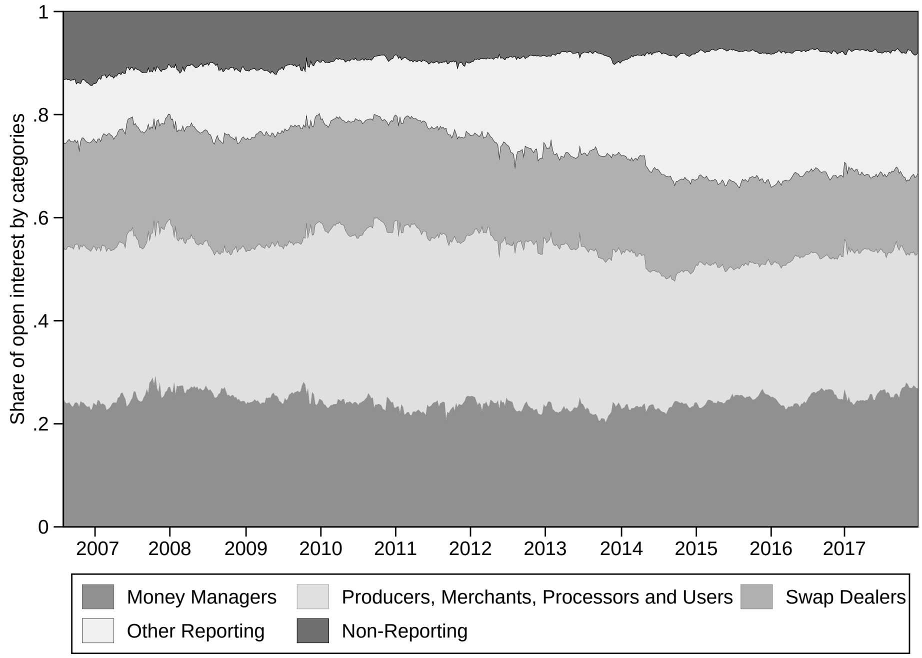


Figure B.II: Total number of stocks traded each week, baseline analysis

Notes: This figure shows the total number stocks traded in each week from August 2006 to December 2017, summed over all commodities with valid data (i.e., those reporting non-missing positions data) in CFTC reports. In our baseline analysis, we restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1.

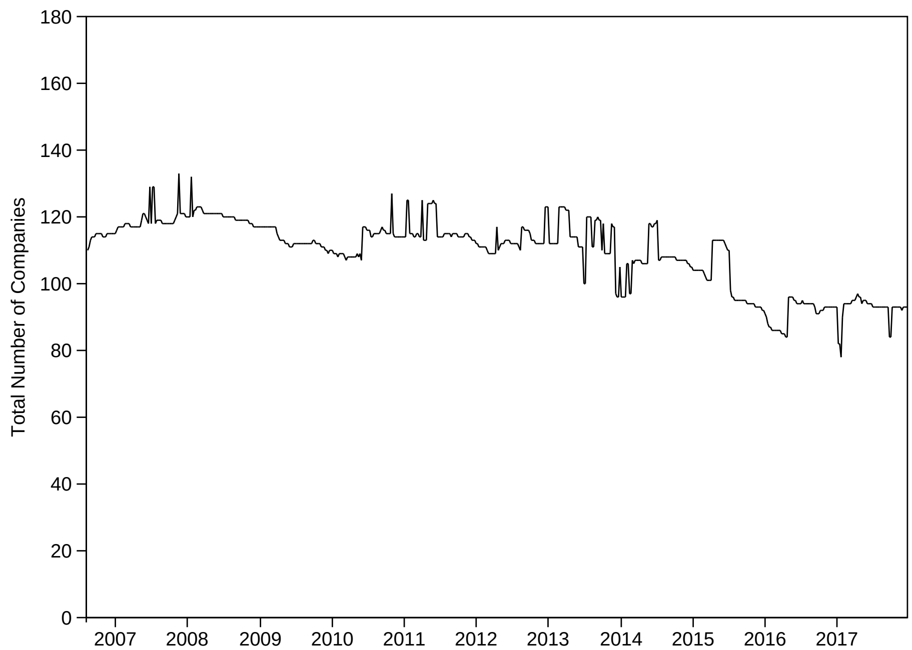
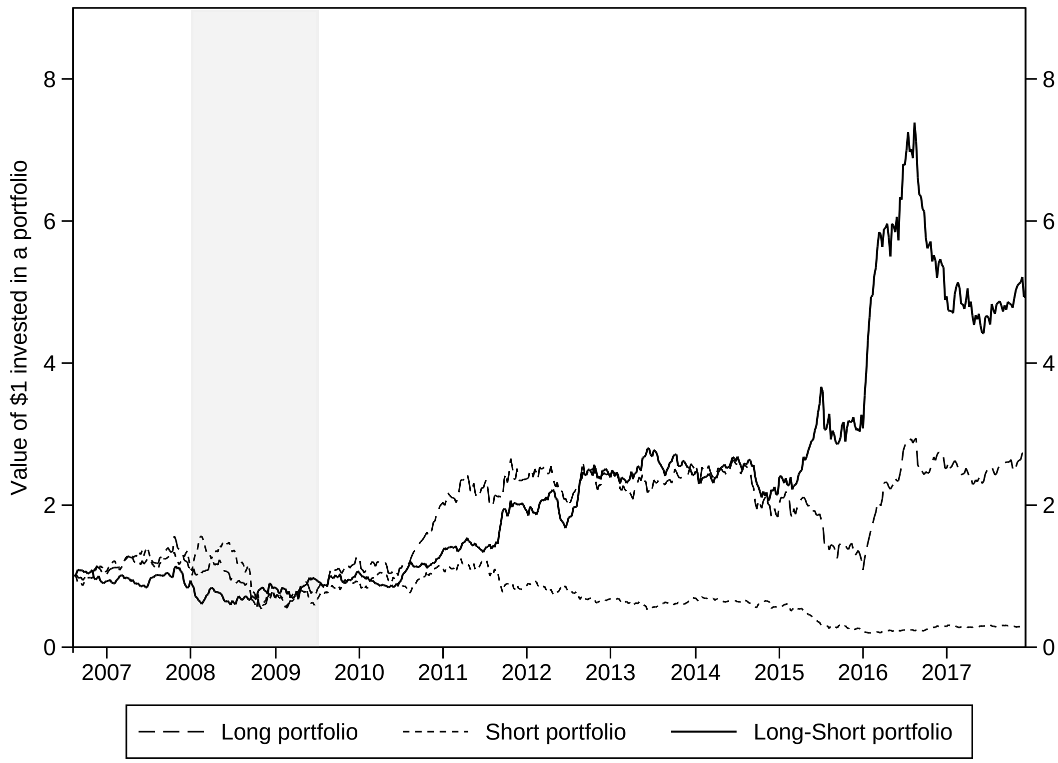


Figure B.III: Cumulative Gains from Investments, Signaled by the MA(2) Managed Money Short Proportion Growth (Monday-to-Friday convention, All-Weight). The shaded area corresponds to the NBER recession periods.



C. Robustness of Table 3

Table C.1: Stambaugh and Yu's 4-Factor Alpha Results (%, per Week)

Notes: We estimate the Stambaugh and Yuan (2016) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the MM category (as defined in Table 1) in the commodity futures market. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table report Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the whole sample period, which extends from August 2006 to December 2016 due to availability of the factor data, while Panel B focuses on non-NBER recession periods only, without the January 2008-June 2009 period. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.378**	0.674***	0.244*	0.465***	0.457***	0.758***	0.265**	0.493***
	(2.07)	(3.1)	(1.67)	(2.62)	(2.78)	(3.39)	(2.01)	(2.69)
2	0.372**	0.624***	0.327**	0.575***	0.444***	0.672***	0.375***	0.582***
	(2.19)	(3.02)	(2.17)	(3.34)	(2.72)	(3.11)	(2.6)	(3.27)
3	0.433**	0.604***	0.245*	0.542***	0.457***	0.678***	0.305**	0.608***
	(2.47)	(2.85)	(1.68)	(3.15)	(2.73)	(3.11)	(2.21)	(3.53)
4	0.361**	0.584***	0.1	0.324*	0.466***	0.775***	0.211	0.498***
	(2.08)	(2.83)	(0.7)	(1.88)	(2.8)	(3.62)	(1.56)	(2.8)
8	0.238	0.398**	0.181	0.288*	0.309*	0.49**	0.208	0.315*
	(1.37)	(2.07)	(1.27)	(1.66)	(1.92)	(2.53)	(1.51)	(1.73)
12	0.561***	0.745***	0.564***	0.665***	0.589***	0.73***	0.592***	0.635***
	(3.24)	(3.75)	(3.72)	(3.87)	(3.52)	(3.59)	(4.11)	(3.69)

Money Managers' Long Short Ratio Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.385**	0.68***	0.249*	0.459***	0.448***	0.751***	0.24*	0.461**
	(2.2)	(3.18)	(1.73)	(2.6)	(2.73)	(3.36)	(1.81)	(2.51)
2	0.344**	0.595***	0.327**	0.547***	0.411**	0.68***	0.338**	0.56***
	(2.03)	(2.97)	(2.2)	(3.26)	(2.52)	(3.25)	(2.39)	(3.22)
3	0.358**	0.55***	0.275*	0.552***	0.345**	0.629***	0.285**	0.617***
	(2.06)	(2.67)	(1.86)	(3.16)	(2.09)	(2.96)	(2.06)	(3.47)
4	0.306*	0.626***	0.141	0.403**	0.398**	0.789***	0.247*	0.555***
	(1.74)	(2.83)	(0.99)	(2.3)	(2.33)	(3.27)	(1.79)	(3.03)
8	0.125	0.39**	0.106	0.347*	0.273*	0.551***	0.203	0.451**
	(0.71)	(1.96)	(0.72)	(1.85)	(1.71)	(2.65)	(1.44)	(2.26)
12	0.183	0.468**	0.1	0.398**	0.307*	0.503**	0.281**	0.473**
	(1.05)	(2.34)	(0.65)	(2.17)	(1.94)	(2.43)	(2.02)	(2.5)

Money Managers' Long Proportion Growth

	Panel A: Whole sample				Panel B: Without Recession			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.37**	0.643***	0.254*	0.496***	0.438***	0.714***	0.262**	0.506***
	(2.03)	(2.98)	(1.71)	(2.75)	(2.7)	(3.22)	(2)	(2.77)
2	0.357**	0.62***	0.331**	0.516***	0.401**	0.644***	0.348**	0.509***
	(2.07)	(2.99)	(2.23)	(2.98)	(2.42)	(2.97)	(2.49)	(2.81)
3	0.402**	0.628***	0.185	0.489***	0.445***	0.716***	0.246*	0.556***
	(2.27)	(2.97)	(1.28)	(2.85)	(2.65)	(3.26)	(1.84)	(3.12)
4	0.373**	0.663***	0.151	0.388**	0.491***	0.836***	0.247*	0.559***
	(2.11)	(3.12)	(1.05)	(2.28)	(2.92)	(3.73)	(1.83)	(3.15)
8	0.283	0.457**	0.193	0.452**	0.407**	0.623***	0.281**	0.534***
	(1.61)	(2.24)	(1.38)	(2.57)	(2.51)	(2.93)	(2.08)	(2.86)
12	0.431**	0.714***	0.286**	0.503***	0.457***	0.634***	0.366***	0.483***
	(2.52)	(3.52)	(1.97)	(2.91)	(2.92)	(3.09)	(2.8)	(2.77)

Money Managers' Short Proportion Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.359**	-0.659***	-0.251*	-0.471***	-0.444***	-0.764***	-0.272**	-0.497***
	(-1.97)	(-2.98)	(-1.73)	(-2.66)	(-2.68)	(-3.37)	(-2.06)	(-2.73)
2	-0.343**	-0.654***	-0.302**	-0.578***	-0.409**	-0.702***	-0.352**	-0.59***
	(-1.98)	(-3.12)	(-2)	(-3.4)	(-2.51)	(-3.23)	(-2.47)	(-3.37)
3	-0.354**	-0.598***	-0.213	-0.504***	-0.364**	-0.67***	-0.289**	-0.597***
	(-2.04)	(-2.83)	(-1.48)	(-2.92)	(-2.24)	(-3.11)	(-2.12)	(-3.44)
4	-0.277	-0.583***	-0.13	-0.351**	-0.371**	-0.784***	-0.233*	-0.531***
	(-1.6)	(-2.76)	(-0.92)	(-2.05)	(-2.22)	(-3.55)	(-1.74)	(-3.02)
8	-0.193	-0.47**	-0.21	-0.406**	-0.259	-0.544***	-0.263**	-0.45***
	(-1.13)	(-2.48)	(-1.53)	(-2.42)	(-1.64)	(-2.86)	(-2)	(-2.58)
12	-0.404**	-0.737***	-0.502***	-0.711***	-0.438***	-0.76***	-0.575***	-0.784***
	(-2.41)	(-3.79)	(-3.37)	(-4.3)	(-2.77)	(-3.89)	(-4.18)	(-4.84)

Open Interest Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.138	0.064	0.073	-0.034	0.137	0.078	-0.011	-0.086
	(0.94)	(0.37)	(0.57)	(-0.22)	(1.05)	(0.44)	(-0.09)	(-0.53)
2	0.061	0.077	0.038	-0.008	0.042	0.087	-0.006	-0.026
	(0.43)	(0.45)	(0.3)	(-0.06)	(0.32)	(0.49)	(-0.05)	(-0.17)
3	-0.065	0.021	0.077	0.109	-0.038	-0.01	0.045	0.071
	(-0.43)	(0.12)	(0.61)	(0.71)	(-0.26)	(-0.05)	(0.39)	(0.47)
4	-0.183	-0.065	-0.111	-0.04	-0.199	-0.076	-0.146	-0.064
	(-1.21)	(-0.37)	(-0.84)	(-0.25)	(-1.38)	(-0.41)	(-1.14)	(-0.39)
8	-0.041	-0.045	-0.065	-0.163	-0.138	-0.071	-0.129	-0.136
	(-0.27)	(-0.25)	(-0.46)	(-1.03)	(-0.96)	(-0.38)	(-1.01)	(-0.84)
12	0.104	0.326*	-0.013	0.146	-0.234	-0.037	-0.314**	-0.186
	(0.64)	(1.78)	(-0.09)	(0.79)	(-1.64)	(-0.21)	(-2.34)	(-1.01)

Table C.2: Carhart 4-Factor Alpha Results with CRSP Share Codes 10, 11 & 12 (%, per Week)

Notes: This table presents the Carhart (1997) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the MM category (as defined in Table 1) in the commodity futures market. We include in our sample ordinary common shares (CRSP share codes 10 and 11), as well as U.S.-listed foreign incorporated commodity producers (CRSP share code 12). The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table reports Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the entire sample period, i.e., from August 2006 to December 2017, while Panel B focuses on non-NBER recession periods only, i.e., without the January 2008 to June 2009 period. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.361**	0.488***	0.256*	0.328**	0.367**	0.544***	0.228*	0.361**
	(2.2)	(2.59)	(1.95)	(2.13)	(2.26)	(2.71)	(1.81)	(2.23)
2	0.333**	0.512***	0.34**	0.532***	0.328**	0.499**	0.346**	0.503***
	(2.09)	(2.78)	(2.39)	(3.37)	(2.07)	(2.55)	(2.54)	(3.12)
3	0.353**	0.549***	0.185	0.459***	0.386**	0.569***	0.25*	0.523***
	(2.15)	(2.9)	(1.32)	(2.86)	(2.38)	(2.88)	(1.84)	(3.22)
4	0.265	0.508***	0.072	0.296*	0.376**	0.65***	0.2	0.444***
	(1.59)	(2.7)	(0.52)	(1.82)	(2.32)	(3.25)	(1.51)	(2.65)
8	0.151	0.337*	0.157	0.288*	0.198	0.34*	0.141	0.23
	(0.87)	(1.78)	(1.05)	(1.66)	(1.26)	(1.85)	(1.05)	(1.38)
12	0.467***	0.593***	0.499***	0.596***	0.464***	0.509***	0.486***	0.462***
	(2.68)	(3.03)	(3.23)	(3.42)	(2.91)	(2.73)	(3.59)	(3.04)

Money Managers' Long Short Ratio Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.357**	0.495***	0.253*	0.327**	0.352**	0.538***	0.203	0.331**
	(2.2)	(2.64)	(1.93)	(2.12)	(2.17)	(2.68)	(1.61)	(2.04)
2	0.295*	0.482***	0.341**	0.512***	0.293*	0.518***	0.345***	0.523***
	(1.86)	(2.68)	(2.46)	(3.3)	(1.85)	(2.7)	(2.59)	(3.24)
3	0.267*	0.506***	0.215	0.457***	0.265*	0.542***	0.241*	0.527***
	(1.67)	(2.78)	(1.55)	(2.91)	(1.68)	(2.81)	(1.79)	(3.24)
4	0.226	0.573***	0.115	0.352**	0.307*	0.708***	0.224*	0.478***
	(1.33)	(2.83)	(0.83)	(2.19)	(1.84)	(3.14)	(1.66)	(2.77)
8	-0.024	0.286	0.024	0.312*	0.189	0.421**	0.18	0.374**
	(-0.14)	(1.63)	(0.17)	(1.88)	(1.22)	(2.24)	(1.34)	(2.12)
12	0.115	0.316*	0.077	0.276	0.209	0.367*	0.209	0.327*
	(0.71)	(1.74)	(0.53)	(1.6)	(1.37)	(1.95)	(1.59)	(1.95)

Money Managers' Long Proportion Growth

	Panel A: Whole sample				Panel B: Without Recession			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.386**	0.483**	0.256**	0.34**	0.37**	0.526***	0.232*	0.359**
	(2.31)	(2.54)	(1.96)	(2.23)	(2.31)	(2.61)	(1.86)	(2.22)
2	0.357**	0.55***	0.343**	0.492***	0.298*	0.49**	0.336**	0.472***
	(2.15)	(2.93)	(2.46)	(3.21)	(1.84)	(2.5)	(2.53)	(2.9)
3	0.341**	0.6***	0.141	0.392***	0.373**	0.627***	0.212	0.481***
	(2.06)	(3.19)	(1.04)	(2.6)	(2.29)	(3.13)	(1.61)	(2.94)
4	0.284*	0.622***	0.097	0.336**	0.381**	0.758***	0.217*	0.488***
	(1.65)	(3.15)	(0.72)	(2.16)	(2.31)	(3.6)	(1.68)	(2.94)
8	0.136	0.328*	0.094	0.36**	0.29*	0.468**	0.232*	0.421**
	(0.82)	(1.76)	(0.7)	(2.23)	(1.84)	(2.42)	(1.78)	(2.5)
12	0.366**	0.556***	0.224	0.396**	0.37**	0.47**	0.29**	0.339**
	(2.07)	(2.81)	(1.51)	(2.33)	(2.45)	(2.54)	(2.32)	(2.18)

Money Managers' Short Proportion Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.323**	-0.47**	-0.255*	-0.317**	-0.342**	-0.539***	-0.228*	-0.351**
	(-1.98)	(-2.48)	(-1.94)	(-2.06)	(-2.11)	(-2.68)	(-1.82)	(-2.17)
2	-0.281*	-0.51***	-0.314**	-0.516***	-0.287*	-0.501**	-0.328**	-0.488***
	(-1.76)	(-2.75)	(-2.22)	(-3.28)	(-1.82)	(-2.54)	(-2.41)	(-3.04)
3	-0.27*	-0.523***	-0.155	-0.435***	-0.289*	-0.545***	-0.232*	-0.509***
	(-1.67)	(-2.75)	(-1.12)	(-2.69)	(-1.83)	(-2.77)	(-1.72)	(-3.11)
4	-0.187	-0.506***	-0.091	-0.316*	-0.28*	-0.657***	-0.209	-0.466***
	(-1.12)	(-2.63)	(-0.66)	(-1.95)	(-1.72)	(-3.18)	(-1.59)	(-2.8)
8	-0.119	-0.385**	-0.19	-0.377**	-0.141	-0.372**	-0.194	-0.338**
	(-0.68)	(-2.04)	(-1.29)	(-2.16)	(-0.9)	(-2.07)	(-1.49)	(-2.13)
12	-0.382**	-0.631***	-0.493***	-0.62***	-0.396**	-0.587***	-0.502***	-0.567***
	(-2.22)	(-3.26)	(-3.25)	(-3.67)	(-2.49)	(-3.18)	(-3.81)	(-3.86)

Open Interest Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.028	-0.063	0.018	-0.125	0.028	-0.038	-0.067	-0.15
	(0.2)	(-0.41)	(0.15)	(-0.9)	(0.23)	(-0.24)	(-0.63)	(-1.05)
2	-0.164	-0.176	-0.136	-0.17	-0.17	-0.154	-0.171	-0.184
	(-1.17)	(-1.13)	(-1.05)	(-1.24)	(-1.31)	(-1)	(-1.52)	(-1.42)
3	-0.183	-0.16	-0.056	-0.06	-0.165	-0.164	-0.068	-0.062
	(-1.24)	(-0.98)	(-0.44)	(-0.42)	(-1.19)	(-0.99)	(-0.62)	(-0.46)
4	-0.351**	-0.325**	-0.308**	-0.291**	-0.355**	-0.322*	-0.296**	-0.289*
	(-2.31)	(-1.96)	(-2.3)	(-1.96)	(-2.45)	(-1.85)	(-2.3)	(-1.87)
8	-0.294*	-0.215	-0.287**	-0.282*	-0.238*	-0.106	-0.197	-0.15
	(-1.93)	(-1.25)	(-2.1)	(-1.9)	(-1.68)	(-0.6)	(-1.61)	(-1.01)
12	-0.121	0.07	-0.147	-0.015	-0.35**	-0.104	-0.375***	-0.182
	(-0.75)	(0.39)	(-1)	(-0.09)	(-2.55)	(-0.62)	(-2.98)	(-1.06)

Table C.3: Carhart 4-Factor Alpha Results, after winsorizing the yearly distribution of stocks' weekly returns at 1st and 99th percentiles (%, per Week)

Notes: This table presents the Carhart (1997) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the MM category (as defined in Table 1) in the commodity futures market. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1. The commodity producers' weekly stock returns are winsorized at the 1st and 99.9th percentiles to remove outliers present in the distribution of weekly stock returns, using annually updated cutoffs calculated from our matched sample. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table report Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the whole sample period, from August 2006 to December 2017, while Panel B focuses on non-NBER recession periods only, without the January 2008-June 2009 period. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.424**	0.653***	0.272*	0.448***	0.459***	0.661***	0.267**	0.435***
	(2.51)	(3.39)	(1.95)	(2.84)	(2.98)	(3.41)	(2.13)	(2.75)
2	0.391**	0.588***	0.347**	0.544***	0.443***	0.581***	0.385***	0.508***
	(2.4)	(3.18)	(2.4)	(3.46)	(2.87)	(3.07)	(2.83)	(3.25)
3	0.437***	0.594***	0.272*	0.534***	0.456***	0.617***	0.329**	0.548***
	(2.66)	(3.12)	(1.91)	(3.31)	(2.93)	(3.2)	(2.45)	(3.48)
4	0.376**	0.547***	0.139	0.323**	0.472***	0.703***	0.251*	0.475***
	(2.25)	(2.92)	(0.96)	(2)	(3)	(3.7)	(1.88)	(2.93)
8	0.306*	0.459**	0.25*	0.354**	0.334**	0.479***	0.221	0.307*
	(1.72)	(2.36)	(1.68)	(2.02)	(2.1)	(2.6)	(1.64)	(1.83)
12	0.6***	0.823***	0.617***	0.749***	0.539***	0.67***	0.555***	0.571***
	(3.43)	(4.16)	(4.07)	(4.3)	(3.43)	(3.57)	(4.16)	(3.63)

Money Managers' Long Short Ratio Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.429***	0.657***	0.28**	0.447***	0.444***	0.652***	0.242*	0.403**
	(2.63)	(3.47)	(2.04)	(2.84)	(2.9)	(3.36)	(1.93)	(2.55)
2	0.363**	0.533***	0.346**	0.493***	0.404***	0.573***	0.349***	0.478***
	(2.24)	(2.94)	(2.43)	(3.23)	(2.62)	(3.07)	(2.63)	(3.11)
3	0.371**	0.508***	0.302**	0.521***	0.342**	0.537***	0.307**	0.542***
	(2.28)	(2.79)	(2.1)	(3.28)	(2.23)	(2.87)	(2.3)	(3.39)
4	0.33**	0.527***	0.206	0.409***	0.385**	0.616***	0.282**	0.502***
	(1.98)	(2.87)	(1.45)	(2.59)	(2.44)	(3.15)	(2.08)	(3.06)
8	0.126	0.321*	0.123	0.309*	0.262*	0.447**	0.211	0.38**
	(0.74)	(1.77)	(0.84)	(1.83)	(1.7)	(2.39)	(1.55)	(2.17)
12	0.169	0.424**	0.115	0.37**	0.258*	0.42**	0.243*	0.357**
	(0.98)	(2.25)	(0.77)	(2.19)	(1.7)	(2.2)	(1.84)	(2.13)

Money Managers' Long Proportion Growth

	Panel A: Whole sample				Panel B: Without Recession			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.431**	0.623***	0.279**	0.478***	0.441***	0.616***	0.269**	0.446***
	(2.56)	(3.26)	(1.98)	(3)	(2.93)	(3.2)	(2.17)	(2.83)
2	0.388**	0.6***	0.344**	0.496***	0.399**	0.543***	0.353***	0.439***
	(2.36)	(3.21)	(2.43)	(3.24)	(2.57)	(2.87)	(2.69)	(2.8)
3	0.415**	0.614***	0.233*	0.494***	0.44***	0.629***	0.281**	0.5***
	(2.49)	(3.26)	(1.65)	(3.2)	(2.83)	(3.28)	(2.16)	(3.16)
4	0.378**	0.578***	0.189	0.382**	0.479***	0.705***	0.274**	0.52***
	(2.23)	(3.08)	(1.33)	(2.45)	(3.04)	(3.64)	(2.07)	(3.22)
8	0.273	0.379**	0.211	0.402**	0.402**	0.539***	0.306**	0.487***
	(1.58)	(1.99)	(1.5)	(2.43)	(2.57)	(2.86)	(2.29)	(2.86)
12	0.446**	0.702***	0.297*	0.486***	0.424***	0.576***	0.348***	0.428***
	(2.49)	(3.5)	(1.95)	(2.84)	(2.81)	(3.09)	(2.76)	(2.74)

Money Managers' Short Proportion Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.405**	-0.643***	-0.28**	-0.45***	-0.448***	-0.678***	-0.274**	-0.437***
	(-2.36)	(-3.3)	(-2.01)	(-2.85)	(-2.85)	(-3.45)	(-2.19)	(-2.77)
2	-0.36**	-0.603***	-0.326**	-0.548***	-0.408***	-0.599***	-0.365***	-0.514***
	(-2.15)	(-3.19)	(-2.24)	(-3.49)	(-2.59)	(-3.1)	(-2.68)	(-3.31)
3	-0.37**	-0.58***	-0.237*	-0.489***	-0.366**	-0.594***	-0.311**	-0.546***
	(-2.24)	(-3.03)	(-1.69)	(-3.01)	(-2.36)	(-3.08)	(-2.36)	(-3.44)
4	-0.313*	-0.544***	-0.172	-0.347**	-0.384**	-0.696***	-0.275**	-0.499***
	(-1.86)	(-2.85)	(-1.2)	(-2.15)	(-2.39)	(-3.56)	(-2.06)	(-3.09)
8	-0.279	-0.53***	-0.298**	-0.476***	-0.288*	-0.521***	-0.287**	-0.436***
	(-1.58)	(-2.73)	(-2.05)	(-2.73)	(-1.82)	(-2.84)	(-2.17)	(-2.67)
12	-0.515***	-0.861***	-0.59***	-0.789***	-0.471***	-0.753***	-0.573***	-0.722***
	(-2.92)	(-4.38)	(-3.85)	(-4.65)	(-2.91)	(-4.02)	(-4.23)	(-4.77)

Open Interest Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.113	0.09	0.046	-0.015	0.084	0.059	-0.051	-0.102
	(0.8)	(0.58)	(0.37)	(-0.11)	(0.67)	(0.39)	(-0.46)	(-0.75)
2	-0.002	0.087	0.022	0.011	-0.073	0.062	-0.082	-0.051
	(-0.01)	(0.55)	(0.17)	(0.07)	(-0.56)	(0.4)	(-0.72)	(-0.38)
3	-0.081	0.059	0.062	0.106	-0.126	0.009	-0.021	0.042
	(-0.54)	(0.35)	(0.49)	(0.73)	(-0.89)	(0.06)	(-0.18)	(0.3)
4	-0.226	-0.085	-0.162	-0.084	-0.303**	-0.14	-0.25*	-0.147
	(-1.45)	(-0.49)	(-1.18)	(-0.56)	(-2.07)	(-0.8)	(-1.88)	(-0.95)
8	-0.091	-0.133	-0.124	-0.232	-0.175	-0.111	-0.159	-0.155
	(-0.59)	(-0.78)	(-0.89)	(-1.51)	(-1.26)	(-0.64)	(-1.29)	(-1.03)
12	0.088	0.281	-0.026	0.119	-0.277**	-0.055	-0.354***	-0.181
	(0.53)	(1.56)	(-0.17)	(0.7)	(-2.03)	(-0.34)	(-2.81)	(-1.17)

Table C.4: Carhart 4-Factor Alpha Results, after removing micro-cap stocks (%, per Week)

Notes: This table presents the Carhart (1997) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the MM category (as defined in Table 1) in the commodity futures market. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1. We remove stocks in the bottom 25% of market capitalization using annually updated cutoffs calculated from the CRSP universe. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table report Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the whole sample period, from August 2006 to December 2017, while Panel B focuses on non-NBER recession periods only, without the January 2008-June 2009 period. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.424**	0.591***	0.275*	0.342**	0.468***	0.624***	0.27**	0.332*
	(2.38)	(2.9)	(1.88)	(2.02)	(2.87)	(3.02)	(2.05)	(1.95)
2	0.389**	0.566***	0.355**	0.526***	0.449***	0.583***	0.411***	0.514***
	(2.3)	(2.98)	(2.35)	(3.26)	(2.76)	(2.98)	(2.87)	(3.2)
3	0.446**	0.566***	0.285*	0.494***	0.46***	0.602***	0.333**	0.495***
	(2.57)	(2.87)	(1.91)	(2.96)	(2.75)	(3.02)	(2.35)	(3.03)
4	0.381**	0.481**	0.135	0.226	0.477***	0.642***	0.246*	0.365**
	(2.18)	(2.52)	(0.91)	(1.38)	(2.87)	(3.32)	(1.78)	(2.22)
8	0.311*	0.469**	0.265*	0.393**	0.329**	0.485***	0.225	0.332*
	(1.71)	(2.36)	(1.74)	(2.19)	(2)	(2.61)	(1.58)	(1.94)
12	0.648***	0.897***	0.674***	0.881***	0.582***	0.767***	0.609***	0.739***
	(3.57)	(4.45)	(4.2)	(4.76)	(3.53)	(4.12)	(4.22)	(4.33)

Money Managers' Long Short Ratio Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.429**	0.578***	0.282**	0.337**	0.453***	0.598***	0.245*	0.297*
	(2.48)	(2.89)	(1.96)	(2.01)	(2.79)	(2.9)	(1.86)	(1.75)
2	0.354**	0.517***	0.348**	0.465***	0.403**	0.583***	0.367***	0.472***
	(2.1)	(2.77)	(2.34)	(2.98)	(2.47)	(2.99)	(2.62)	(2.99)
3	0.377**	0.443**	0.316**	0.437***	0.343**	0.479**	0.314**	0.443***
	(2.18)	(2.35)	(2.11)	(2.68)	(2.07)	(2.46)	(2.22)	(2.69)
4	0.338*	0.42**	0.197	0.293*	0.392**	0.505***	0.272*	0.377**
	(1.92)	(2.3)	(1.34)	(1.82)	(2.32)	(2.61)	(1.93)	(2.27)
8	0.149	0.319*	0.138	0.31*	0.28*	0.424**	0.212	0.362**
	(0.85)	(1.75)	(0.92)	(1.86)	(1.72)	(2.26)	(1.48)	(2.12)
12	0.203	0.467**	0.154	0.478***	0.282*	0.439**	0.273**	0.48***
	(1.16)	(2.5)	(1)	(2.71)	(1.79)	(2.39)	(1.98)	(2.73)

Money Managers' Long Proportion Growth

J	Panel A: Whole sample				Panel B: Without Recession			
	AW	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.42**	0.503**	0.278*	0.396**	0.435***	0.504**	0.27**	0.36**
	(2.35)	(2.56)	(1.89)	(2.34)	(2.71)	(2.56)	(2.07)	(2.14)
2	0.373**	0.527***	0.354**	0.458***	0.39**	0.487**	0.376***	0.434***
	(2.15)	(2.8)	(2.39)	(2.9)	(2.34)	(2.56)	(2.71)	(2.68)
3	0.42**	0.524***	0.24	0.445***	0.438***	0.542***	0.28**	0.445***
	(2.36)	(2.75)	(1.64)	(2.79)	(2.58)	(2.82)	(2.05)	(2.72)
4	0.387**	0.481***	0.188	0.3*	0.484***	0.595***	0.27**	0.438***
	(2.16)	(2.61)	(1.29)	(1.91)	(2.86)	(3.2)	(1.97)	(2.69)
8	0.299*	0.404**	0.22	0.414**	0.418**	0.54***	0.303**	0.478***
	(1.68)	(2.15)	(1.53)	(2.51)	(2.53)	(2.93)	(2.17)	(2.83)
12	0.494***	0.809***	0.332**	0.618***	0.462***	0.665***	0.374***	0.561***
	(2.65)	(4.01)	(2.12)	(3.42)	(2.94)	(3.82)	(2.84)	(3.43)

Money Managers' Short Proportion Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.407**	-0.579***	-0.283*	-0.336**	-0.462***	-0.647***	-0.277**	-0.328*
	(-2.28)	(-2.75)	(-1.94)	(-2)	(-2.8)	(-3.01)	(-2.11)	(-1.94)
2	-0.359**	-0.559***	-0.331**	-0.523***	-0.417**	-0.58***	-0.389***	-0.514***
	(-2.09)	(-2.84)	(-2.19)	(-3.25)	(-2.55)	(-2.85)	(-2.72)	(-3.22)
3	-0.381**	-0.527***	-0.251*	-0.408**	-0.373**	-0.548***	-0.319**	-0.446***
	(-2.21)	(-2.62)	(-1.71)	(-2.42)	(-2.27)	(-2.67)	(-2.28)	(-2.68)
4	-0.317*	-0.432**	-0.171	-0.217	-0.386**	-0.58***	-0.271**	-0.351**
	(-1.82)	(-2.2)	(-1.16)	(-1.32)	(-2.31)	(-2.86)	(-1.97)	(-2.15)
8	-0.283	-0.472**	-0.306**	-0.463**	-0.282*	-0.44**	-0.281**	-0.399**
	(-1.56)	(-2.35)	(-2.04)	(-2.57)	(-1.72)	(-2.32)	(-2.02)	(-2.35)
12	-0.548***	-0.86***	-0.633***	-0.902***	-0.496***	-0.765***	-0.611***	-0.869***
	(-3)	(-4.2)	(-3.98)	(-5)	(-2.92)	(-3.93)	(-4.3)	(-5.28)

Open Interest Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.119	0.038	0.061	-0.028	0.122	0.025	-0.024	-0.129
	(0.79)	(0.23)	(0.46)	(-0.18)	(0.94)	(0.15)	(-0.21)	(-0.84)
2	0.014	-0.006	0.01	-0.088	-0.037	-0.036	-0.066	-0.155
	(0.1)	(-0.04)	(0.07)	(-0.56)	(-0.26)	(-0.22)	(-0.54)	(-1.03)
3	-0.08	0.036	0.056	0.113	-0.103	-0.019	-0.003	0.05
	(-0.51)	(0.2)	(0.42)	(0.73)	(-0.69)	(-0.11)	(-0.03)	(0.35)
4	-0.25	-0.146	-0.185	-0.12	-0.316**	-0.197	-0.252*	-0.173
	(-1.53)	(-0.81)	(-1.28)	(-0.75)	(-2.04)	(-1.06)	(-1.81)	(-1.06)
8	-0.109	-0.224	-0.137	-0.294*	-0.199	-0.231	-0.18	-0.248*
	(-0.69)	(-1.31)	(-0.96)	(-1.91)	(-1.37)	(-1.39)	(-1.39)	(-1.67)
12	0.079	0.194	-0.025	0.09	-0.295**	-0.207	-0.357***	-0.258
	(0.46)	(1.01)	(-0.16)	(0.49)	(-2.05)	(-1.23)	(-2.71)	(-1.58)

D. Carhart 4-Factor Alpha for the Monday-to-Friday Convention

Table D: Carhart 4-Factor Alpha Results for the Monday-to-Friday Convention (%, per Week)

Notes: This table presents the Carhart (1997) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the MM category (as defined in Table 1) in the commodity futures market. The results are based on the *Monday-to-Friday* convention, which uses the CFTC report release date as the signal generation date. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table report Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the whole sample period, from August 2006 to December 2017, while Panel B focuses on non-NBER recession periods only, without the January 2008-June 2009 period. Panel C shows the regression results on the sample period post Dodd-Frank Act, i.e., from August 2011 to December 2017. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Money Managers' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**				**Panel C: Post Dodd-Frank Act**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.442***	0.594***	0.239*	0.422***	0.425**	0.482**	0.186	0.339**	0.448**	0.54**	0.166	0.351
	(2.59)	(3.2)	(1.68)	(2.65)	(2.49)	(2.53)	(1.31)	(2.07)	(2.11)	(2.3)	(0.93)	(1.64)
2	0.321*	0.464**	0.29*	0.499***	0.345*	0.443**	0.338**	0.515***	0.453**	0.54**	0.485**	0.671***
	(1.81)	(2.4)	(1.86)	(2.87)	(1.9)	(2.15)	(2.12)	(2.81)	(1.96)	(2.2)	(2.45)	(2.89)
3	0.355**	0.463**	0.29*	0.448***	0.366**	0.531***	0.307*	0.49***	0.442**	0.656**	0.361*	0.553**
	(2.03)	(2.35)	(1.86)	(2.63)	(2.1)	(2.58)	(1.94)	(2.75)	(1.98)	(2.49)	(1.8)	(2.37)
4	0.405**	0.633***	0.358**	0.505***	0.45**	0.722***	0.36**	0.536***	0.559**	0.896***	0.499**	0.699***
	(2.18)	(3.09)	(2.32)	(2.9)	(2.46)	(3.31)	(2.36)	(2.95)	(2.22)	(3.01)	(2.42)	(2.8)
8	0.484**	0.603***	0.317**	0.429**	0.372**	0.467**	0.192	0.263	0.435*	0.545**	0.172	0.317
	(2.51)	(2.96)	(1.97)	(2.35)	(2.08)	(2.39)	(1.29)	(1.47)	(1.89)	(2.12)	(0.88)	(1.31)
12	0.56***	0.783***	0.542***	0.655***	0.4**	0.548***	0.399***	0.461**	0.477**	0.629**	0.424**	0.429*
	(2.99)	(3.72)	(3.35)	(3.42)	(2.29)	(2.68)	(2.72)	(2.51)	(2.08)	(2.31)	(2.29)	(1.73)

Money Managers' Long Short Ratio Growth

	Panel A: Whole sample				Panel B: Without Recession				Panel C: Post Dodd-Frank Act			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.398**	0.547***	0.26*	0.449***	0.4**	0.466**	0.207	0.384**	0.429**	0.536**	0.192	0.42**
	(2.37)	(3.02)	(1.84)	(2.83)	(2.37)	(2.48)	(1.44)	(2.34)	(2.04)	(2.32)	(1.07)	(1.96)
2	0.2	0.379**	0.234	0.407**	0.203	0.375*	0.263*	0.438**	0.333	0.528**	0.392**	0.591***
	(1.14)	(1.96)	(1.52)	(2.32)	(1.14)	(1.81)	(1.66)	(2.34)	(1.48)	(2.14)	(2.01)	(2.58)
3	0.251	0.417**	0.274*	0.396**	0.249	0.506**	0.264*	0.428**	0.395*	0.744***	0.355*	0.552**
	(1.43)	(2.04)	(1.74)	(2.22)	(1.43)	(2.31)	(1.65)	(2.27)	(1.76)	(2.63)	(1.77)	(2.26)
4	0.352*	0.673***	0.394**	0.582***	0.359*	0.722***	0.412***	0.595***	0.535**	1.003***	0.572***	0.777***
	(1.83)	(2.93)	(2.47)	(3.27)	(1.87)	(2.84)	(2.68)	(3.22)	(2)	(2.85)	(2.77)	(3.2)
8	0.281	0.433**	0.192	0.355**	0.274	0.422**	0.184	0.338*	0.33	0.483*	0.273	0.464*
	(1.58)	(2.28)	(1.3)	(2.08)	(1.55)	(2.07)	(1.29)	(1.83)	(1.42)	(1.76)	(1.45)	(1.83)
12	0.003	0.343	-0.022	0.262	0.043	0.309	0.113	0.291	0.003	0.377	0.065	0.341
	(0.02)	(1.64)	(-0.13)	(1.43)	(0.26)	(1.47)	(0.75)	(1.57)	(0.01)	(1.3)	(0.34)	(1.35)

Money Managers' Long Proportion Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.556***	0.623***	0.317**	0.53***	0.407**	0.394**	0.209	0.397**	0.434*	0.469*	0.22	0.473**
	(3.19)	(3.28)	(2.19)	(3.29)	(2.28)	(2.02)	(1.46)	(2.4)	(1.93)	(1.95)	(1.22)	(2.16)
2	0.338*	0.508**	0.264*	0.46***	0.341*	0.436**	0.299*	0.472***	0.461**	0.54**	0.444**	0.624***
	(1.85)	(2.47)	(1.69)	(2.62)	(1.83)	(2.01)	(1.88)	(2.58)	(1.96)	(2.12)	(2.27)	(2.7)
3	0.366**	0.472**	0.229	0.366**	0.423**	0.533**	0.241	0.368**	0.56**	0.744***	0.357*	0.476*
	(2.07)	(2.23)	(1.5)	(2.09)	(2.4)	(2.38)	(1.59)	(2)	(2.48)	(2.63)	(1.8)	(1.95)
4	0.47**	0.721***	0.408**	0.549***	0.54***	0.799***	0.443***	0.578***	0.657***	1.017***	0.6***	0.714***
	(2.5)	(3.15)	(2.56)	(3.18)	(2.87)	(3.18)	(2.88)	(3.24)	(2.59)	(2.97)	(2.9)	(2.92)
8	0.432**	0.543***	0.338**	0.499***	0.432**	0.547***	0.324**	0.451**	0.423*	0.549**	0.429**	0.594**
	(2.36)	(2.73)	(2.28)	(2.98)	(2.46)	(2.66)	(2.3)	(2.56)	(1.84)	(2.01)	(2.42)	(2.53)
12	0.345*	0.653***	0.218	0.47**	0.211	0.413**	0.167	0.317*	0.119	0.407	0.164	0.326
	(1.79)	(2.95)	(1.32)	(2.46)	(1.26)	(2.01)	(1.18)	(1.8)	(0.56)	(1.49)	(0.94)	(1.4)

Money Managers' Short Proportion Growth

J	Panel A: Whole sample				Panel B: Without Recession				Panel C: Post Dodd-Frank Act			
	AW	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.329*	-0.547***	-0.197	-0.413***	-0.343**	-0.473**	-0.134	-0.319*	-0.369*	-0.535**	-0.109	-0.315
	(-1.89)	(-2.92)	(-1.37)	(-2.6)	(-2.04)	(-2.46)	(-0.93)	(-1.94)	(-1.77)	(-2.19)	(-0.6)	(-1.47)
2	-0.235	-0.478**	-0.27*	-0.493***	-0.222	-0.44**	-0.307**	-0.51***	-0.313	-0.508*	-0.421**	-0.642***
	(-1.31)	(-2.41)	(-1.77)	(-2.89)	(-1.22)	(-2.08)	(-1.96)	(-2.83)	(-1.36)	(-1.95)	(-2.17)	(-2.81)
3	-0.288	-0.52***	-0.259*	-0.434***	-0.263	-0.575***	-0.315**	-0.492***	-0.312	-0.64**	-0.362*	-0.52**
	(-1.61)	(-2.59)	(-1.65)	(-2.58)	(-1.48)	(-2.7)	(-2)	(-2.8)	(-1.36)	(-2.27)	(-1.82)	(-2.23)
4	-0.346*	-0.677***	-0.323**	-0.476***	-0.353*	-0.75***	-0.354**	-0.536***	-0.481*	-0.893***	-0.496**	-0.673***
	(-1.83)	(-3.22)	(-2.13)	(-2.74)	(-1.94)	(-3.34)	(-2.33)	(-2.97)	(-1.9)	(-2.88)	(-2.41)	(-2.67)
8	-0.455**	-0.645***	-0.369**	-0.566***	-0.3	-0.504**	-0.217	-0.406**	-0.371	-0.525**	-0.206	-0.446*
	(-2.35)	(-3.15)	(-2.32)	(-3.11)	(-1.64)	(-2.54)	(-1.47)	(-2.28)	(-1.58)	(-2.02)	(-1.09)	(-1.84)
12	-0.513***	-0.826***	-0.536***	-0.735***	-0.314*	-0.598***	-0.366***	-0.539***	-0.377*	-0.643**	-0.37**	-0.57**
	(-2.82)	(-4.04)	(-3.39)	(-4.04)	(-1.88)	(-2.96)	(-2.6)	(-3.2)	(-1.74)	(-2.46)	(-2.09)	(-2.56)

Open Interest Growth

J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.106	0.167	-0.027	-0.009	0.114	0.181	-0.016	-0.008	0.127	0.194	-0.03	0.026
	(0.69)	(0.95)	(-0.2)	(-0.05)	(0.81)	(1.07)	(-0.13)	(-0.05)	(0.73)	(0.92)	(-0.19)	(0.12)
2	-0.107	-0.001	-0.05	-0.119	-0.078	0.022	-0.044	-0.105	-0.134	-0.003	-0.069	-0.202
	(-0.7)	(-0.01)	(-0.36)	(-0.75)	(-0.51)	(0.12)	(-0.34)	(-0.64)	(-0.71)	(-0.01)	(-0.41)	(-0.9)
3	-0.172	-0.011	-0.081	-0.036	-0.194	-0.032	-0.113	-0.053	-0.249	0 (0)	-0.183	-0.103
	(-1.08)	(-0.06)	(-0.6)	(-0.22)	(-1.24)	(-0.17)	(-0.87)	(-0.33)	(-1.24)		(-1.11)	(-0.49)
4	-0.235	-0.069	-0.229*	-0.107	-0.25*	-0.038	-0.15	-0.015	-0.358*	-0.074	-0.26	-0.092
	(-1.43)	(-0.37)	(-1.67)	(-0.64)	(-1.65)	(-0.2)	(-1.19)	(-0.09)	(-1.8)	(-0.3)	(-1.6)	(-0.42)
8	-0.182	-0.25	-0.317**	-0.428**	-0.341**	-0.29	-0.405***	-0.408**	-0.431**	-0.187	-0.5***	-0.366*
	(-1.09)	(-1.31)	(-2.19)	(-2.55)	(-2.04)	(-1.47)	(-2.85)	(-2.36)	(-2.08)	(-0.76)	(-2.85)	(-1.66)
12	-0.005	0.235	-0.028	0.2	-0.234	-0.002	-0.213	0.035	-0.405**	-0.056	-0.394**	-0.011
	(-0.03)	(1.16)	(-0.18)	(1.03)	(-1.48)	(-0.01)	(-1.55)	(0.19)	(-2.11)	(-0.23)	(-2.37)	(-0.05)

E. Signals of the Commercial Hedger (PM) Category

Table E.1: Carhart 4-Factor Alpha Results for the Monday-to-Friday Convention based on PM Signals (%, per Week)

Notes: This table presents the Carhart (1997) four-factor alphas of the weekly returns for portfolios of commodity producing firms sorted by various signal measures (as described in Section 3.1.2) based on the positions of traders in the PM category (as defined in Table 1) in the commodity futures market. Per CFTC, a PM category trader is an entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities. The results are based on the *Monday-to-Friday* convention, which uses the CFTC report release date as the signal generation date. We restrict our attention to ordinary common shares (CRSP share codes 10 and 11) of U.S.-listed commodity producers as described in Section 3.1.1. The Long-Short portfolios are rebalanced weekly, and we follow a strategy of buying the producers stocks with positive signal growth and selling short the stocks with negative signal growth. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where the look-back horizon J is equal to 2, 3, 4, 8, or 12 weeks. The table report Jensen's alphas together with t-statistics (based on Newey-West adjusted standard errors) reported in parentheses. Panel A shows the results for the regressions on the whole sample period, from August 2006 to December 2017, while Panel B focuses on non-NBER recession periods only, without the January 2008-June 2009 period. Panel C shows the regression results on the sample period post Dodd-Frank Act, i.e., from August 2011 to December 2017. AW, DW, VW and NW stand for All-Weights, Degree-Weights, Value-Weights and No-Weight, respectively, as defined in Section 3.2.2. The weekly Jensen's alphas have been multiplied by 100 so they can be interpreted as percentages. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

PM Traders' Net Change

	Panel A: Whole sample				**Panel B: Without Recession**				**Panel C: Post Dodd-Frank Act**			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.116	-0.092	0.001	-0.061	-0.096	-0.111	-0.043	-0.175	-0.062	-0.194	-0.065	-0.29
	(-0.7)	(-0.52)	(0.01)	(-0.39)	(-0.58)	(-0.59)	(-0.31)	(-1.07)	(-0.29)	(-0.81)	(-0.36)	(-1.32)
2	-0.206	-0.289	-0.108	-0.217	-0.131	-0.303	-0.032	-0.214	-0.176	-0.359	-0.081	-0.266
	(-1.22)	(-1.54)	(-0.79)	(-1.37)	(-0.81)	(-1.58)	(-0.24)	(-1.29)	(-0.85)	(-1.43)	(-0.47)	(-1.16)
3	-0.243	-0.258	-0.151	-0.193	-0.179	-0.263	-0.162	-0.284*	-0.31	-0.437*	-0.254	-0.442**
	(-1.36)	(-1.38)	(-1.06)	(-1.24)	(-1.03)	(-1.36)	(-1.23)	(-1.76)	(-1.36)	(-1.69)	(-1.48)	(-2)
4	-0.271	-0.386*	-0.245*	-0.246	-0.095	-0.26	-0.119	-0.146	-0.231	-0.456	-0.193	-0.152
	(-1.45)	(-1.94)	(-1.66)	(-1.55)	(-0.54)	(-1.24)	(-0.88)	(-0.91)	(-1.02)	(-1.6)	(-1.09)	(-0.71)
8	-0.473**	-0.607***	-0.461***	-0.549***	-0.148	-0.363	-0.172	-0.337	-0.45*	-0.597	-0.459**	-0.543*
	(-2.45)	(-2.68)	(-2.98)	(-2.81)	(-0.82)	(-1.46)	(-1.21)	(-1.55)	(-1.9)	(-1.63)	(-2.42)	(-1.65)
12	-0.434**	-0.636***	-0.336**	-0.44**	-0.149	-0.36	-0.223	-0.319	-0.351	-0.69*	-0.384**	-0.554*
	(-2.33)	(-2.64)	(-2.15)	(-2.16)	(-0.87)	(-1.38)	(-1.64)	(-1.52)	(-1.64)	(-1.87)	(-2.32)	(-1.88)

PM Traders' Long Short Ratio Growth

	Panel A: Whole sample				Panel B: Without Recession				Panel C: Post Dodd-Frank Act			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.111	-0.084	0 (0)	-0.072	-0.09	-0.101	-0.044	-0.188	-0.047	-0.174	-0.058	-0.3
	(-0.67)	(-0.47)		(-0.46)	(-0.55)	(-0.54)	(-0.33)	(-1.15)	(-0.22)	(-0.73)	(-0.33)	(-1.36)
2	-0.229	-0.308	-0.158	-0.271*	-0.152	-0.32*	-0.095	-0.285*	-0.199	-0.372	-0.156	-0.355
	(-1.34)	(-1.64)	(-1.15)	(-1.71)	(-0.93)	(-1.67)	(-0.72)	(-1.71)	(-0.95)	(-1.49)	(-0.88)	(-1.53)
3	-0.24	-0.246	-0.153	-0.203	-0.139	-0.22	-0.125	-0.25	-0.233	-0.371	-0.165	-0.374*
	(-1.33)	(-1.31)	(-1.05)	(-1.31)	(-0.78)	(-1.13)	(-0.92)	(-1.54)	(-0.99)	(-1.41)	(-0.94)	(-1.7)
4	-0.276	-0.392**	-0.238	-0.289*	-0.09	-0.264	-0.123	-0.204	-0.217	-0.458	-0.162	-0.223
	(-1.46)	(-2)	(-1.63)	(-1.85)	(-0.5)	(-1.29)	(-0.92)	(-1.31)	(-0.93)	(-1.64)	(-0.93)	(-1.09)
8	-0.488**	-0.578**	-0.423***	-0.466**	-0.165	-0.349	-0.156	-0.299	-0.47**	-0.58	-0.44**	-0.492
	(-2.53)	(-2.47)	(-2.75)	(-2.36)	(-0.9)	(-1.33)	(-1.12)	(-1.34)	(-1.97)	(-1.48)	(-2.33)	(-1.45)
12	-0.45**	-0.621***	-0.41***	-0.481**	-0.151	-0.368	-0.271*	-0.359*	-0.361*	-0.719**	-0.475***	-0.584**
	(-2.45)	(-2.63)	(-2.61)	(-2.41)	(-0.89)	(-1.43)	(-1.94)	(-1.73)	(-1.69)	(-1.98)	(-2.74)	(-2.01)

PM Traders' Long Proportion Growth

	Panel A: Whole sample				Panel B: Without Recession				Panel C: Post Dodd-Frank Act			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	-0.075	-0.056	0.032	-0.006	-0.07	-0.092	-0.035	-0.129	-0.03	-0.177	-0.032	-0.207
	(-0.44)	(-0.31)	(0.23)	(-0.04)	(-0.42)	(-0.48)	(-0.26)	(-0.78)	(-0.14)	(-0.71)	(-0.18)	(-0.93)
2	-0.198	-0.269	-0.147	-0.281*	-0.131	-0.289	-0.106	-0.312*	-0.174	-0.335	-0.15	-0.372
	(-1.13)	(-1.38)	(-1.07)	(-1.75)	(-0.79)	(-1.45)	(-0.81)	(-1.87)	(-0.81)	(-1.28)	(-0.85)	(-1.61)
3	-0.268	-0.247	-0.186	-0.22	-0.2	-0.247	-0.158	-0.289*	-0.328	-0.421	-0.232	-0.456**
	(-1.46)	(-1.31)	(-1.29)	(-1.45)	(-1.12)	(-1.27)	(-1.18)	(-1.82)	(-1.41)	(-1.62)	(-1.34)	(-2.12)
4	-0.292	-0.378*	-0.279*	-0.311**	-0.1	-0.249	-0.13	-0.197	-0.231	-0.448	-0.188	-0.227
	(-1.53)	(-1.89)	(-1.88)	(-1.99)	(-0.55)	(-1.19)	(-0.98)	(-1.26)	(-1)	(-1.58)	(-1.09)	(-1.1)
8	-0.514***	-0.602***	-0.459***	-0.548***	-0.174	-0.367	-0.158	-0.392*	-0.51**	-0.635*	-0.436**	-0.615*
	(-2.68)	(-2.61)	(-3)	(-2.77)	(-0.96)	(-1.42)	(-1.12)	(-1.74)	(-2.19)	(-1.65)	(-2.28)	(-1.8)
12	-0.405**	-0.514**	-0.329**	-0.409**	-0.157	-0.332	-0.233*	-0.359*	-0.379*	-0.653*	-0.448***	-0.627**
	(-2.15)	(-2.1)	(-2.15)	(-2.05)	(-0.91)	(-1.26)	(-1.73)	(-1.74)	(-1.78)	(-1.75)	(-2.69)	(-2.17)

PM Traders' Short Proportion Growth

	Panel A: Whole sample				Panel B: Without Recession				Panel C: Post Dodd-Frank Act			
J	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**	**AW**	**DW**	**VW**	**NW**
1	0.212	0.195	0.027	0.108	0.166	0.202	0.061	0.215	0.143	0.236	0.077	0.323
	(1.33)	(1.09)	(0.19)	(0.68)	(1.03)	(1.07)	(0.45)	(1.3)	(0.68)	(0.95)	(0.43)	(1.47)
2	0.256	0.344*	0.056	0.185	0.212	0.419**	0.08	0.283*	0.282	0.491*	0.14	0.349
	(1.58)	(1.85)	(0.41)	(1.17)	(1.33)	(2.14)	(0.61)	(1.71)	(1.36)	(1.92)	(0.8)	(1.55)
3	0.172	0.24	0.089	0.138	0.118	0.281	0.154	0.274*	0.284	0.47*	0.274	0.464**
	(1.01)	(1.28)	(0.65)	(0.9)	(0.69)	(1.42)	(1.15)	(1.7)	(1.22)	(1.73)	(1.54)	(2.13)
4	0.3*	0.443**	0.221	0.265*	0.149	0.346*	0.135	0.192	0.288	0.523*	0.25	0.273
	(1.67)	(2.27)	(1.52)	(1.71)	(0.87)	(1.67)	(1.03)	(1.22)	(1.28)	(1.86)	(1.43)	(1.3)
8	0.437**	0.514**	0.303**	0.293*	0.286	0.443*	0.2	0.277*	0.513**	0.752**	0.361**	0.435*
	(2.38)	(2.36)	(1.99)	(1.75)	(1.63)	(1.81)	(1.48)	(1.66)	(2.17)	(2.08)	(2.06)	(1.9)
12	0.426**	0.478**	0.363**	0.373*	0.147	0.182	0.181	0.177	0.312	0.419	0.372**	0.345
	(2.36)	(2.26)	(2.27)	(1.94)	(0.94)	(0.89)	(1.36)	(0.95)	(1.56)	(1.54)	(2.32)	(1.37)

F. Additional Fama-Macbeth Regression Results for Section 4.3

Table F.1: Fama-Macbeth Regressions: Managed Money Long Short Ratio Growth, Non-Recession Periods Only

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

Non-Recession Periods Only

	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	+0.004***	+0.006***	+0.003**	+0.004***	+0.003**	+0.005**
Long Short Ratio Growth	(+3.116)	(+3.629)	(+2.207)	(+2.602)	(+1.985)	(+2.434)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.047)		(+0.029)		(+0.009)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.682)		(-0.754)		(-0.749)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.601)		(+0.672)		(+0.584)
$ret_{-2,-12}$		+0.001*		+0.001*		+0.001*
		(+1.873)		(+1.857)		(+1.757)
$\Delta CPrice_{-1}$		+0.005		+0.012*		+0.007
		(+0.671)		(+1.716)		(+1.023)
N–Companies	196	189	196	188	192	188
N–Observations	255509	241833	254429	241127	253604	240510
$Adj.R^2$		0.06757		0.06737		0.06761

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	+0.006***	+0.007***	+0.005*	+0.005**	+0.005	+0.005
Long Short Ratio Growth	(+3.178)	(+3.095)	(+1.944)	(+2.099)	(+1.437)	(+1.385)
$ln(BE/ME)$		+0.000		−0.000		−0.000
		(+0.021)		(-0.138)		(-0.073)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.801)		(-0.848)		(-0.826)
ret_{-1}		+0.001		+0.001		+0.000
		(+0.647)		(+0.465)		(+0.292)
$ret_{-2,-12}$		+0.001*		+0.001*		+0.001
		(+1.711)		(+1.671)		(+1.606)
$\Delta CPrice_{-1}$		+0.008		+0.014**		+0.014*
		(+1.091)		(+1.998)		(+1.906)
N–Companies	192	187	190	187	190	187
N–Observations	252911	239934	250671	238127	246986	235671
$Adj.R^2$		0.06833		0.06756		0.06711

Table F.2: Fama-Macbeth Regressions: Managed Money Long Short Ratio Growth, All Observations

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

All Observations

	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	+0.003*	+0.006***	+0.004**	+0.004**	+0.004*	+0.004*
Long Short Ratio Growth	(+1.869)	(+3.179)	(+2.326)	(+2.152)	(+1.789)	(+1.805)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.344)		(+0.282)		(+0.226)
$ln(ME)$		−0.000*		−0.000*		−0.000*
		(-1.827)		(-1.878)		(-1.889)
ret_{-1}		+0.000		+0.001		+0.000
		(+0.419)		(+0.487)		(+0.426)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.601)		(+1.593)		(+1.494)
$\Delta CPrice_{-1}$		+0.005		+0.009		+0.005
		(+0.678)		(+1.414)		(+0.780)
N–Companies	197	190	197	189	193	189
N–Observations	299041	284505	297961	283799	297136	283182
$Adj.R^2$		0.06841		0.06831		0.06831

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	+0.006**	+0.006**	+0.006*	+0.007**	+0.005	+0.010*
Long Short Ratio Growth	(+2.392)	(+2.455)	(+1.741)	(+1.965)	(+1.119)	(+1.934)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.264)		(+0.137)		(+0.196)
$ln(ME)$		−0.000**		−0.000**		−0.000*
		(-1.970)		(-1.969)		(-1.880)
ret_{-1}		+0.001		+0.000		+0.000
		(+0.472)		(+0.303)		(+0.073)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.491)		(+1.440)		(+1.396)
$\Delta CPrice_{-1}$		+0.007		+0.012*		+0.014**
		(+1.088)		(+1.847)		(+2.120)
N–Companies	193	188	191	188	191	188
N–Observations	296443	282606	294203	280799	290518	278343
$Adj.R^2$		0.06902		0.06839		0.06801

Table F.3: Fama-Macbeth Regressions: Managed Money Net Change, Non-Recession Periods Only

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

Non-Recession Periods Only

	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	+0.004***	+0.006***	+0.004***	+0.004***	+0.004***	+0.005***
Net Change	(+3.373)	(+3.753)	(+2.740)	(+2.884)	(+2.648)	(+2.970)
$ln(BE/ME)$		+0.000		−0.000		−0.000
		(+0.001)		(-0.042)		(-0.061)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.647)		(-0.698)		(-0.678)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.597)		(+0.657)		(+0.602)
$ret_{-2,-12}$		+0.001*		+0.001*		+0.001*
		(+1.935)		(+1.900)		(+1.811)
$\Delta CPrice_{-1}$		+0.004		+0.011		+0.009
		(+0.519)		(+1.561)		(+1.366)
N–Companies	196	189	196	188	192	188
N–Observations	255877	242138	254670	241360	253800	240698
$Adj.R^2$		0.06718		0.06726		0.06729

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	+0.006***	+0.007***	+0.001	+0.004	+0.007*	+0.012***
Net Change	(+3.156)	(+3.279)	(+0.428)	(+1.222)	(+1.858)	(+2.884)
$ln(BE/ME)$		−0.000		−0.000		−0.000
		(-0.087)		(-0.081)		(-0.040)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.697)		(-0.747)		(-0.779)
ret_{-1}		+0.001		+0.001		+0.000
		(+0.621)		(+0.551)		(+0.352)
$ret_{-2,-12}$		+0.001*		+0.001*		+0.001*
		(+1.739)		(+1.725)		(+1.787)
$\Delta CPrice_{-1}$		+0.008		+0.014**		+0.017**
		(+1.123)		(+1.997)		(+2.413)
N–Companies	192	187	190	187	190	187
N–Observations	253075	240090	250711	238167	247026	235711
$Adj.R^2$		0.06786		0.06765		0.06708

Table F.4: Fama-Macbeth Regressions: Managed Money Net Change, All Observations

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

All Observations

	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	+0.003*	+0.006***	+0.005***	+0.005**	+0.005**	+0.005**
Net Change	(+1.820)	(+3.037)	(+3.193)	(+2.492)	(+2.385)	(+1.988)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.278)		(+0.210)		(+0.141)
$ln(ME)$		−0.000*		−0.000*		−0.000*
		(-1.807)		(-1.865)		(-1.862)
ret_{-1}		+0.000		+0.001		+0.000
		(+0.412)		(+0.464)		(+0.427)
$ret_{-2,-12}$		+0.001*		+0.001		+0.001
		(+1.645)		(+1.624)		(+1.530)
$\Delta CPrice_{-1}$		+0.004		+0.009		+0.008
		(+0.582)		(+1.384)		(+1.192)
N–Companies	197	190	197	189	193	189
N–Observations	299457	284810	298202	284032	297332	283370
$Adj.R^2$		0.06806		0.06823		0.06807

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	+0.006**	+0.007**	+0.005	+0.006	+0.009*	+0.013***
Net Change	(+2.197)	(+2.238)	(+1.261)	(+1.639)	(+1.952)	(+2.915)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.166)		(+0.165)		(+0.238)
$ln(ME)$		−0.000*		−0.000*		−0.000*
		(-1.891)		(-1.929)		(-1.930)
ret_{-1}		+0.001		+0.000		+0.000
		(+0.439)		(+0.355)		(+0.166)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.551)		(+1.517)		(+1.542)
$\Delta CPrice_{-1}$		+0.008		+0.012*		+0.016**
		(+1.124)		(+1.855)		(+2.328)
N–Companies	193	188	191	188	191	188
N–Observations	296607	282762	294243	280839	290558	278383
$Adj.R^2$		0.06870		0.06863		0.06809

Table F.5: Fama-Macbeth Regressions: Managed Money Long Proportion Growth, Non-Recession Periods Only

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

Non-Recession Periods Only	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	+0.013***	+0.014***	+0.012***	+0.010*	+0.015***	+0.010
Long Proportion Growth	(+3.325)	(+2.994)	(+2.670)	(+1.923)	(+2.757)	(+1.624)
$ln(BE/ME)$		−0.000		−0.000		−0.000
		(-0.069)		(-0.097)		(-0.149)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.533)		(-0.634)		(-0.619)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.907)		(+0.911)		(+0.843)
$ret_{-2,-12}$		+0.001*		+0.001*		+0.001*
		(+1.718)		(+1.893)		(+1.790)
$\Delta CPrice_{-1}$		+0.007		+0.013*		+0.013*
		(+0.989)		(+1.944)		(+1.890)
N–Companies	196	189	196	188	196	188
N–Observations	259659	245281	258734	244785	258022	244344
$Adj.R^2$		0.06598		0.06567		0.06608

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	+0.012*	+0.012*	+0.017*	+0.019**	+0.019	+0.033**
Long Proportion Growth	(+1.902)	(+1.787)	(+1.850)	(+2.098)	(+1.520)	(+2.557)
$ln(BE/ME)$		−0.000		−0.000		−0.000
		(-0.130)		(-0.154)		(-0.075)
$ln(ME)$		−0.000		−0.000		−0.000
		(-0.676)		(-0.853)		(-0.843)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.846)		(+0.728)		(+0.687)
$ret_{-2,-12}$		+0.001		+0.001		+0.001*
		(+1.643)		(+1.625)		(+1.722)
$\Delta CPrice_{-1}$		+0.013*		+0.015**		+0.014**
		(+1.952)		(+2.393)		(+2.120)
N–Companies	196	187	190	187	190	187
N–Observations	257355	243893	255181	242251	251469	239805
$Adj.R^2$		0.06644		0.06650		0.06571

Table F.6: Fama-Macbeth Regressions: Managed Money Long Proportion Growth, All Observations

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

All Observations

	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	+0.010*	+0.011**	+0.015***	+0.007	+0.016***	+0.003
Long Proportion Growth	(+1.921)	(+2.126)	(+2.984)	(+1.139)	(+2.593)	(+0.436)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.197)		(+0.160)		(+0.089)
$ln(ME)$		−0.000*		−0.000*		−0.000*
		(-1.687)		(-1.812)		(-1.763)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.722)		(+0.692)		(+0.641)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.448)		(+1.602)		(+1.521)
$\Delta CPrice_{-1}$		+0.008		+0.011*		+0.012*
		(+1.078)		(+1.800)		(+1.782)
N–Companies	197	190	197	189	197	189
N–Observations	303419	287953	302494	287457	301782	287016
$Adj.R^2$		0.06706		0.06668		0.06683

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	+0.010	+0.004	+0.020*	+0.023*	+0.027*	+0.051***
Long Proportion Growth	(+1.271)	(+0.461)	(+1.808)	(+1.960)	(+1.886)	(+3.114)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.109)		(+0.115)		(+0.178)
$ln(ME)$		−0.000*		−0.000**		−0.000*
		(-1.891)		(-2.045)		(-1.943)
ret_{-1}		+0.001		+0.001		+0.001
		(+0.662)		(+0.537)		(+0.446)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.458)		(+1.442)		(+1.521)
$\Delta CPrice_{-1}$		+0.012*		+0.013**		+0.014**
		(+1.933)		(+2.004)		(+2.201)
N–Companies	197	188	197	188	191	188
N–Observations	301115	286565	298773	284923	295001	282477
$Adj.R^2$		0.06724		0.06741		0.06657

Table F.7: Fama-Macbeth Regressions: Managed Money Short Proportion Growth, Non-Recession Periods Only

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

Non-Recession Periods Only

	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	-0.005^{***}	-0.008^{***}	-0.005^{**}	-0.007^{***}	-0.005^{*}	-0.006^{**}
Short Proportion Growth	(-2.961)	(-3.455)	(-2.181)	(-3.138)	(-1.794)	(-2.132)
$ln(BE/ME)$		-0.000		-0.000		-0.000
		(-0.004)		(-0.034)		(-0.005)
$ln(ME)$		-0.000		-0.000		-0.000
		(-0.616)		(-0.654)		(-0.637)
ret_{-1}		$+0.001$		$+0.001$		$+0.001$
		(+0.625)		(+0.653)		(+0.626)
$ret_{-2,-12}$		$+0.001^{*}$		$+0.001^{*}$		$+0.001^{*}$
		(+1.882)		(+1.783)		(+1.717)
$\Delta CPrice_{-1}$		$+0.004$		$+0.010$		$+0.010$
		(+0.596)		(+1.431)		(+1.465)
N–Companies	196	189	196	188	195	188
N–Observations	258932	244198	257850	243485	257000	242888
$Adj.R^2$		0.06726		0.06735		0.06755

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	-0.008^{***}	-0.010^{***}	$+0.000$	-0.003	-0.008	-0.011^{**}
Short Proportion Growth	(-2.726)	(-3.121)	(+0.030)	(-0.697)	(-1.587)	(-2.264)
$ln(BE/ME)$		-0.000		-0.000		-0.000
		(-0.049)		(-0.046)		(-0.054)
$ln(ME)$		-0.000		-0.000		-0.000
		(-0.654)		(-0.662)		(-0.677)
ret_{-1}		$+0.001$		$+0.001$		$+0.001$
		(+0.631)		(+0.581)		(+0.382)
$ret_{-2,-12}$		$+0.001^{*}$		$+0.001^{*}$		$+0.001^{*}$
		(+1.660)		(+1.737)		(+1.736)
$\Delta CPrice_{-1}$		$+0.008$		$+0.015^{**}$		$+0.019^{***}$
		(+1.190)		(+2.233)		(+2.617)
N–Companies	195	187	195	187	192	187
N–Observations	256291	242342	253995	240669	250395	238460
$Adj.R^2$		0.06805		0.06767		0.06683

Table F.8: Fama-Macbeth Regressions: Managed Money Short Proportion Growth, All Observations

Notes: This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags) of firms' subsequent daily return on lagged signal and other lagged controls for expected returns. The daily return of the firm occurs within 7 calendar days (the first is always a Wednesday and the last is always a Tuesday unless they are postponed by due to holiday) following the newest CFTC Disaggregated Commitments of Traders report. We run the first stage of Fama-Macbeth regression at daily frequency. The signal from the futures market is constructed as a 1-week lag or as a J-week moving average, where J is equal to 2, 3, 4, 8, or 12. ret_{-1} is the stock return over the previous month; $ret_{-2,-12}$ is the stock return over the 11 months preceding the previous month; ln(BE/ME) denotes the log of the ratio of book value of equity to market value of equity; ln(ME) is the log of the market value of equity. $\Delta CPrice_{-1}$ is the change in commodiy pice over the previous week. We present t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. $Adj.R^2$ reports the average of the cross-sectional adjusted R^2's. N–Companies is the number of unique firms, and N–Observations is the number of firm-day return observations utilized in the regression.

All Observations	lag1		MA(2)		MA(3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money	-0.003^{*}	-0.008^{***}	-0.007^{***}	-0.008^{***}	-0.007^{**}	-0.006
Short Proportion Growth	(-1.676)	(-2.885)	(-2.802)	(-2.881)	(-2.088)	(-1.562)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.278)		(+0.211)		(+0.189)
$ln(ME)$		-0.000^{*}		-0.000^{*}		-0.000^{*}
		(-1.782)		(-1.821)		(-1.852)
ret_{-1}		+0.000		+0.001		+0.001
		(+0.426)		(+0.454)		(+0.445)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.608)		(+1.529)		(+1.454)
$\Delta CPrice_{-1}$		+0.005		+0.008		+0.008
		(+0.671)		(+1.220)		(+1.294)
N–Companies	197	190	197	189	196	189
N–Observations	302512	286870	301382	286157	300532	285560
$Adj.R^2$		0.06806		0.06829		0.06828

	MA(4)		MA(8)		MA(12)	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money	-0.009^{**}	-0.011^{**}	-0.006	-0.008	-0.011^{*}	-0.013^{**}
Short Proportion Growth	(-2.137)	(-2.442)	(-1.152)	(-1.423)	(-1.754)	(-2.097)
$ln(BE/ME)$		+0.000		+0.000		+0.000
		(+0.193)		(+0.211)		(+0.241)
$ln(ME)$		-0.000^{*}		-0.000^{*}		-0.000^{*}
		(-1.859)		(-1.833)		(-1.821)
ret_{-1}		+0.001		+0.000		+0.000
		(+0.430)		(+0.370)		(+0.185)
$ret_{-2,-12}$		+0.001		+0.001		+0.001
		(+1.480)		(+1.522)		(+1.482)
$\Delta CPrice_{-1}$		+0.008		$+0.014^{**}$		$+0.016^{**}$
		(+1.271)		(+2.126)		(+2.411)
N–Companies	196	188	196	188	193	188
N–Observations	299823	285014	297527	283341	293927	281132
$Adj.R^2$		0.06883		0.06874		0.06813

G. Additional Double-Sorting Results for Section 4.6

Table G.1: Double Sorting: Money Managers' Long-Short Ratio Growth (%, per Week)

Notes: This table presents results from our double-sorted cross-sectional exercise. Specifically, each week, all the producer stocks are first sorted into three friction portfolios using one of the three firm-level proxies of friction (LIQ, VOL, and AD), with the requirement that each commodity appears across those three portfolios. LIQ, VOL and AD stand for the Amihud's illiquidity measure, the 60-day *historical* stock volatility and the *ex ante* analyst dispersion, respectively. Then, the two signal portfolios are formed dependently within each of the three friction portfolios, based on the MM Long Short Ratio Growth signal. The signal from the futures market is constructed with a 1-week lag, and the same is true for the three proxies of market friction. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. This 3-by-2 double-sorting procedure produces six portfolios. Finally, we both equally weight (Panel A) or value-weight (Panel B) the sorts. The significance of the sorting variable is assessed by calculating the Jensen's alpha relative to the Carhart (1997) four-factor model (C4 α) and the Fama and French (2015) five-factor model (FF5 α). The table reports average returns, together with t-statistics reported in parentheses, and the t-statistics for the Jensen's alphas are based on Newey-West adjusted standard errors. The returns and Jensen's alphas, per week, have been multiplied by 100. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

	Panel A: Equal-Weight				Panel B: Value-Weight			
Signal \ AD	1	2	3	(3 − 1)	1	2	3	(3 − 1)
1	0.215	0.038	-0.282	-0.492**	0.216	0.035	-0.291	-0.501**
	(1.06)	(0.19)	(-1.01)	(-2.52)	(1.12)	(0.18)	(-1.07)	(-2.56)
2	0.343*	0.381*	0.309	-0.036	0.297	0.339*	0.293	-0.01
	(1.68)	(1.86)	(1.14)	(-0.19)	(1.58)	(1.71)	(1.10)	(-0.05)
(2-1)	0.128	0.342**	0.598**	0.462*	0.092	0.318*	0.608**	0.512**
	(0.69)	(2.08)	(2.46)	(1.81)	(0.50)	(1.93)	(2.55)	(2.05)
C4 α	0.132	0.324**	0.626**	0.487*	0.116	0.307*	0.629***	0.509**
	(0.70)	(1.97)	(2.51)	(1.86)	(0.62)	(1.86)	(2.59)	(2.01)
FF5 α	0.088	0.294*	0.673***	0.579**	0.042	0.282*	0.665***	0.619**
	(0.46)	(1.78)	(2.65)	(2.16)	(0.23)	(1.70)	(2.75)	(2.41)
SY4 α	0.181	0.41**	0.653**	0.472*	0.154	0.388**	0.654**	0.504*
	(0.94)	(2.38)	(2.50)	(1.73)	(0.78)	(2.25)	(2.57)	(1.89)
Signal \ VOL	1	2	3	(3 − 1)	1	2	3	(3 − 1)
1	0.178	0.062	-0.381	-0.559***	0.102	0.063	-0.374	-0.474**
	(1.12)	(0.27)	(-1.36)	(-2.93)	(0.66)	(0.28)	(-1.33)	(-2.43)
2	0.296*	0.328	0.437	0.141	0.254	0.35	0.488*	0.235
	(1.77)	(1.56)	(1.52)	(0.65)	(1.53)	(1.59)	(1.70)	(1.09)
(2-1)	0.118	0.267*	0.818***	0.7***	0.152	0.287*	0.868***	0.715***
	(0.85)	(1.67)	(3.27)	(2.81)	(1.11)	(1.80)	(3.37)	(2.78)
C4 α	0.111	0.291*	0.821***	0.71***	0.157	0.312*	0.858***	0.7***
	(0.79)	(1.81)	(3.18)	(2.77)	(1.13)	(1.95)	(3.28)	(2.69)
FF5 α	0.08	0.281*	0.898***	0.818***	0.113	0.289*	0.929***	0.814***
	(0.57)	(1.77)	(3.33)	(3.06)	(0.83)	(1.81)	(3.44)	(3.04)
SY4 α	0.151	0.282	0.914***	0.763***	0.219	0.308*	0.97***	0.749***
	(0.97)	(1.58)	(3.26)	(2.72)	(1.42)	(1.75)	(3.41)	(2.60)

LIQ / Signal	Panel A: Equal-Weight				Panel B: Value-Weight			
	1	2	3	$(3-1)$	1	2	3	$(3-1)$
1	0.023	-0.017	-0.078	-0.102	0.026	0.065	-0.184	-0.211
	(0.12)	(-0.07)	(-0.32)	(-0.56)	(0.15)	(0.27)	(-0.74)	(-1.12)
2	0.258	0.402*	0.445*	0.188	0.25	0.458**	0.405	0.155
	(1.37)	(1.83)	(1.73)	(1.01)	(1.43)	(2.09)	(1.56)	(0.83)
(2-1)	0.235	0.419**	0.524**	0.289	0.224	0.394**	0.589**	0.365
	(1.58)	(2.27)	(2.21)	(1.15)	(1.53)	(2.25)	(2.41)	(1.42)
C4 α	0.251*	0.436**	0.511**	0.26	0.254*	0.409**	0.573**	0.319
	(1.67)	(2.36)	(2.08)	(1.00)	(1.71)	(2.33)	(2.28)	(1.21)
FF5 α	0.214	0.454**	0.56**	0.346	0.217	0.414**	0.619**	0.402
	(1.39)	(2.41)	(2.26)	(1.33)	(1.45)	(2.32)	(2.47)	(1.53)
SY4 α	0.252	0.458**	0.579**	0.328	0.281*	0.42**	0.636**	0.356
	(1.55)	(2.24)	(2.19)	(1.17)	(1.74)	(2.17)	(2.32)	(1.25)

Table G.2: Double Sorting: Money Managers' Long Proportion Growth (%, per Week)

Notes: This table presents results from our double-sorted cross-sectional exercise. Specifically, each week, all the producer stocks are first sorted into three friction portfolios using one of the three firm-level proxies of friction (LIQ, VOL, and AD), with the requirement that each commodity appears across those three portfolios. LIQ, VOL and AD stand for the Amihud's illiquidity measure, the 60-day *historical* stock volatility and the *ex ante* analyst dispersion, respectively. Then, the two signal portfolios are formed dependently within each of the three friction portfolios, based on the MM Long Proportion Growth signal. The signal from the futures market is constructed with a 1-week lag, and the same is true for the three proxies of market friction. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. This 3-by-2 double-sorting procedure produces six portfolios. Finally, we both equally weight (Panel A) or value-weight (Panel B) the sorts. The significance of the sorting variable is assessed by calculating the Jensen's alpha relative to the Carhart (1997) four-factor model (C4 α) and the Fama and French (2015) five-factor model (FF5 α). The table reports average returns, together with t-statistics reported in parentheses, and the t-statistics for the Jensen's alphas are based on Newey-West adjusted standard errors. The returns and Jensen's alphas, per week, have been multiplied by 100. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

	Panel A: Equal-Weight				**Panel B: Value-Weight**			
Signal \ AD	1	2	3	(3 − 1)	1	2	3	(3 − 1)
1	0.199	0.002	-0.354	-0.548***	0.208	0.004	-0.352	-0.555***
	(0.97)	(0.01)	(-1.25)	(-2.77)	(1.08)	(0.02)	(-1.27)	(-2.80)
2	0.382*	0.439**	0.348	-0.044	0.333*	0.392**	0.315	-0.02
	(1.89)	(2.16)	(1.31)	(-0.24)	(1.79)	(1.99)	(1.21)	(-0.11)
(2-1)	0.183	0.437***	0.709***	0.519**	0.125	0.402**	0.688***	0.556**
	(1.00)	(2.77)	(2.93)	(2.05)	(0.69)	(2.54)	(2.91)	(2.24)
C4 α	0.184	0.412***	0.747***	0.556**	0.145	0.386**	0.717***	0.565**
	(0.99)	(2.61)	(3.02)	(2.14)	(0.79)	(2.43)	(2.99)	(2.24)
FF5 α	0.151	0.349**	0.755***	0.597**	0.103	0.35**	0.724***	0.614**
	(0.81)	(2.19)	(3.03)	(2.25)	(0.56)	(2.18)	(3.06)	(2.41)
SY4 α	0.232	0.46***	0.744***	0.512*	0.188	0.428***	0.713***	0.525**
	(1.21)	(2.80)	(2.85)	(1.88)	(0.98)	(2.60)	(2.81)	(1.98)
Signal \ VOL	1	2	3	(3 − 1)	1	2	3	(3 − 1)
1	0.196	0.077	-0.434	-0.63***	0.114	0.047	-0.451	-0.566***
	(1.24)	(0.34)	(-1.57)	(-3.27)	(0.75)	(0.20)	(-1.64)	(-2.91)
2	0.279*	0.342	0.48	0.201	0.262	0.393*	0.56*	0.298
	(1.69)	(1.61)	(1.64)	(0.92)	(1.59)	(1.79)	(1.90)	(1.34)
(2-1)	0.083	0.265	0.915***	0.832***	0.148	0.347**	1.011***	0.864***
	(0.61)	(1.64)	(3.59)	(3.24)	(1.11)	(2.16)	(3.77)	(3.19)
C4 α	0.075	0.279*	0.906***	0.831***	0.147	0.363**	0.989***	0.842***
	(0.55)	(1.72)	(3.45)	(3.13)	(1.09)	(2.24)	(3.64)	(3.07)
FF5 α	0.044	0.264*	0.973***	0.929***	0.124	0.35**	1.041***	0.918***
	(0.32)	(1.67)	(3.56)	(3.42)	(0.93)	(2.20)	(3.73)	(3.29)
SY4 α	0.115	0.274	1.023***	0.908***	0.212	0.367**	1.097***	0.885***
	(0.77)	(1.54)	(3.54)	(3.10)	(1.42)	(2.08)	(3.63)	(2.87)

LIQ / Signal	Panel A: Equal-Weight				Panel B: Value-Weight			
	1	2	3	$(3-1)$	1	2	3	$(3-1)$
1	-0.003	-0.026	-0.034	-0.031	0.006	0.066	-0.166	-0.172
	(-0.02)	(-0.11)	(-0.14)	(-0.17)	(0.03)	(0.28)	(-0.68)	(-0.93)
2	0.308	0.423*	0.392	0.083	0.295*	0.47**	0.397	0.101
	(1.63)	(1.91)	(1.51)	(0.45)	(1.68)	(2.14)	(1.50)	(0.53)
(2-1)	0.312**	0.449**	0.426*	0.114	0.29**	0.404**	0.563**	0.274
	(2.13)	(2.44)	(1.80)	(0.45)	(1.99)	(2.31)	(2.29)	(1.04)
C4 α	0.321**	0.458**	0.407*	0.086	0.312**	0.412**	0.54**	0.228
	(2.16)	(2.48)	(1.67)	(0.33)	(2.10)	(2.34)	(2.14)	(0.84)
FF5 α	0.276*	0.447**	0.471*	0.195	0.286*	0.394**	0.579**	0.293
	(1.84)	(2.40)	(1.91)	(0.75)	(1.94)	(2.21)	(2.30)	(1.08)
SY4 α	0.331**	0.483**	0.49*	0.159	0.338**	0.416**	0.63**	0.291
	(2.06)	(2.38)	(1.84)	(0.56)	(2.12)	(2.15)	(2.27)	(0.99)

Table G.3: Double Sorting: Money Managers' Short Proportion Growth (%, per Week)

Notes: This table presents results from our double-sorted cross-sectional exercise. Specifically, each week, all the producer stocks are first sorted into three friction portfolios using one of the three firm-level proxies of friction (LIQ, VOL, and AD), with the requirement that each commodity appears across those three portfolios. LIQ, VOL and AD stand for the Amihud's illiquidity measure, the 60-day *historical* stock volatility and the *ex ante* analyst dispersion, respectively. Then, the two signal portfolios are formed dependently within each of the three friction portfolios, based on the MM Short Proportion Growth signal. The signal from the futures market is constructed with a 1-week lag, and the same is true for the three proxies of market friction. The results are based on the *Wednesday-to-Tuesday* convention, which uses the CFTC report compilation date as the signal generation date. This 3-by-2 double-sorting procedure produces six portfolios. Finally, we both equally weight (Panel A) or value-weight (Panel B) the sorts. The significance of the sorting variable is assessed by calculating the Jensen's alpha relative to the Carhart (1997) four-factor model (C4 α) and the Fama and French (2015) five-factor model (FF5 α). The table reports average returns, together with t-statistics reported in parentheses, and the t-statistics for the Jensen's alphas are based on Newey-West adjusted standard errors. The returns and Jensen's alphas, per week, have been multiplied by 100. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

	Panel A: Equal-Weight				**Panel B: Value-Weight**			
Signal \ AD	1	2	3	$(3-1)$	1	2	3	$(3-1)$
1	0.353	0.434**	0.451	0.09	0.279	0.385*	0.442	0.142
	(1.61)	(2.05)	(1.61)	(0.45)	(1.36)	(1.85)	(1.61)	(0.72)
2	0.159	0.067	-0.267	-0.444**	0.16	0.061	-0.294	-0.465**
	(0.84)	(0.33)	(-0.97)	(-2.42)	(0.91)	(0.31)	(-1.11)	(-2.51)
(2-1)	-0.194	-0.367**	-0.725***	-0.513**	-0.13	-0.338**	-0.731***	-0.587**
	(-1.07)	(-2.21)	(-2.98)	(-2.03)	(-0.71)	(-2.07)	(-3.10)	(-2.40)
C4 α	-0.186	-0.355**	-0.756***	-0.553**	-0.129	-0.324*	-0.75***	-0.606**
	(-1.02)	(-2.12)	(-3.04)	(-2.15)	(-0.72)	(-1.96)	(-3.13)	(-2.47)
FF5 α	-0.126	-0.297*	-0.801***	-0.66**	-0.078	-0.277*	-0.778***	-0.687***
	(-0.70)	(-1.78)	(-3.17)	(-2.55)	(-0.44)	(-1.69)	(-3.26)	(-2.78)
SY4 α	-0.221	-0.413**	-0.781***	-0.561**	-0.174	-0.386**	-0.781***	-0.611**
	(-1.17)	(-2.38)	(-2.99)	(-2.08)	(-0.91)	(-2.26)	(-3.13)	(-2.36)
Signal \ VOL	1	2	3	$(3-1)$	1	2	3	$(3-1)$
1	0.27	0.369*	0.468	0.198	0.23	0.415*	0.538*	0.308
	(1.62)	(1.69)	(1.54)	(0.86)	(1.38)	(1.82)	(1.79)	(1.34)
2	0.208	0.066	-0.303	-0.511***	0.127	0.04	-0.304	-0.431**
	(1.32)	(0.30)	(-1.13)	(-2.85)	(0.84)	(0.18)	(-1.12)	(-2.34)
(2-1)	-0.062	-0.303**	-0.772***	-0.709***	-0.104	-0.375**	-0.842***	-0.738***
	(-0.46)	(-1.99)	(-3.08)	(-2.86)	(-0.77)	(-2.38)	(-3.29)	(-2.87)
C4 α	-0.052	-0.324**	-0.753***	-0.701***	-0.099	-0.398**	-0.819***	-0.72***
	(-0.38)	(-2.10)	(-2.93)	(-2.73)	(-0.73)	(-2.49)	(-3.17)	(-2.77)
FF5 α	-0.014	-0.304*	-0.831***	-0.817***	-0.054	-0.377**	-0.88***	-0.826***
	(-0.10)	(-1.95)	(-3.08)	(-3.06)	(-0.41)	(-2.33)	(-3.27)	(-3.08)
SY4 α	-0.056	-0.303*	-0.855***	-0.799***	-0.134	-0.406**	-0.956***	-0.822***
	(-0.37)	(-1.78)	(-3.02)	(-2.85)	(-0.89)	(-2.29)	(-3.36)	(-2.87)

	Panel A: Equal-Weight				**Panel B: Value-Weight**			
LIQ / Signal	1	2	3	$(3-1)$	1	2	3	$(3-1)$
1	0.272	0.43*	0.415	0.143	0.261	0.479**	0.429	0.168
	(1.45)	(1.87)	(1.55)	(0.73)	(1.48)	(2.09)	(1.55)	(0.84)
2	0.03	0.003	0.033	0.003	0.021	0.091	-0.113	-0.134
	(0.16)	(0.01)	(0.14)	(0.02)	(0.12)	(0.40)	(-0.47)	(-0.77)
(2-1)	-0.242*	-0.427**	-0.382	-0.14	-0.239*	-0.388**	-0.541**	-0.302
	(-1.68)	(-2.49)	(-1.61)	(-0.56)	(-1.69)	(-2.38)	(-2.17)	(-1.19)
C4 α	-0.255*	-0.434**	-0.358	-0.104	-0.263*	-0.394**	-0.516**	-0.253
	(-1.73)	(-2.50)	(-1.47)	(-0.41)	(-1.82)	(-2.38)	(-2.03)	(-0.98)
FF5 α	-0.214	-0.442**	-0.38	-0.166	-0.227	-0.399**	-0.524**	-0.298
	(-1.43)	(-2.49)	(-1.53)	(-0.65)	(-1.56)	(-2.34)	(-2.04)	(-1.16)
SY4 α	-0.255	-0.479**	-0.362	-0.107	-0.295*	-0.438**	-0.551*	-0.255
	(-1.62)	(-2.52)	(-1.37)	(-0.39)	(-1.89)	(-2.41)	(-1.95)	(-0.90)

H. Contributions of Portfolio Return by Commodity

Figure H.I: Contributions of the returns of the Value-Weight Short portfolio by commodity, in the years 2015-2016, utilizing the signal of MA(2) Managed Money Net Change

Notes: This figure focus on the years 2015 and 2016 only. The right axis of the figure plots the Short portfolio's cumulative weekly returns in dollar amount assuming $1 was invested in August 2006, with returns first value-weighted across firms within a commodity equity-based portfolio, then equal-weighted across all commodity equity-based portfolios traded, signaled by the MA(2) MM Net Change measure. The portfolio are constructed per Section 3.2 following the *Wednesday-to-Tuesday* convention. On the left axis, this figure decomposes the weekly contributions in % of each commodity equity-based portfolio to the return of the Short portfolio. For instance, the Short Portfolio realizes, in the week 31 of 2015, a weekly return of -3.9%. During that week, 7 commodity-equity portfolios were signaled short and traded as part of the Short portfolio (while coal, petroleum and steel were signaled long). Among the shorted commodity-equity portfolios, 6 commodities realized negative returns, on average -4.7% (Silver, Oil & Gas, Gold, MiscMetal, Copper and Biofuel contributes to 24.1%, 20%, 19.9%, 16.8%, 14% and 5.2% of this negative average, respectively) and one commodity (Lumber) demonstrated positive returns, on average 0.8%. Together these 6 commodities yield a weekly return of -3.9% for the Short portfolio.

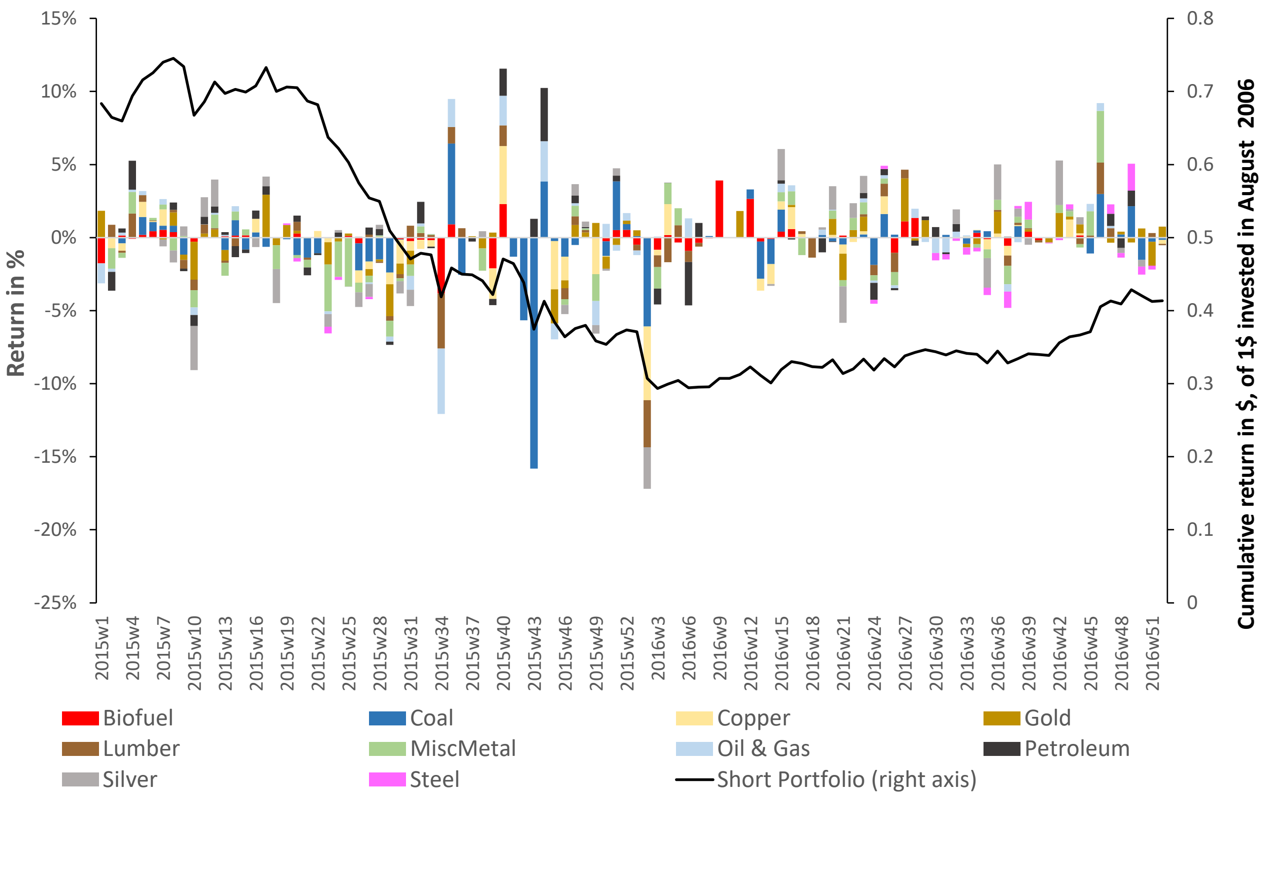


Figure H.II: Contributions to the returns of the Value-Weight Long portfolio by commodity, in the years 2015-2016, utilizing the signal of MA(2) Managed Money Net Change

Notes: This figure focus on the years 2015 and 2016 only. The right axis of the figure plots the Long portfolio's cumulative weekly returns in dollar amount assuming $1 was invested in August 2006, with returns first value-weighted across firms within a commodity equity-based portfolio, then equal-weighted across all commodity equity-based portfolios traded, signaled by the MA(2) MM Net Change measure. The portfolio are constructed per Section 3.2 following the *Wednesday-to-Tuesday* convention. On the left axis, this figure decomposes the weekly contributions in % of each commodity equity-based portfolio to the return of the Long portfolio. For instance, the Long Portfolio realizes, in the week 45 of 2016, a weekly return of 2.35%. During that week, 6 commodity-equity portfolios were signaled long and traded as part of the Long portfolio (the other 4 commodities were signaled short). Among the longed commodity-equity portfolios, 3 commodities realized positive returns, on average 3.63% (silver, copper and steel contributed to 42.1%, 23.4%, 34.5% of this positive average, respectively) and 3 commodities demonstrated negative returns, on average -1.28% (gold, petroleum and biofuel contributed to 65.4%, 29.2% and 5.4% of this negative average, respectively), and together the 6 commodities yield a weekly return of 2.35% for the Long portfolio.